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Rachmadi Norcahyo
rachmadinorcahyo@ugm.ac.id
Universitas Gadjah Mada
Achmad Pratama Rifai
Universitas Gadjah Mada
Setyo Tri Windras Mara
UNSW Canberra
Bobby Oedy Pramoedyo Soepangkat
Institut Teknologi Sepuluh Nopember
Mohammad Khoirul Effendi
Institut Teknologi Sepuluh Nopember

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A back propagation neural network with improved sine cosine algorithm approach for multi-response drilling optimization of carbon fiber reinforced polymer (CFRP)

Rachmadi Norcahyo[1*], Achmad Pratama Rifai[1], Setyo Tri Windras Mara[2], Bobby Oedy Pramoedyo Soepangkat[3], Mohammad Khoirul Effendi[3]

[1] Universitas Gadjah Mada, Yogyakarta, Indonesia, Departemen of Mechanical and Industrial Engineering

[2] UNSW Canberra, Canberra, ACT, Australia, School of System and Computing.

[3] Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia, Department of Mechanical Engineering.

* Corresponding author: rachmadinorcahyo@ugm.ac.id

Abstract

In this study, the integration of Back Propagation Neural Network (BPNN) with an Improved Sine-Cosine Algorithm (ISCA) is proposed to predict and optimize the drilling process of carbon fiber reinforced polymer (CFRP). The BPNN is firstly performed to model and predict the optimal values of the drilling responses, in which multiple characteristics of drilling performances have been taken into account, namely thrust force (F_{Th}), torque (M), hole entry delamination (FD_{en}), and hole exit delamination (FD_{ex}). The model is then being optimized by the ISCA to obtain the best drilling parameters level combination. Two mechanisms are presented to improve the general framework of Sine Cosine Algorithm (SCA): 1) adaptive selection of operators, and 2) population management technique. The results have clearly shown that the proposed approach is able to improve the performance of the standard BPNN-SCA.

Keywords: Back propagation neural network; CFRP; Drilling; Multi-response optimization; Sine-cosine algorithm

1 Introduction

Excellence durability and strength-to-weight ratio made carbon fiber reinforced polymer (CFRP) used in the wide application of the aerospace and aviation industry. The drilling process is a vital machining process to make a hole for connecting the CFRP's structural parts by riveting or bolting in the final assembly. Several composite's machining damages such as fiber-matrix debonding, fiber pull-out, and delamination often occurs during inadequate cutting

conditions, which dreadfully deteriorate the hole quality and the longevity of the components. Hence, a lot of studies were done to address this problem by investigating the effect of machining quality under different drilling parameters and its optimization to improve the machining quality.

Drilling parameters such as cutting speed, feed rate, and drill bit geometry have an impact on the CFRP's dimensional precision and delamination damage. The study by Durao et al. (2010) shown that feeding speed and drill bit geometry have a great influence to generate thrust force that affect the delamination damage around the drilled hole. Torque and thrust force generated during the drilling process of the composite are known as the principle causes of delamination damage (Soepangkat et al., 2019). Qiu et al. (2018) measured the influence of stepped drill geometry and varied drilling parameters on the hole wall damage and thrust force. They found that the spindle speed and feed rate are the main contributors to the hole wall damage size. Similarly, Krishnamoorthy et al. (2012) also found that feed rate is the dominant factor that affects the hole entry and hole exit delamination during a CFRP drilling process. During the drilling process of composites, the hole exit delamination has more severe damage than the hole entry delamination (Liu et al., 2012). Further study regarding composite drilling phenomenon and optimization of composite drilling was done by Soepangkat et al. (2019). During a drilling process of CFRP, it was stated that the most influential drilling parameters to the delamination damage, generated thrust force, and torque is the feed rate, followed by the spindle speed and drill bit geometry. Considering all those studies, it is concluded that the delamination damage can be minimized with a proper combination of drill bit type, spindle speed, and feed rate.

Recently, a data-driven approeches have continued to advance the understanding of CFRP drilling damage. Ghasemian Fard et al. (2024) developed a partial least squares regression model that predicted CFRP delamination defects across different drill geometries with high accuracy, while Benkhelladi et al. (2024) combined an Adaptive Neuro-Fuzzy Inference System (ANFIS) with a deep neural network to predict cutting parameters and hole quality in hybrid composite drilling, reinforcing the value of hybrid data-driven models for this class of problem.

A prominent part in the field of machining prediction and optimization has been played by soft computing techniques. As stated by Chandrasekaran et al. (2010), with the surging popularity of capital-intensive CNC machine tools, the challenging efforts to model and optimize machining process are practically required as these efforts may lead to a cost-efficient state of machining processes. Within this context, various methods such as neural networks

and metaheuristic algorithms have been implemented due to the advancement of computer technology and its ability to deal with complex engineering problems. Thus, in this study, the delamination damage during drilling process of CFRP will be minimized by utilizing the back propagation neural network and improved version of Sine-Cosine Algorithm (SCA). The drilling experiments are carried out by varying the drill bit geometry, feed rate, and spindle speed, whereas the thrust force, torque, and delamination are considered as the drilling responses.

The remainder of this paper is structured as follows. Section 2 presents the literature review and highlights the shortcomings of related literature. The Back Propagation Neural Network (BPNN) is presented respectively in Section 3, while Improved Sine-Cosine Algorithm (ISCA) is outlined Section 4. Section 5 reports the computation experiment results and analyzes the findings. At last, Section 6 concludes the study and discuss the future research.

2 Literature Review

Metaheuristic is an active research area. A survey from Hussain et al. (2018) reported 1222 literature related to metaheuristic have been published from 1983 to 2016, and still continuously growing until now. To this end, a large number of algorithm frameworks have been introduced and this fact has led to a considerable problem for the research community: the proliferation of metaphor-based algorithms. A strong critic from Sorensen (2015) pointed out that the "tsunami" of novel metaheuristic methods has produced numerous publications with low quality of theoretical contributions and distracting attention away from several methods with truly marvelous mathematical ideas.

Among the recently proposed metaheuristic framework with interesting mathematical ideas, the SCA from Mirjalili (2016) stands out as one the most promising algorithm. The applicability of SCA to solve a diverse range of optimization problems have been shown in recent publications. For instances, the SCA has been implemented to optimize the optimal power flow problem (2018) and various feature selection tasks (Hafez et al., 2016; Sindhu et al., 2017; Belazzoug et al., 2019). The effectiveness of this algorithm also has been shown in handling the pathological brain detection using magnetic resonance imaging (MRI) in healthcare analytics (Nayak et al., 2018) and other problems that need to be optimized such as the parameter optimization of support vector (Li et al., 2018), traveling salesman problem (Tawhid and Savsani, 2019), and data clustering (Kumar and Kumar, 2017). Further, the implementation of SCA in training the multi-layer perceptron of neural networks has been executed by Sahlol et al. (2016) and Gupta and Deep (2019) with promising results.

In this study, the possibility to improve the classical SCA with population management technique and adaptive operator selection has been taken into account. The former mechanism was formally defined by Sorensen and Sevaux [20] that introduced the population management for a memetic algorithm that is a population-based metaheuristic framework with multiple solution agents, similar to the classical SCA. The effectiveness of this approach to control the diversity of solutions has been illustrated mainly in the operations management field, such as the heterogeneous fleet vehicle routing problem (Sorensen and Sevaux, 2006), traveling salesman problem with drone (Ha et al., 2019), and integrated production-distribution problem (Prins, 2009). To the best of our knowledge, this is the first study to incorporate the population management technique into the SCA. Meanwhile, the latter mechanism is modified from the adaptive large neighborhood search (Pisinger and Ropke, 2007), in which a range of diverse operators are executed with continuously updated probabilities that are based on the historical performance of each operator. Similarly, in the proposed ISCA, the parameter P_y (see Equation 3) that controls the selection probability of the sine and cosine function is continuously updated based on the performance of each function, thus, the function that historically returns the better solutions will be given a higher chance to be selected in each iteration.

