BPNN-ACO application on minimization of hole delamination during GFRP drilling process

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Abstract. Delamination defects during the drilling process on the glass fiber reinforced polymer (GFRP) have a great contribution to the component failure. Hence, it is necessary to properly choose the combination of machining variables to minimize hole entry delamination (EnDel) and hole exit delamination (ExDel) during drilling process simultaneously. This study underlines the modelling and minimizing the EnDel and hole ExDel during GFRP drilling process by combining a backpropagation neural network (BPNN) method and ant colony optimization (ACO). The varied drilling parameters were type of drill point angle, feeding speed, and cutting speed. The optimum BPNN architecture could be obtained by using 3-4-2-5-8-2 network architecture with tan-sig activation function. The optimum GFRP drilling parameters that can minimize EnDel and ExDel simultaneously were 116° of drill point angle, 51.3 mm min⁻¹ of feeding speed and 4975 rpm of spindle speed.

Keywords: ACO, BPNN, delamination, optimization

1. Introduction
Fiber-reinforced polymer (FRP) types such as glass fiber reinforced polymer (GFRP) and carbon fiber reinforced plastics (CFRP) had been in a promising business. Especially in aircraft industries, where weight reduction is required to get higher strength-to-weight ratio. Furthermore, higher strength-to-weight ratio leads to more efficient structure that may saves a lot of money for the aircraft company. This reason drives demands growth on FRP in recent years [1,2].

FRP consist of a combination of two different materials (fiber and polymer) in a proper percentage. Under its incredible properties like high strength-to-weight ratio, high corrosion resistance, and flexible formability, it is appropriate to replace metal with FRP to increased fuel consumption by reducing its weight. In aviation industries, FRP act as thousands structural parts which needed to be assembled. In that case, mechanical joint such as rivet comes in play. Thus, an enormous quantity of holes is necessary to be drilled. Drilling covers 40% total of machining operations during assembly. However, delamination, thermal alterations, and fatigue are various problems that take place in the drilling process we-have-to-deal-with. This undesired problem
results in poor hole tolerance and surface finish. Therefore, a vast majority of parts done by drilling process have to come to the rejection section [2].

The delamination in FRP related to separated plies and matrix cohesiveness that leads to a component failure. Delamination of fibers is a significant problem during the machining process of a composite material. Nowadays, many research discovered the thrust force is the significant factor of delamination [3-5]. Hocheng et al. [6] found that the minimum force which causes delamination while drilling the FRP is the critical delamination force. Furthermore, to dismiss delamination when drilling FRP, the thrust force applied to FRP must not surpass the critical thrust force of the not-drilled part composite plate.

Numerous latest researches cover the effect of drilling parameters such as diameter, drill geometries on thrust force, delamination, and torque [3-5]. Sorentino et al. [7] demonstrate how the delamination factor increased with higher feed rates and its relation to thrust forces. Hence, optimization is required to increase effectiveness and reduce production costs significantly.

The revolutionary of intelligent algorithms attracts a lot of attention in the FRP research. Bououden et al. [8] found that optimization methods, such as ant colony optimization (ACO), attempted to achieve better solutions. This heuristic-based optimization guarantee solution in difficult non-linear optimization tasks using prior iterations. Several techniques have been developed to optimize drilling on FRP. Statistically based optimization methods are commonly used. For example, response surface methodology (RSM), Taguchi method, Principal component analysis (PCA), and grey relational analysis (GRA) [9-11]. For analyzing the parametric effect on the different results, RSM is the most commonly used ones to achieve the solutions [12].

How the human brain works gives an inspiration for an ANN basis. Biological neural networks motivate the development of ANN to become more advance. Various problems related to optimization, are being designed using artificial neural network [13, 14]. Thus, ANN has a robust adaptive and well-organized system that can prevent unclear connections between input and output [6,15]. Anarghya et al. [16] have used a multi-layered perceptron neural network (MLPNN) model for predicting the Thrust and torque force during drilling of Aramid-FRP composite and found the developed MLPNN-GA model provided higher accuracy than RSM. Various parameters were used, such as drill point geometry, drill diameter, feed rate, and spindle speed, with delamination factor as a result of this study.

Research in GFRP has been developed into a significant number of journals, despite that, no study is found to obtain minimum hole entry delamination (EnDel) and hole exit delamination (ExDel) simultaneously using the BPNN-ACO method. BPNN is used to mimicking the relationship between drilling process (i.e., drill point angle, feeding rate, and spindle speed) as an input parameters and drilling responses (i.e., EnDel and ExDel) an output. At last procedure, ACO will obtained the optimized EnDel and ExDel simultaneously.