Few previous works have already attempted to introduce an adaptive mechanism for the SCA. For instances, Bureerat and Pholdee (2017) presented an adaptive SCA with differential evolution algorithm as a mutation operator, in which the adaptive mechanism was introduced with a novel equation to update the values of parameters r_2 and r_3. Issa et al. (2018) separately proposed an adaptive mechanism for SCA by integrating it with the classical particle swarm optimization (PSO) that handles the exploration tasks better than the SCA operators within a multi-layer structure. Jusof et al. (2019) modified the original Equation (4) with a pre-defined exponential equation in order to enhance the exploitation process of SCA, while Gupta and Deep (2020) proposed a modification into the classical sine and cosine functions with a self-adaptation based vector that separates the original equation into two different components, namely the social component that provides the searching direction towards the best solution of the current population and the cognitive component that explains the searching direction towards the previously obtained best solutions that stored in a memory vector. More recently, Wang et al. (2020) presented a modification of the SCA with symmetric functions of sine and cosine functions in Equation (3) to improve the convergence speed and accuracy of the SCA, then propose an adaptive operator selection mechanism based on the selection frequency of the novel symmetric functions and the original sine-cosine functions. Within this regard, this study

is by no means saying that these previously mentioned mechanisms are not effective and impressive, however, it is easy to point out that all previous studies were either incorporating new equations or hybridizing the SCA with another metaheuristic framework, based on preliminary experiments. On the other hand, this study is motivated to exhibit that simple mechanism such as updating selection probability based on previous performances to select either the sine or cosine function for updating the search agent may already improve the exploitation aspect of the classical SCA. Likewise, a similar logic applies to the motivation to engage a simple population management technique into the proposed ISCA, as the classical SCA does not have any mechanism to control the diversity of solutions and may still become a victim of premature convergence even though it falls into the class of population-based algorithm [20]. In a similar trends, Pham et al. (2024) hybridized the SCA with roulette wheel selection and opposition-based learning to strengthen the balance between exploration and exploitation in engineering optimization problems, while Wei et al. (2024) proposed a multi-strategy-based adaptive SCA that dynamically adjusts its search behavior according to the evolving state of the population. Both studies reinforce that adaptively steering the SCA's operator behavior, rather than solely re-deriving its trigonometric update equations, remains an active and productive line of improvement.

Moving forward, the implementation of SCA in the machining optimization process is very limited. The only study that was implementing the SCA to optimize the machining operation was conducted by Khalilpourazari and Khaillpourazary (2017). The author utilized SCA to minimize total production time of multi-pass milling process. Further, they incorporated the SCA with Whale Optimization Algorithm (Mirjalili and Lewis, 2016) and found that their proposed algorithm gave a better result compared to the approaches of dynamic programming, Genetic Algorithm (GA), Simulated Annealing, and Hybrid Fuzzy Particle Swarm Optimization. This result motivates us to implement the SCA as a promising optimization method for problems in the field of manufacturing processes.

In contrast, some classical metaheuristic algorithms have been vastly applied for optimizing the manufacturing processes. Daniel et al. (2020) implemented the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for simultaneously minimizing the temperature and maximizing the metal removal rate during a drilling process of Al5059-SiC-2%MoS_2 matrix composite. An Adaptive Network-based Fuzzy Inference System (ANIFS) and GA was integrated by Kumar and Hynes (2020) to predict and optimize the surface roughness in thermal drilling of galvanized steel. Krishnaraj et al. (2012) optimized the delamination, hole diameter, and the circularity of a CFRP drilling process by deploying GA for obtaining the optimal

combination of spindle speed and feed rate. Abhisek et al. (2016) applied a Fuzzy Embedded Harmony Search (HS) algorithm to minimize the delamination factor, surface roughness, torque, and thrust force during a CFRP drilling process, and recently, Wang and Jia (2020) utilized a hybrid method integrating the Artificial Neural Network (ANN), NSGA-II, and Fuzzy C-means to find the best material removal rate, delamination and thrust force of the CFRP drilling parameters.

Beyond SCA, other metaheuristic and adaptive control approaches have also been explored for composite machining optimization in the last few years. Kharwar and Verma (2023) applied a nature-inspired grey wolf algorithm to optimize milling parameters of polymer nanocomposites, and Mahmood et al. (2023) proposed an adaptive control strategy paired with an enhanced optimization algorithm to improve drilling efficiency in composite materials, indicating that adaptive, nature-inspired optimization continues to gain traction across composite machining processes more broadly.

In summary, the contributions of this study are as follow. Firstly, the mechanisms of adaptive operator selection and population management are proposed to improve the general framework of SCA, and this is the first study to introduce the combination of these mechanisms into the SCA. Secondly, this study attempts to implement the SCA-based framework to develop a heuristic algorithm for a machining optimization problem, which is still rare to be done. Thirdly, this is the first study to implement a SCA-based algorithm for optimizing the parameters of the drilling process. Lastly, the proposed ISCA is implemented to optimize a multi-response BPNN model of CFRP composites drilling process.

3 Back Propagation Artificial Neural Network

BPNN is a popular type of artificial neural network (ANN) that introduced by McClelland et al. (1986). The BPNN is a supervised learning procedure with main aim to overcome the limitation of perceptron, which is the main issue of the classical ANN. The BPNN typically deploys an architecture with interconnected layers in the following manner: a single input layer, a single output layer, and one or multiple hidden layers. Within this architecture, an activation function such as sigmoid function and various hyperbolic functions is commonly required to process the incoming signal at the neurons of hidden and output layers.

The BPNN is developed based on the rule of error correction learning. This rule utilizes an error function to modify and adjust the weights of the connections between neurons, with the aim for gradually reducing the deviation between the actual and the desired network output (error). The adjustment of weight prompts the hidden units within the hidden layers to

continuously rearrange their weights in order to represent the prominent features of the task domain, and this domain will also determine the amount of hidden units in each hidden layer. Furthermore, the BPNN learning process comprises of two main stages, namely the forward and backward propagation.

1. *First stage - Forward propagation*

The outputs of the forward propagation are computed according to the inputs and the current weights. For calculating the net excitation, every hidden and output nodes is considered with regards to these criteria: 1) the values of the previous layer nodes related to the current nodes, 2) the weights of the antecedent layer nodes and the considered nodes, and 3) the threshold value of the current nodes. This continuous net excitation value is then forwarded to the activation function with aim to appraise the output value of the current nodes.

2. *Second stage – Backward propagation*

This stage deals with the deviation between the actual and the expected network output of every individual output node. This value of error is propagated into the previous layer to align the weight of each node. The main goal of this task is to lessen the error at each output node. The computation is then executed by reiterating the forward and backward steps and stopped when the designated level of error is attained.

4 Improved Sine-Cosine Algorithm

4.1 Sine-Cosine Algorithm

The SCA is a population-based metaheuristic framework proposed by Mirjalili (2016). It mainly employs two trigonometric functions to update the candidate solutions: the sine and cosine functions. They are respectively shown in Equation (1) and Equation (2), where $(X_b)_j^t$ represent the position of j-th dimension of the best solution at t-th iteration.

$$X_j^{t+1} = X_j^t + r_1 \sin(r_2) \left| r_3 (X_b)_j^t - X_j^t \right| \quad (1)$$

$$X_j^{t+1} = X_j^t + r_1 \cos(r_2) \left| r_3 (X_b)_j^t - X_j^t \right| \quad (2)$$

Those two equations are then randomly deployed in the following manner:

$$X_j^{t+1} \begin{cases} X_j^t + r_1 \sin(r_2) \left| r_3 (X_b)_j^t - X_j^t \right| & if\ r < P \\ X_j^t + r_1 \cos(r_2) \left| r_3 (X_b)_j^t - X_j^t \right| & if\ r \geq P \end{cases} \quad (3)$$

where $r = U[0,1]$ and P_y is set to 0.5 in the classical design of SCA.

In the aforementioned equations, several random numbers r_1, r_2, and r_3 are presented. The random variable r_1 is used to stabilize the exploitation and the exploration of searching processes and is continuously updated with Equation (4), in which a is a constant parameter and T is the number of maximum generation. The random variable r_2 determines the movement direction of the searching process and is varied within the interval $[0,2\pi]$. Lastly, the random variable r_3 is calculated as in Equation (5) and it stochastically emphasizes or deemphasize the effect of $(X_b)_j^t$ to the searching process, where b is a constant parameter. The *pseudocode* of the general SCA is explained in Algorithm 1.

$$r_1 = a - t(\frac{a}{T}) \tag{4}$$

$$r_3 = (b)\ x\ U[0,1] \tag{5}$$

Algorithm 1: Classical Sine-Cosine Algorithm

Input: $T, N, a,$ and b
Generate a set of initial population $P_0 = \{X_i^1, \dots, X_N^1\}$
While $t < T$
    Calculate the fitness values of each solution
    Update the best solution of this iteration $({X_b}^t)$
    Update r_1, r_2, r_3
    Perform the solution modification according to Equation (3)
End while
Output: P_T and ${X_b}^T$

4.2 Improved Sine-Cosine Algorithm

This study presents an improved version of the SCA (ISCA). The ISCA is presented to enhance the original SCA in two prominent aspects of search algorithms: the exploration and exploitation of the search space. As noted by Gupta and Deep (2019), although the original SCA is able to explore the search space efficiently, but its nature as a population-based algorithm means that the algorithm still sometimes suffers from the overflow of diversity due to the over-exploration. Henceforth, an additive mechanism is required to help the algorithm finds a high potential searching area and exploits the area efficiently, this reasoning leads us to propose a simple adaptive mechanism which adopted from the popular adaptive large neighborhood search (Pisinger and Ropke, 2007) by iteratively updates the value of the parameter P_y that controls the selection probability of the sine (Equation 1) and cosine function (Equation 2).

Compared to the class of trajectory optimization algorithm, the population-based algorithms are generally superior in terms of its ability to explore the search space due to its employment of multiple search agents. However, as famously discussed by Sorensen and Sevaux (2006), the class of population-based algorithms such as GA and SCA may still suffer from a premature convergence during its searching process, which leads to their proposal for a population management technique. Thus, by considering the decision to append an adaptive mechanism to the operators of the proposed ISCA which logically will decrease its exploration ability and enhance the exploitation ability, the searching agents need to be avoided from premature convergence by preserving the diversity of solutions using the aforementioned population management technique.

4.2.1 Adaptive mechanism

This study adds an adaptive mechanism to select the operator for updating the search agents. Here, the probabilities of sine and cosine functions P_y to be selected are influenced by its weight ω_y as described in Equation (6). In every iteration, the weights of operators ω_y are updated according to their historical performance, formulated in Equation (7).

$$P_y = \omega_y / \sum_{y \in \mathrm{Y}} \omega_y \qquad \forall\, y \in \mathrm{Y} \tag{6}$$

$$\omega_{y,I+1} = \lambda(\omega_{y,I}) + (1-\lambda)(\eta_{y,I}) \tag{7}$$

$$\eta_{y,I} = \begin{cases} \Omega_1 & \text{if } \sigma^I \leq \sigma^* \\ \Omega_2 & \text{if } \sigma^I \leq \sigma^{I-1} \\ \Omega_3 & \text{if } \sigma^I > \sigma^{I-1} \end{cases} \tag{8}$$

where $\omega_{y,I+1}$ is the weight of operator y for upcoming iteration $I+1$, while $\omega_{y,I}$ is its current weight. Decay λ is a parameter that controls the sensitivity or weight to change. The parameter $\eta_{y,I}$ indicates the performance of the selected destroy or repair operators in the current iteration. Its value is simply determined based on fitness-based weight adjustment parameter Ω according to the Equation (8). It uses the sum of all objectives σ as the deciding factor.

4.2.2 Population management technique

The acceptance of new agents to be included in the population is determined using the population management technique. In this technique, a new solution X may enter the population P_{I+1} only if $d_P(X) \geq \Delta$, where $d_P(X)$ is the distance of solution X relative to other solutions in the population and Δ is a given threshold that controls the acceptance and rejection. Here we

adopt the mechanism suggested by Prodhon and Prins (2008). At first, Δ is initialized as $\Delta_{\max}$, thus it has high standard of acceptance. Let $\Gamma_{\max}$ is the threshold of a maximum number of rejections. Once the number of successive rejections reaches $\Gamma_{\max}$, the Δ parameter decreases according to the correction schedule $\Delta \leftarrow \Delta(\alpha)$. The decreased Δ thus allows for a lower standard of acceptance. However, the minimum possible value of Δ is always maintained at $\Delta_{\min}$. Once a solution is accepted, the Δ value is set back as $\Delta \leftarrow \Delta_{\max}$. The accepted solution then replaces a member of the current population which has the lowest fitness.

Algorithm 2: Improved Sine-Cosine Algorithm

Input: $T, N, a, b, \Gamma_{\max}, \Omega$, and λ
Generate a set of initial population $P_0 = \{X_i^1, \dots, X_N^1\}$
Set the initial population diversity parameter Δ
Set the initial selection probability $P_y = 0.5$ for $y \in Y$
While $t < T$
    Calculate the fitness values of each solution
    Update the best solution of this iteration ($X_b{}^t$)
    Select the operator based on its probability P_y
    Update r_1, r_2, r_3
    Perform the solution modification according to Equation (3)
    Update the selection probability P_y for $y \in Y$
    Calculate the distance $d_P(X)$
    if $d_P(X) \geq \Delta$ **then**
        Accept the new solution X to enter the population
    Update diversity parameter Δ
End while
Output: P_T and $X_b{}^T$

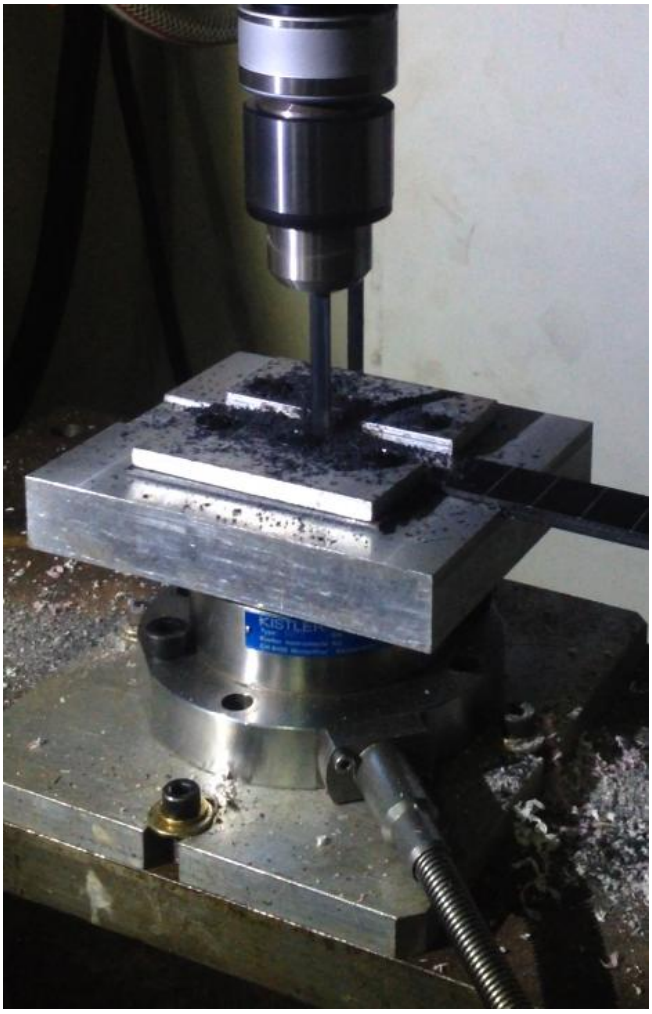


Figure 1. CFRP drilling experiment setups

5 Results and Discussions

Figure 1 presents the CNC Drill & Tapping Machine, Brother TC-22A-O, dynamometer, and specimen fixture which is deployed for the drilling experiment. The experiment is done without using cutting fluid. The CFRP is fabricated by a hand lay-up method with [45/90/45/90/45/90/45/adhesive film/45/90/45/90/45/90/45] fiber orientation. The specimen plate has a thickness of 3 mm, width of 30 mm, and length of 200 mm, with 53 GPa of tensile modulus and 469 MPa of tensile modulus. Kistler 9272 dynamometer is applied for measuring the drilling torque and thrust force during each experiment. Then, the microscopic delamination photos is done by employing a Carl Zeiss Stemi DV Stereo microscop with an image capturing device. Furthermore, the delamination value in the entry and exit section values are calculated by using Equation (9) below (Gaitonde et al., 2008).

$$D = \frac{\mathrm{D_{max}}}{\mathrm{D_0}}, \tag{9}$$

The experiment utilizes two types of distinct drill bit geometry with 8 mm diameter, namely the two edge twist drill (tool 1) and the brad spur drill (tool 2) with a new set of tools for each drilling experiment as seen in Figure 2. Each experiment is done by varying the combination of drilling parameters with different drill bit geometries (i.e., tool 1,2), spindle speeds (1000, 2000, 3000 rpm), and feeding speeds (50,150,250 mm/min).