2. Research Methodology
In this study, an integration of two method namely backpropagation neural network (BPNN) and ant colony optimization (ACO) has been applied to mimicking the developed EnDel and ExDel throughout drilling process of GFRP. The steps for predicting and minimizing the EnDel and ExDel can be seen in Figure 1. The glass fiber reinforced polymer having a 4 mm in thickness, 200 mm x 30 mm in length and width. The drilling procedure were done with different drill point angle (100°, 118°, 134°) with 10 mm of diameter. Furthermore, the experiment also conducted by varying the drilling parameters, namely feeding rate (50, 110, and 170 mm/min) and cutting speed (62.8, 78.5 and 94.2 m/min). The drilling experiment were performed on CNC vertical machining center without cutting fluid as shown in Figure 2. The measurement of EnDel and ExDel are represented
by delamination factor that defined as a ratio between maximum diameter \(D_{\text{max}}\) in the hole surface area and the drill bit diameter \(D_0\) [17], as expressed in:

\[
D = \frac{D_{\text{max}}}{D_0}
\]  

(1)

Experiment were carried out according to the full factorial design of experiment (DOE). The DOE accommodating three drilling parameters (drill point angle, feed rate, and cutting speed) which result in 27 different drilling combination. Three replications were done for each drilling combination to ensure the accuracy of the drilling prediction using BPNN-ACO.

Figure 1. Steps of EnDel and ExDel Minimization by Utilizing BPNN-ACO Technique

Figure 2. GFRP Drilling Process
Figure 3. Best BPNN Network Architecture
Figure 4. Neural Network Regression for 3-4-2-5-8-2 BPNN Architecture

Table 1. EnDel and ExDel Measurement of GFRP Drilling Process

| No | Drill Point Angle | Feeding Rate [mm/min] | Spindle Speed [rpm] | Hole Entry Delamination (EnDel) | Hole Exit Delamination (ExDel) |
|----|------------------|-----------------------|--------------------|-------------------------------|------------------------------|
|    |                  |                       |                    | R1                            | R2                           |
| 1  | 100              | 50                    | 3000               | 1.191                         | 1.193                        |
| 2  | 100              | 50                    | 4000               | 1.143                         | 1.139                        |
| 3  | 100              | 50                    | 5000               | 1.104                         | 1.105                        |
| 4  | 100              | 110                   | 3000               | 1.332                         | 1.333                        |
| 5  | 100              | 110                   | 4000               | 1.283                         | 1.284                        |
| 6  | 100              | 110                   | 5000               | 1.247                         | 1.215                        |
| 7  | 100              | 170                   | 3000               | 1.442                         | 1.482                        |
| 8  | 100              | 170                   | 4000               | 1.429                         | 1.429                        |
| 9  | 100              | 170                   | 5000               | 1.367                         | 1.377                        |
| 10 | 118              | 50                    | 3000               | 1.238                         | 1.202                        |
| 11 | 118              | 50                    | 4000               | 1.157                         | 1.168                        |
| 12 | 118              | 50                    | 5000               | 1.122                         | 1.121                        |
| 13 | 118              | 110                   | 3000               | 1.357                         | 1.357                        |
| 14 | 118              | 110                   | 4000               | 1.308                         | 1.304                        |
| 15 | 118              | 110                   | 5000               | 1.255                         | 1.258                        |
| 16 | 118              | 170                   | 3000               | 1.491                         | 1.497                        |
| 17 | 118              | 170                   | 4000               | 1.441                         | 1.45                         |
| 18 | 118              | 170                   | 5000               | 1.397                         | 1.399                        |
| 19 | 140              | 50                    | 3000               | 1.222                         | 1.221                        |
| 20 | 140              | 50                    | 4000               | 1.174                         | 1.184                        |
| 21 | 140              | 50                    | 5000               | 1.129                         | 1.134                        |
| 22 | 140              | 110                   | 3000               | 1.373                         | 1.368                        |
| 23 | 140              | 110                   | 4000               | 1.320                         | 1.326                        |
| 24 | 140              | 110                   | 5000               | 1.275                         | 1.276                        |
| 25 | 140              | 170                   | 3000               | 1.511                         | 1.502                        |
| 26 | 140              | 170                   | 4000               | 1.462                         | 1.462                        |
| 27 | 140              | 170                   | 5000               | 1.412                         | 1.406                        |

3. Experiment Results and BPNN-ACO Optimization

After performing drilling experiments according to the full factorial DOE, EnDel and ExDel can be seen in Table 1. After drilling experiment, the next procedure was determining the best BPNN architecture by optimizing its parameters using ACO. The total data (54) was split into three, where 70%, 15% and 15% were applied for training, testing, and validation, respectively.