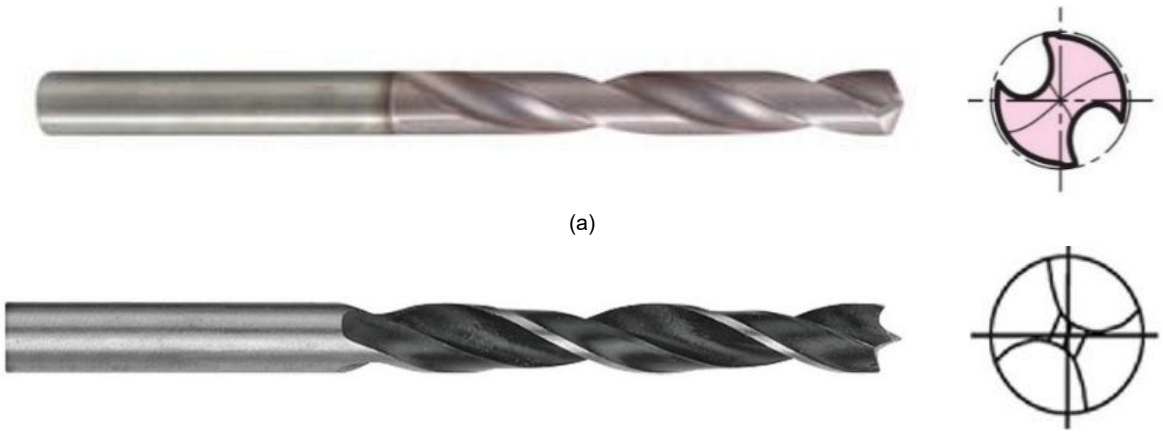
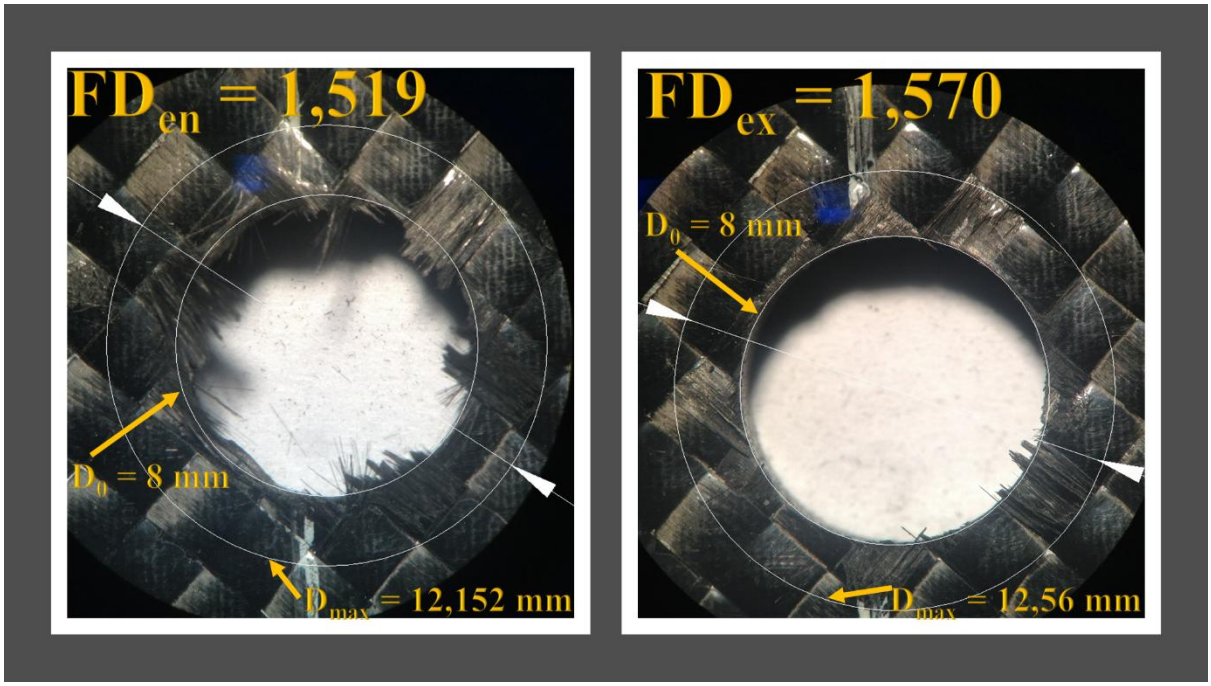


Figure 2. Drill bit geometry (a) tool 1: twist drill and (b) tool 2: brad spur drill

5.1 Results of experiment

The example of delamination measurement in the entry and exit hole section using equation (9) is shown in Figure 3. The torque, hole entry delamination, hole exit delamination, thrust force and material removal rate measurements are executed with three replications for each experiment and the mean result are shown in Figure 4.

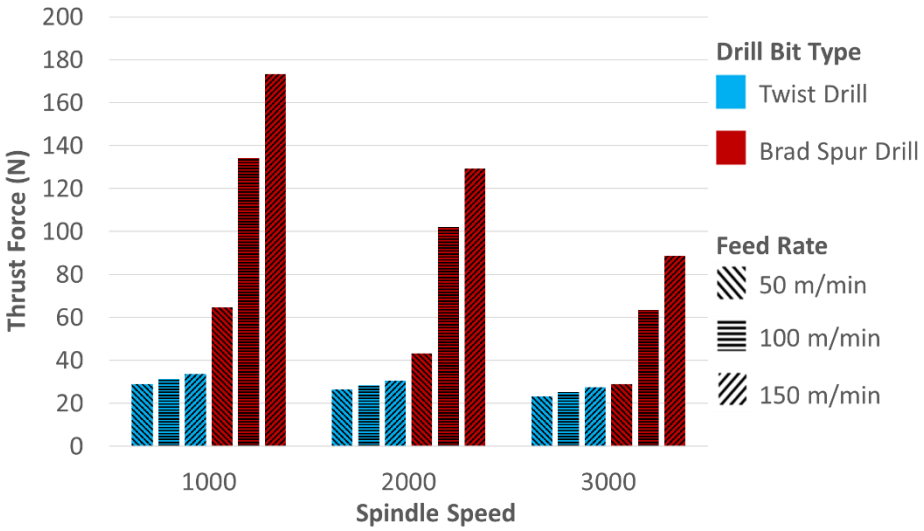


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317 **Figure 3.** Example of delamination measurement in the entry (FD_{en}) and exit (FD_{ex})

318 section

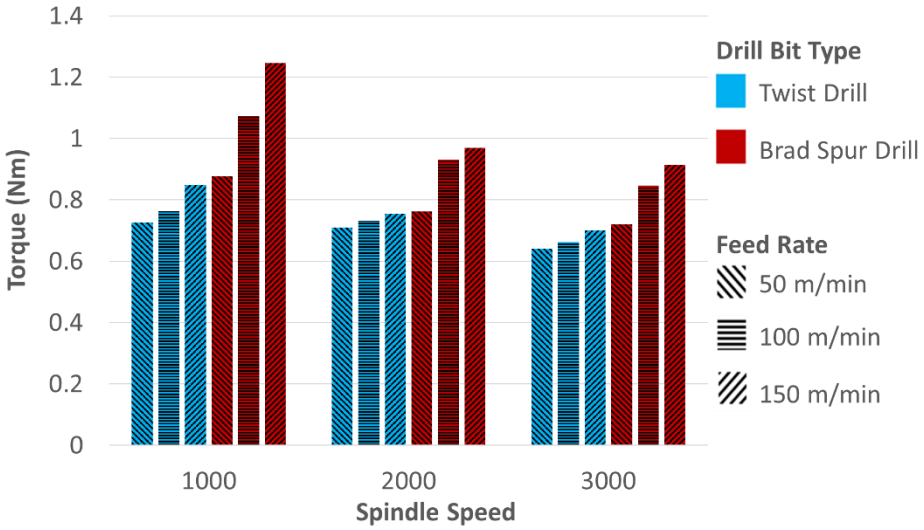
319 **(a)**



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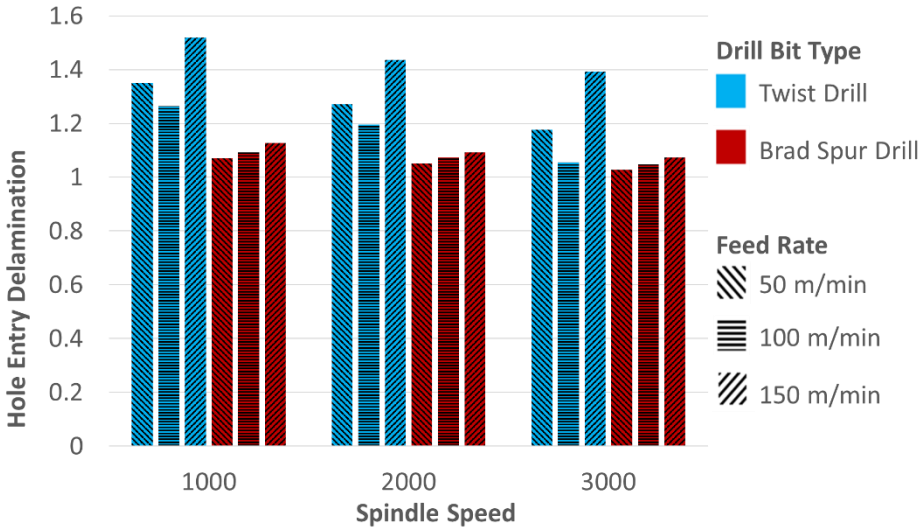
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322 **(b)**



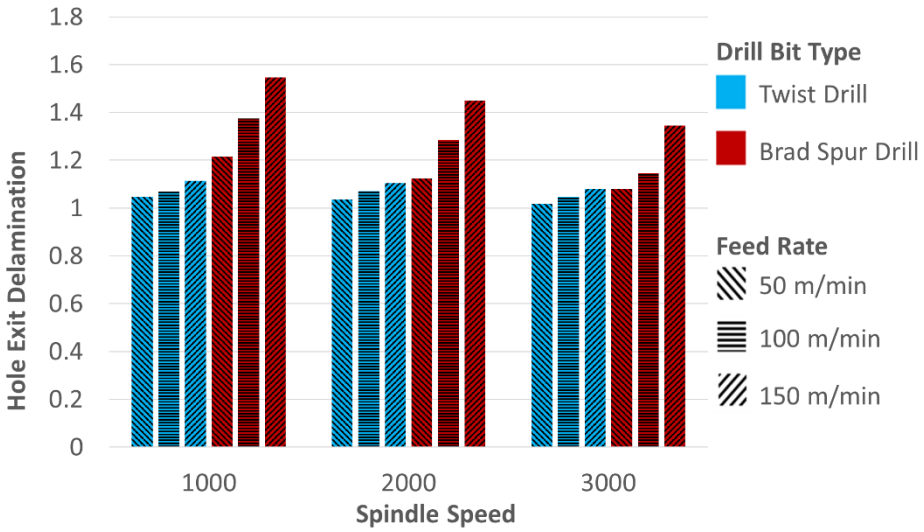
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324 **(c)**



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326 **(d)**



327

328 **(e)**

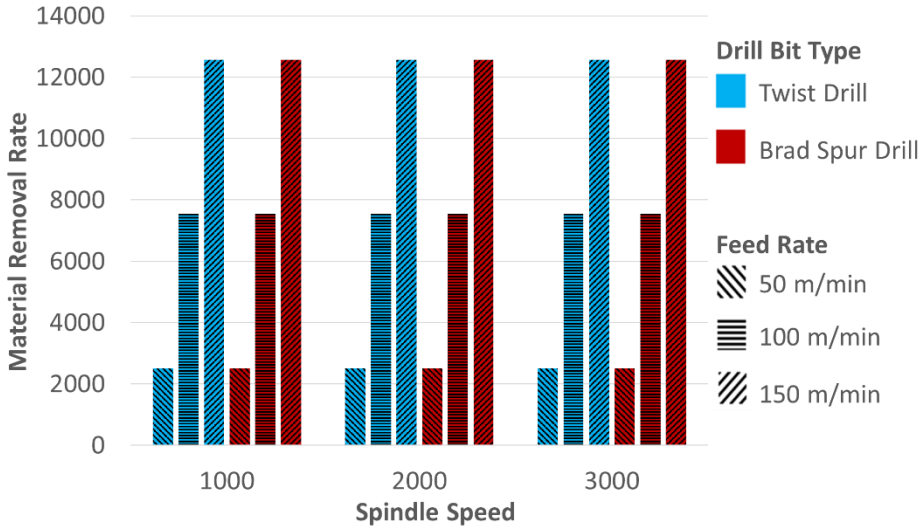


Figure 4. Drilling experiment results for (a) thrust force, (b) torque, (c) hole entry delamination, (d) hole exit delamination, and (e) material removal rate

5.2 Model development using BPNN

5.2.1 Data pre-processing

Before the experiment data can be used as an input and output data of BPNN, a normalization should be performed first. The normalization of experiment data aims to eliminate the dimension and unit of data and to ensure the suitability of the interval value for the activation function in the BPNN modeling. The data normalization converts the data values to a floating value between -1 and 1. A mapminmax function is implemented by involving Equation (10) to execute the pre-processing of data.

$$p_n = \frac{2(p-\min(p))}{(\max(p)-\min(p))} - 1, \tag{10}$$

where p is the experimental data with various interval values and units, while p_n stands for the normalized and unitless data.

5.2.2 BPNN architecture

The optimum BPNN network architecture is needed so that the BPNN can produce an appropriate prediction result. This study constructs an optimum BPNN network architecture by determining a proper combination of the number of hidden layers and the number of neurons in each hidden layer. This study considers three neurons on the input layers and five neurons on the output layers. This combination is deployed to represents the three drilling parameters and five drilling responses, as shown in Figure 4. The number of hidden layers and the number

of neurons in each hidden layer are carefully determined by employing an ant colony optimization (ACO) [40], with the goal to minimize the mean square error (MSE).

From the ACO, it is shown that the minimum MSE (0.00179) is obtained by using three hidden layers. These hidden layers consist of four neurons, seven neurons, and ten neurons for the first, second, and third hidden layers, respectively. Therefore, as seen in Figure 5, the network architecture considered in this study is configurated as 3-4-7-10-5. The tansig and purelin activation functions are considered in the proposed BPNN model, respectively for the hidden and the output layers. The Levenberg-Marquardt training function is implemented and the values of stopping criteria for the training process are set as follows: 1000 for maximum epoch number, 0.0001 for performance goal, 1000 for maximum validation failure in succession, and 0.00001 for minimum performance gradient.

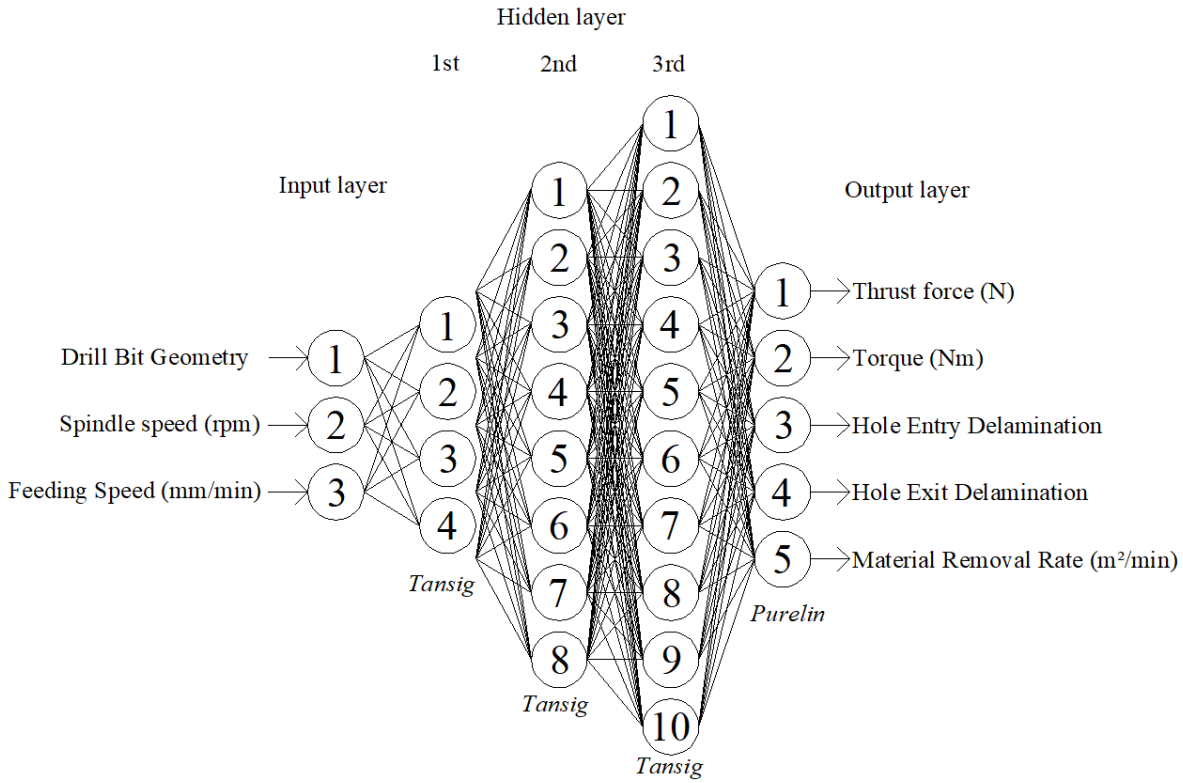
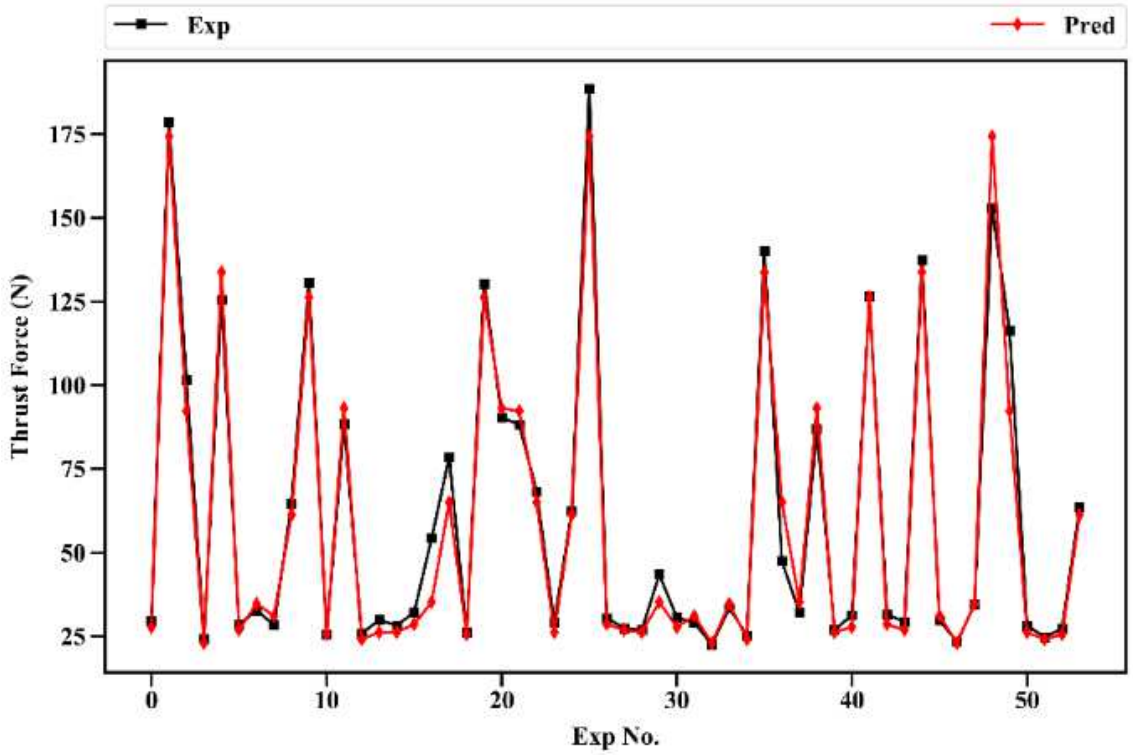