The optimum BPNN architecture to predicting the EnDel and ExDel having three neurons on the input layer, four neurons on the first hidden layer, two neurons on the second hidden layer, five neurons on the third hidden layer, eight neurons on the fourth hidden layer and two neurons on the output layer (3-4-2-5-8-2), with tansig activation function as shown in the Figure 3. By utilizing this network architecture, the resulting neural network training regression was 0.99674 for
training, 0.99246 for testing, 0.99786 for validation, and 0.99625 for all data as shown in Figure 4. Moreover, Figure 5 shows the comparison between experiment result and prediction value of EnDel and ExDel. By analysing the Figure 5, it may be declared that BPNN-ACO was capable to estimate the EnDel and ExDel during GFRP drilling process, since the prediction and experimental results were approximately the same.

![Comparison of EnDel and ExDel](image)

**Figure 5.** Comparison among Prediction and Experimental Results by Utilizing BPNN-ACO for (a) Hole Entry Delamination and (b) Hole Exit Delamination
Next steps, to minimize EnDel and ExDel a fitness function must be determined by using BPNN model. Fitness function applied in this study was computed by using equation (2), while \(\text{Obj}_{\text{EnDel}}\) and \(\text{Obj}_{\text{ExDel}}\) were computed using equations (3-7).

\[
\begin{align*}
F_{\text{fitness}} &= \text{Obj}_{\text{EnDel}} + \text{Obj}_{\text{ExDel}}, \\
\text{Obj}_{\text{ln}} &= \left( \sum_{n=1}^{2} y_{nm} \left( \frac{2}{1+e^{-2d_m}} - 1 \right) \right) + v_{0n}, \\
d_m &= \left( \sum_{m=1}^{8} x_{ml} \left( \frac{2}{1+e^{-2c_l}} - 1 \right) \right) + v_{0m}, \\
c_i &= \left( \sum_{l=1}^{5} w_{lk} \left( \frac{2}{1+e^{-2b_k}} - 1 \right) \right) + v_{0l}, \\
b_k &= \left( \sum_{j=1}^{2} v_{kj} \left( \frac{2}{1+e^{-2a_j}} - 1 \right) \right) + v_{0k}, \\
a_j &= \left( \sum_{j=1}^{4} (u_{ji} + Q_{li}) \right) + u_{0j},
\end{align*}
\]

with:

\(\text{Obj}_{\text{EnDel}}\) : Identified as hole entry delamination objective function.
\(\text{Obj}_{\text{ExDel}}\) : Identified as hole exit delamination objective function.
\(\text{Obj}_{\text{ln}}\) : Identified as objective function, i.e., EnDel and ExDel
\(Q_i\) : Normalization value of GFRP drilling parameters.
\(a_j\) : Activation value for each neuron on first hidden layer.
\(b_k\) : Activation value for each neuron on second hidden layer.
\(c_i\) : Activation value for each neuron on third hidden layer.
\(d_m\) : Activation value for each neuron on fourth hidden layer.
\(i\) : Sign of GFRP drilling process parameters, \(i = 1, 2, 3,\)
\(j\) : Sign of neurons on first hidden layer, \(j = 1, 2, ..., 4,\)
\(k\) : Sign of neurons on second hidden layer, \(k = 1, 2,\)
\(l\) : Sign of neurons on third hidden layer, \(l = 1, 2, ..., 5,\)
\(m\) : Sign of neurons on fourth hidden layer, \(m = 1, 2, ..., 8,\)
\(n\) : Sign of GFRP drilling responses parameters, \(n = 1, 2,\)
\(u_{ji}\) : Weight value for input layer to first hidden layer.
\(u_{0j}\) : Bias value for input layer to first hidden layer bias.
\(v_{kj}\) : Weight value for first hidden layer to second hidden layer.
\(v_{0k}\) : Bias value for first hidden layer to second hidden layer.
\(w_{lk}\) : Weight value second for hidden layer to third hidden layer.
\(w_{0l}\) : Bias value for second hidden layer to third hidden layer.
\(x_{ml}\) : Weight value for third hidden layer to fourth hidden layer.
\(x_{0m}\) : Bias value for third hidden layer to fourth hidden layer.
\(y_{nm}\) : Weight value for fourth hidden layer to output layer.
\(y_{0n}\) : Bias value for fourth hidden layer to output layer.