Figure 5. Optimized BPNN network architecture

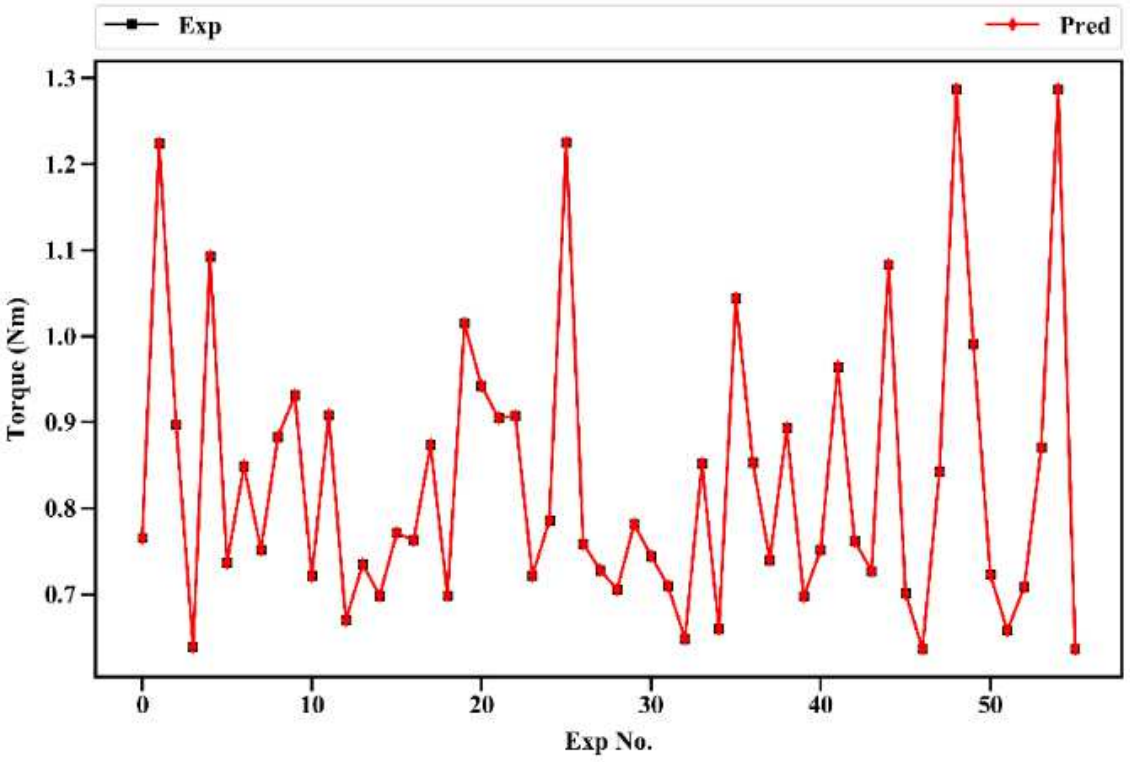
5.2.3 Training, validation, and testing data

Three sets of data are required for building and evaluate the performance of the BPNN model for predicting the response values. These are the training set, testing set, and validation set. In this study, the datasets are partitioned with the proportion as follows: 70% for the training set, 15% for validation set, and 15% for the testing set.

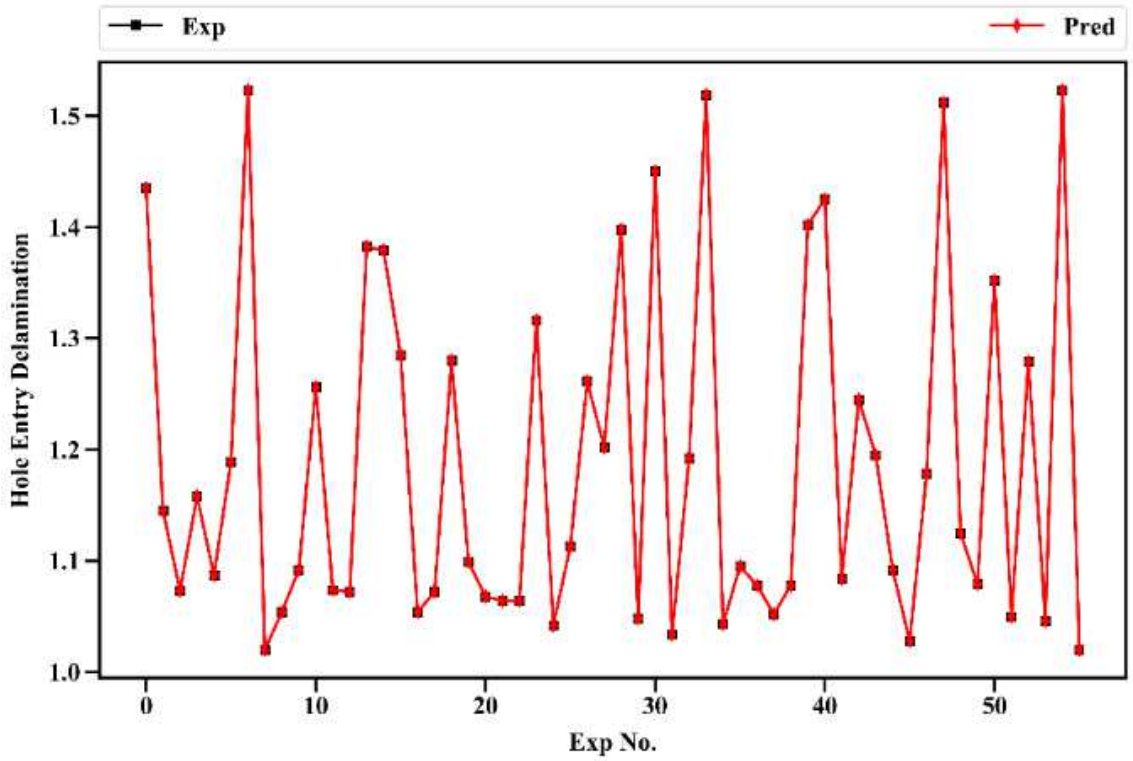
Figure 6 visually presents the overall comparison between the experimental values and the predicted values from BPNN of all the combinations upon each response. The mean average percentage error (MAPE) is used as the metric to evaluate the BPNN model. The MAPE for training data for each response is 3.39% for thrust force, 0.24% for torque, 0.08% for hole entry delamination, 0.02 for hole exit delamination and 0% for material removal rate. It has been shown that the proposed BPNN architecture can produce a prediction with a mean error of no more than 10%. Thus, the proposed approach shows a promising alternative to generate a satisfactory prediction with little differences from the experimental data. Moreover, the comparison of the BPNN outputs and the experimental value are shown in Figure 7.



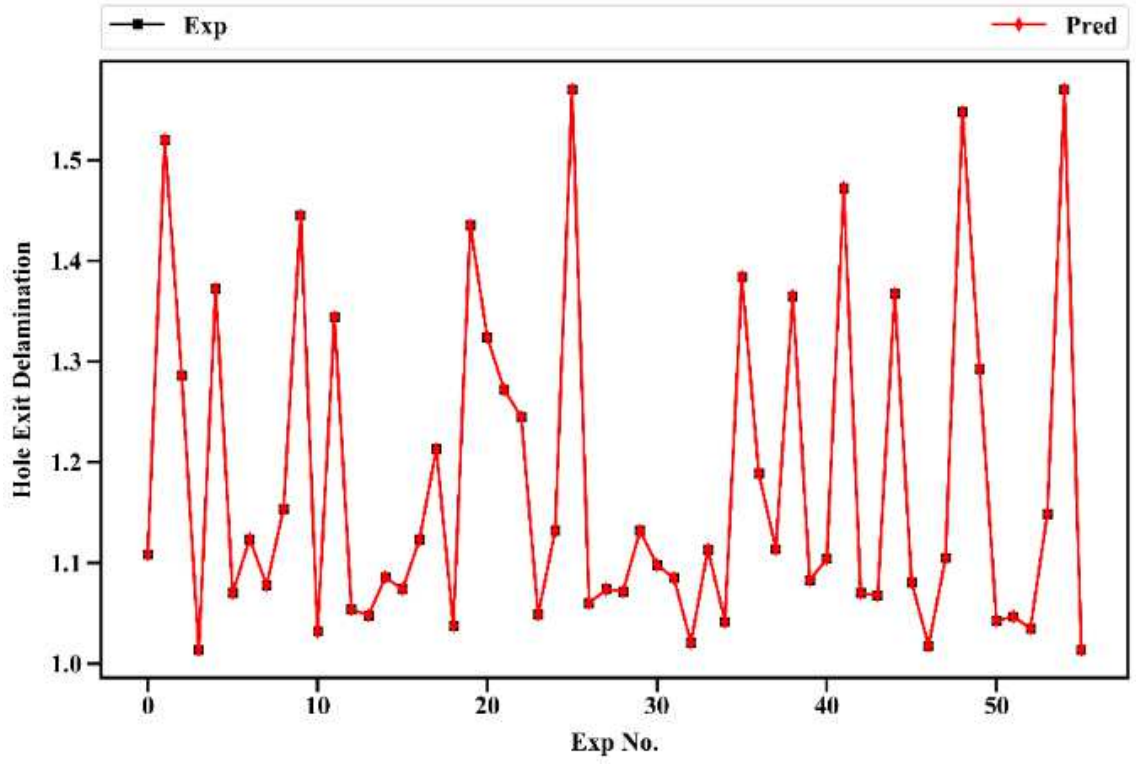
(a)


Exp
Pred
Torque (Nm)
1.3
1.2
1.1
1.0
0.9
0.8
0.7
0
10
20
30
40
50
Exp No.

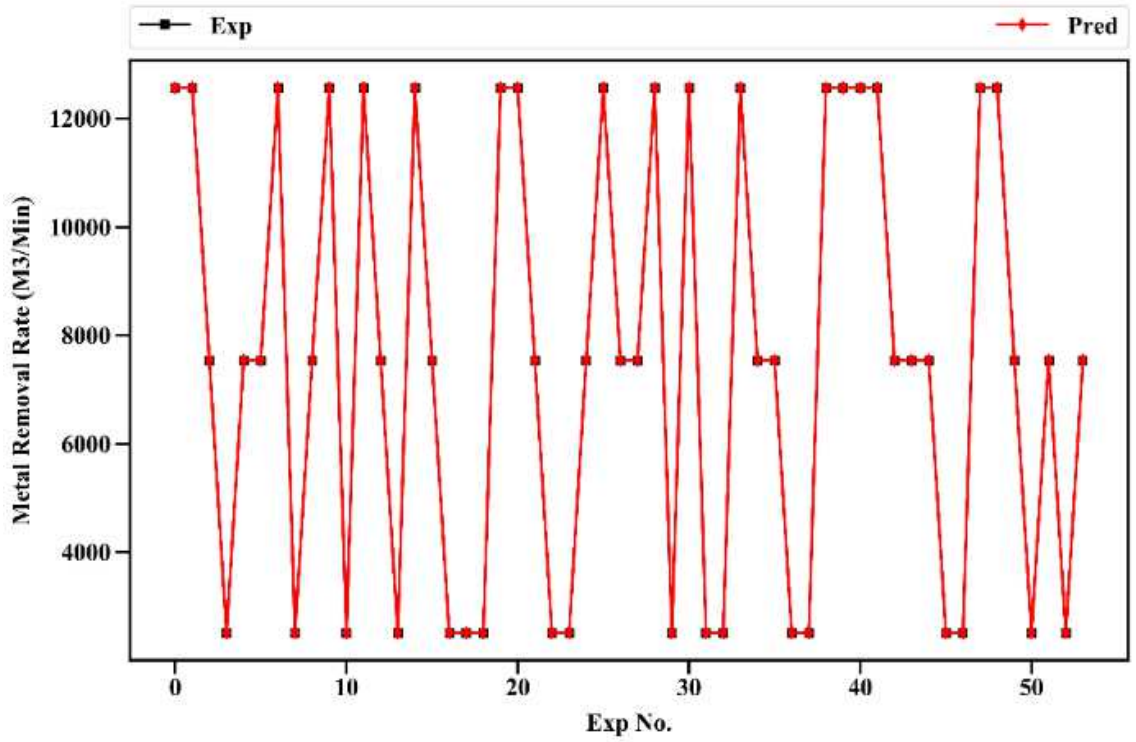
(b)


Exp
Pred
Hole Entry Delamination
1.5
1.4
1.3
1.2
1.1
1.0
0
10
20
30
40
50
Exp No.

(c)



(d)



(e)

Figure 6. Effect of drilling parameters to (a) thrust force, (b) torque, (c) hole entry delamination, (d) hole exit delamination, and (e) material removal rate

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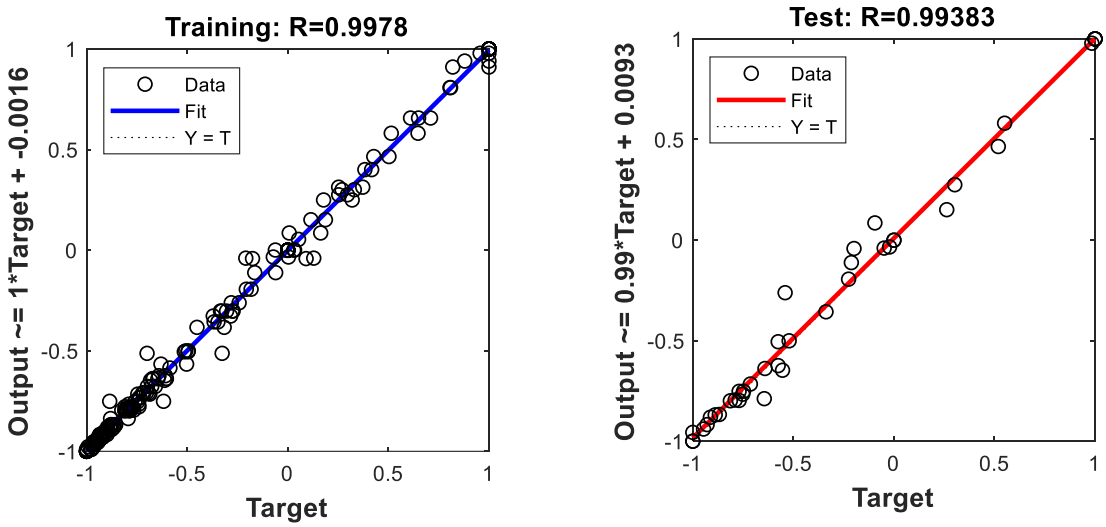


Figure 7. Correlation coefficient graph of BPNN for training and testing data

5.3 Multi-response optimization using I-SCA

5.3.1 Objective function

The algorithm for the optimization process starts with randomly generating a number of initial solutions. Afterward, the quality of these solution agents is then evaluated by utilizing a relevant fitness function. Here, the fitness function is developed by calculating five objective functions [41]. Each objective function corresponds to the value of responses and a tansig transfer function is deployed, as shown in Equation 11-18. Then, after the five objectives are obtained, they are culminated into a single fitness function with aim to minimize the total objective values.

$$minimize\ F_{fitness} = Obj_{thrustforce} + Obj_{torque} + Obj_{holeentrydelamination} + Obj_{holeexitdelamination} + Obj_{materialremovalrate}, \quad (11)$$

$$\mathrm{Obj_n} = \left(\sum_{\mathrm{m}=1}^{5} x_{ml}.\left(\left(\frac{2}{1+e^{-2c_l}}\right)-1\right)\right) + x_{0\mathrm{m}}, \quad (12)$$

$$c_l = \left(\sum_{l=1}^{10} w_{lk}.\left(\left(\frac{2}{1+e^{-2b_k}}\right)-1\right)\right) + w_{0l}, \quad (13)$$

$$b_k = \left(\sum_{k=1}^{7} v_{kj}.\left(\left(\frac{2}{1+e^{-2a_j}}\right)-1\right)\right) + v_{0k}, \quad (14)$$

$$a_j = \left(\sum_{j=1}^{4}(u_{ji}.Q_i)\right) + u_{0j}\,, \quad (15)$$

$$-1 \le Q_1 \le 1, \quad (16)$$

$$-1 \le Q_2 \le 1, \quad (17)$$

$$-1 \le Q_3 \le 1, \quad (18)$$

where the meanings of all notations above are depicted in Table 1.