The applied parameters of ACO in this study were the maximum number of iterations, intensification factor, deviation distance ratio, and the number of ants, in succession were 1000, 0.5 and 1, and 100. According to the BPNN-ACO technique, the minimum EnDel and ExDel can be obtained by using optimum GFRP drilling parameters i.e., 116° of drill point angle, 51.3 mm/min of feeding speed and 4975 rpm of spindle speed. The predicted EnDel and ExDel using optimum GFRP drilling parameters in succession were 1.155 and 1.223. The comparison of hole delamination between before and after optimization can be seen in Table 2.

4. Conclusion
The following are the conclusions from this study:
The optimum BPNN network architecture could be achieved by using three neurons on the input layer, four neurons on the first hidden layer, two neurons on the second hidden layer, five neurons on the third hidden layer, eight neurons on the fourth hidden layer and two neurons on the output layer (3-4-2-5-8-2) with tan sigmoid activation function.

The optimum GFRP drilling parameters were 116° of drill point angle, 51.3 mm/min of feeding speed and 4975 rpm of spindle speed.

The minimum hole entry delamination and hole exit delamination using optimum GFRP drilling parameters in succession were 1.155 and 1.223.

Table 2. Comparison of Hole Delamination Between Before and After Optimization

| GFRP Drilling Parameters | Before Optimization | After Optimization |
|--------------------------|---------------------|--------------------|
| Hole Entry Delamination  | 140°, 170 mm/min, 3000 rpm | 116°, 51.3 mm/min, 4975 rpm |
| FD_{entry} = 1.515       | FD_{entry} = 1.155   |
| Hole Exit Delamination   | FD_{exit} = 1.822    | FD_{exit} = 1.223   |

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6. Reference list
[1] Baraheni M, Tabatabaeian A, Amini S, Reza G 2019 Composites Part B: Engineering 172 612-620.
[2] Krishnaraj V, Prabukarthi A, Ramanathan, Elanghovan N, Kumar M S, Zitoune R, Davim J P 2012 Composites Part B: Engineering 43 1791-1799.
[3] Soo S L, Abdelhafeez A M, Li M, Hood R, Lim C M 2019 Proceedings of The Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 233 1323-1331.
[4] Xu J, Li C, Chen M, Mansori M E, Ren F 2019 International Journal of Advance Manufacturing Technology 103 3425-3442.
[5] Sorrentino L, Turchetta S, Bellini C 2017 Composite Structures 168 549-561.
[6] Bououiden S, Chadli M, Karimi H R 2015 Information Sciences 299 143-158.
[7] Hocheng H, Chen C C, Tsao C C 2018 Composite Structures 203 566-573.
[8] Ferdous W, Manalo A, Aravinthan T 2017 Construction and Building Materials 145 76-87.
[9] Shunmugesh K and Paneerselvam K 2017 Materials Today: Proceedings 4 2861-2870.
[10] Caggiano A, Angelone R, Napolitano F, Nele L, Teti R 2018 Procedia CIRP 78 307-312.
[11] Nagaraja S, Mervin A H, Raviraj S, Divakar S S, Vijay G S 2016 Applied Soft Computing 41 466-478.
[12] Anarghya A, Harshith D N, Rao N, Nayak N S, Gurumurthy B M, Abhishek V N, Patil I G S 2018 Heliyon 4 703.
[13] Soepangkat B O P, Pramujati B, Effendi M K, Norcahyo R, Mufarrih A M 2019 International Journal of Precision Engineering and Manufacturing 20 593-607.
[14] Nurullah F P, Pramujati B, Suhardjono, Effendi M K, Soepangkat B O P, Norcahyo R, AIP Conference Proceedings 2114 030013.
[15] Karatas M A and Gokkaya H A 2018 Defence Technology 14 318-326.
[16] Wang Q and Jia X 2020 Composite Structures 235 111803.
[17] Soepangkat B O P, Norcahyo R, Effendi M K, Pramujati M K 2020 Engineering Science and Technology, an International Journal 23 700-713.