Table 1. Meaning of notations

Notation	Meaning
$\mathrm{Obj}_{\mathrm{thrustforce}}$	Identified as thrust force objective function
$\mathrm{Obj}_{\mathrm{torque}}$	Identified as torque objective function
$\mathrm{Obj}_{\mathrm{holeentrydelamination}}$	Identified as hole entry delamination objective function
$\mathrm{Obj}_{\mathrm{holeexitdelamination}}$	Identified as hole exit delamination objective function
$\mathrm{Obj}_{\mathrm{materialremovalrate}}$	Identified as material removal rate objective function
Obj_n	Identified as objective function
Q_i	Normalization value of CFRP drilling parameters
a_j	Activation value of neuron j on the first hidden layer
b_k	Activation value of neuron k on the second hidden layer
c_l	Activation value of neuron l on the third hidden layer
i	Index of GFRP drilling process parameters, $i = 1, 2, 3$
j	Index of neuron on the first hidden layer, $j = 1, 2, 3, 4$
k	Index of neuron on the second hidden layer, $k = 1, 2$
l	Index of neuron on the third hidden layer, $l = 1, 2, \ldots, 5$
m	Index of GFRP drilling responses parameters, $m = 1, 2, \ldots, 8$
u_{ji}	Weight between input layer and the first hidden layer
u_{0j}	Bias between input layer and the first hidden layer bias
v_{kj}	Weight between the first hidden layer and the second hidden layer
v_{0k}	Bias between the first hidden layer and the second hidden layer
w_{lk}	Weight between the second hidden layer and third hidden layer
w_{0l}	Bias between the second hidden layer and the third hidden layer
x_{ml}	Weight between the third hidden layer and output layer
$x_{0\mathrm{m}}$	Bias between the third hidden layer and output layer

5.3.2 Parameter settings

The determination of parameters is the crucial phase in a metaheuristic deployment and the parameters of ISCA should be determined properly. In this study, the parameters deployed in the ISCA and other variants of SCA are shown in Table 2.

Table 2. ISCA Parameter settings

Parameter	Meaning	Value
N	Population size	100
T	Number of iterations	100
a	Constant parameter	2
b	Constant parameter	2
$\Gamma_{\max}$	Maximum number of rejections	5
Ω_1, Ω_2, Ω_3	weight adjustment parameters	0, 0.2, 0.5
λ	decay parameter	0.9
α	diversity parameter update weight	0.8

The number of iterations T, population size N, and SCA constants a and b are set uniform in all variants of SCA to ensure a fair comparison. The initial population diversity parameter Δ is calculated based on the maximum Euclidean distance between solutions of the initial population. The decay parameter for the adaptive mechanism is set relatively high to prevent aggressive weight update since the SCA only uses two operators.

5.3.3 Optimal solution

Since the drilling optimization problem concerned on this study requires a single unique solution of drilling parameters for the actual implementation, the weighted sum method is used as the approach for the multi-objective optimization. Here, the proposed ISCA is compared to the benchmark method of standard SCA and SCA with adaptive operator selection (ASCA). Table 3 presents the optimization results. The ISCA obtains an optimum combination of drilling parameter values with a twist drill geometry, 3000 rpm spindle speed, 160.1 mm/min feeding speed. These values result in the minimum weighted sum of the objective functions. Since higher MRR is desired, the equation on the weighted sum function is changed to minimizing $-MRR$ in harmony to other objectives. This setting of parameters is then implemented as the input to predict the value of responses using the proposed BPNN model.

Table 3. Comparison between optimization results

Method	Calculation Time (s)	Fitness Value	Drilling Parameters			F_{Th} (N)	M (Nm)	FD_{en}	FD_{ex}	MRR (mm^3/min)
			Drill Bit Geometry	Spindle Speed	Feeding Speed					
BPNN-ISCA	560.39	-41.150	1	3000	160.1	24.40	0.657	1.078	1.045	10277.27
BPNN-SCA	546.83	-41.145	1	3000	159.7	24.43	0.657	1.077	1.045	10265.28
BPNN-ASCA-	554.14	-41.092	1	3000	161.5	24.31	0.657	1.081	1.044	10289.88

5.4 Effects of the drilling parameters

The mean graphs of drilling parameters effect on torque, hole entry delamination, hole exit delamination, thrust force and material removal rate are shown in Figure 4. The results in Figure 4 (a) and (b) indicate that the utilization of brad spur drill bit would the thrust force increase significantly as it has a lower contact area. Hence, the brad spur drill has a advance penetration capability than the twist drill bit. This phenomenon is caused by the characteristic of brad spur drill bit which allows the machining process of CFRP in the cutting and chisel edges to occur simultaneously. On the other hand, the machining process of the CFRP by using the twist drill bit occurs bit by bit from the chisel edge to the outermost cutting edge, making

this type of drill bit capable to generate lower torque during CFRP drilling process. Regarding the influence of spindle speed on torque and thrust force, the cutting temperature will increase simultaneously as the increase of spindle speed. This phenomenon causes the CFRP material to soften during the machining process. Therefore, the increase on spindle speed would lessen the developed torque and thrust force as indicated in Figure 4 (a) and (b). Furthermore, the thrust force will increase as the increasing of feeding speed. This finding corresponds to the empirical equations of torque and thrust force in the drilling process, which state that both torque and thrust force would increase as the feeding speed increases [42].

Figure 4 (c) presents that the use of brad spur drill bit has effect on the decrease of the hole entry delamination. The contact surface area of the drill affects the delamination at the hole entry. In twist drill bit, the length of the two chisel edge and one point of drill tip define as the contact surface area. Meanwhile, the contact area of brad spur drill bit is merely determined by the three point of drill tip, without the influence of the length of chisel edge. Thus, this leads the twist drill bit to have more contact surface area and produce larger hole entry than the brad spur drill bit. Before, it has been mentioned that the thrust force during the drilling process would decrease as the spindle speed increase, hence producing smaller hole entry delamination. This figure further confirms that the rising of spindle speed level would lessen the delamination in the hole entry section. In addition, Figure 4 (c) also indicates that lower feeding speed leads to lessening the thrust force, which in consequence produces smaller delamination in the hole entry section.

Figure 4 (d) depicts that delamination in the hole exit section is lessen during the cutting process using the twist drill bit than by using brad spur drill bit. The extended drill tip of the brad spur drill bit makes uncut CFRP laminate zone wider because of the enormous thrust force. Therefore, the twist drill bit produces smaller delamination in the hole exit section than the brad spur drill. Similar to the effect on the hole entry delamination, the lessen on the feeding speed is observed to decrease the thrust force during CFRP machining process, thus decreasing the delamination in the hole exit section. Figure 4 (d) also presents that the increase in spindle speed would lessen the thrust force, which in turn producing smaller delamination in the hole exit section.

The influence of drilling parameters to the material removal rate is shown in Figure 4 (e). The magnitude of material removal rate in the drilling process is affected by the drill bit diameter, feeding speed, and cutting speed. The cutting speed increase corresponds to the spindle speed, while the increasing of feeding speed would increase the material removal rate proportionally during the CFRP drilling process. Since the diameter of both used drill bit, i.e.,

twist drill and brad spur, is the same, the magnitude of material removal rate is only affected by feeding speed and spindle speed. The increase of spindle speed equates to the increase of the cutting process at the same time, and similarly, the increasing feeding speed would also increase the total volume of CFRP being cut.

6 Conclusion

This article studies the integration of BPNN and ISCA to predict and optimize the CFRP drilling process. The BPNN is firstly performed to model and predict the optimal values of the drilling responses, in which multiple characteristics of drilling performances have been taken into account, namely torque (M), hole entry delamination (FD_{en}), hole exit delamination (FD_{ex}), thrust force (F_{Th}) and material removal rate (MRR). It has been shown that the constructed model can predict the value of response parameters into a satisfactory degree. Then, the model is being optimized by the ISCA to obtain the best drilling parameters level combination. Two mechanisms are presented to improve the general framework of Sine Cosine Algorithm (SCA): 1) adaptive selection of operators, and 2) population management technique. The results have clearly shown that the proposed approach outperforms the benchmark method of standard BPNN-SCA.

Finally, future works should focus on the development of other soft computing techniques to optimize the drilling process of CFRP. In this study, the architecture of BPNN is optimized by arbitrarily selecting the ACO technique for finding the proper number of hidden layers and the number of neurons in each hidden layer. This process can be re-optimized again by comparing the ACO with other state-of-the-art optimization techniques, which in our opinion, will also be an interesting research direction. Our literature review also finds that numerous works have attempted to implement metaheuristic algorithms for optimizing some machining tasks, however, limited works have attempted to discuss the simultaneous optimization of conflicting multiple objectives. Thus, future works should also put their effort to fill this research gap.

Author contributions

R.N. conceptualized the study, developed the methodology, and conducted validation, investigation, and resource provision. S.T.W.M. and A.P.R. developed the software, performed formal analysis, and curated the data. B.O.P.S. and M.K.E. contributed to the methodology and provided resources. R.N., S.T.W.M., and A.P.R. wrote the original draft. R.N. reviewed and edited the manuscript and supervised the study.

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Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest

The authors declare no conflict of interest.

Ethical Approval

Not applicable.

Consent to participate

Not applicable.

Consent to pubication

Not applicable.

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