Multi-objective Optimization of AISI 1045 on Drilling Process Based on Hybrid BPNN and Firefly Algorithm

Ridhani Anita Fajardini(✉), Mohammad Khoirul Effendi, Bobby O. P. Soepangkat, Mazwan, and Satrio Darma Utama

Department of Mechanical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia
ridhaniaf.id@gmail.com

Abstract. During the drilling process with minimum quantity lubrication (MQL) for AISI 1045, the thrust force and torque influence the drilled hole's surface quality. Therefore, it is important to select the appropriate combination levels of machining parameters in order to minimize the thrust force, torque, and surface roughness of drilled holes simultaneously. This paper predicts the optimal value of thrust force, torque, and surface roughness of the AISI 1045 in the drilling process by implementing a hybrid method of backpropagation neural network (BPNN) and firefly algorithm (FA). BPNN was developed to obtain an appropriate model and then applied the firefly algorithm for multi-objective optimization. Several experiments on CNC machines were carried out using L_{18} orthogonal arrays based on the Taguchi technique. Tool type, point angle, feed rate, and cutting speed were selected as process parameters. Based on the prediction of BPNN and FA to achieve optimal responses, the cutting process was obtained using a tool type HSS-M2 with a point angle of 131°, feed rate of 0.04 mm/rev, and cutting speed of 32.5 m/min.

Keywords: BPNN-FA · Drilling · Thrust Force · Torque · Surface Roughness

1 Introduction

The machining of steel requires the appropriate setting of the cutting parameters. The cutting parameters of the drilling process usually considered are drill material, drill bit geometry, cutting speed, and feed rate. Several studies have shown that drill material, drill point angle, cutting speed, and feed rate influence surface roughness, cutting force, and torque [1–4]. On the other hand, cutting conditions with minimum quantity lubrication (MQL) result in an efficient process in contrast to dry machining conditions. When the tool and workpiece are in contact, MQL can reduce heat and friction, resulting in better surface quality, high productivity, and longer tool life [5, 6].

The thrust force and torque determine the surface quality of drilled hole in the drilling process. The surface roughness resulting from the machining process affects properties such as fatigue strength, coefficient of friction, wear resistance, and corrosion. Poor

T. P. Syawitri et al. (Eds.): MEST 2022, AER 222, pp. 530–540, 2023.
https://doi.org/10.2991/978-94-6463-134-0_50

surface quality can increase the cost and duration of the re-production process as well as cause material failures such as friction, low dimensional accuracy, and heat production in the hole walls [7, 8]. Poor machining performance can be avoided by conducting experimental studies and optimization to produce quality products, reduce costs, and increase productivity.

Various analysis, optimization, and modeling methods have been developed to determine the optimal cutting parameters. The procedure to select the optimal parameter settings is conducted in two parts. The first is the development of a mathematical equation or model that illustrates the connection between the process parameters and the output. Fuzzy logic, artificial neural networks (ANN), and response surface methodology were all employed to develop the model. Furthermore, using the mathematical model, the optimal solution can be determined. On the other side, metaheuristic algorithms, i.e., genetic algorithm, particle swarm optimization, simulated annealing algorithm, firefly algorithm, etc., also can be applied to figure out the appropriate optimal solution [9].

A comparative study between ANN and regression methods has been used to predict the cutting force and thrust force on the orthogonal cutting of AISI 316L stainless steel material. The ANN model developed had a lower error than the regression. It showed that ANN was better at predicting the cutting force and thrust force [10]. Anand et al. [11] conducted a similar study which showed that ANN modeling was better at predicting the response of delamination, thrust force, and torque in the drilling process than regression and fuzzy logic methods. Norcahyo et al. [12] developed a model to estimate hole delamination and thrust force based on a backpropagation neural network (BPNN). Based on the developed model, the predictive values were close to experimental results. The results indicated that BPNN produced predictive values efficiently. Gautam and Mishra [13] proposed a metaheuristic method based on swarm intelligence, namely the firefly algorithm (FA), to improve the kerf quality of the basalt fiber-reinforced polymer composite material in laser cutting. The prediction determined the best cutting geometry parameters based on the kerf values made using the firefly method. The optimization results showed an increase in kerf quality by 26.75%. Effendi et al. [14] applied a BPNN and firefly algorithm (FA) to determine the setting parameters of the drilling operation, ensuring minimum surface roughness and cutting force on GFRP material. According to the results of the confirmation experiment, the BPNN-FA predicted value for the optimum responses was acceptable, with an error below 5%.

Notable researchers have been conducting research using a combination of different process parameters and then analyzing using certain methods to obtain the optimal response. The backpropagation neural network (BPNN) method produces a model close to the experimental results. The resulting error rate is small, and the BPNN prediction results are acceptable. Furthermore, the metaheuristic algorithm, a non-traditional optimization, is quite popular because the results are quite good. One of the metaheuristic optimization methods, called the firefly algorithm, has the capability to predict the optimum value of the responses simultaneously. Bharathi et al. [15] stated that the FA method might generally be adapted and applied to conventional machining operations like turning and grinding and other non-traditional machining processes. The firefly algorithm can resolve problems by selecting the appropriate value of process parameters to get the optimal solution. The study in this paper, inspired by the literature mentioned above, aims to determine the drilling process settings parameter in AISI 1045 steel to obtain minimum thrust force, torque, and surface roughness. The backpropagation neural network method is used for modeling, while multi-objective optimization is carried out using the firefly algorithm.

2 Materials and Methods

2.1 Experimental Setup

The drilling process was carried out on a CNC Milling machine with a maximum spindle speed of 4000 rpm. The material used was AISI 1045. Minimum quantity lubrication (MQL) was used for the cutting process in conditions near dry. Palm oil was used as the MQL cutting fluids with a nozzle angle was 45°. The tool type, point angle, feed rate, and cutting speed were used as the drilling process parameters, whose values and levels can be seen in Table 1. The thrust force (F_t) and torque (T) were measured using the Kistler dynamometer. The surface roughness tester Mitutoyo SJ-310 was utilized to measure the drilled hole's surface roughness (SR).

2.2 Design of Experiment

The experiment was designed using an orthogonal array L_{18} based on the Taguchi technique. The orthogonal array L_{18} is depicted in Table 2 with 18 combinations of the experiment.

2.3 Development of Backpropagation Neural Network A Subsection Sample

A data processing and modeling method called an artificial neural network (ANN) is applied to create mathematical models of the learning process inspired by the human nervous system's mechanisms. Backpropagation is a systematic methodology for training multilayer ANNs. A backpropagation neural network (BPNN) structure consists of a multilayer network, i.e., the input layer, hidden layer, and output layer. There are four stages of algorithm training using the backpropagation method: initialization of weights, feed-forward, backpropagation error, and lastly, updating weights and biases [16].

Each layer is interconnected with weights and biases. These weights pass information from each input layer to all hidden layers. The final value is obtained through the activation function, which has processed information from the hidden layer to the neuron output layer. Bias is used to eliminate or compensate for the dominant solution in the hidden layer and output layers. The process from the input to the output layer is called feed-forward. The final value obtained in the output layer is compared with the target value. The difference in value between the final and target values is evaluated. Then the backpropagation process is carried out until the weights are optimized to get the minimum error between the target value and the predicted value [10, 17].

The steps in modeling using BPNN are pre-processing the normalizing data, developing the network architecture (input layer, hidden layer, and output layer), determining the criteria for stopping BPNN, and finally conducting training, testing, and validation.

Table 1. Value of process parameters.

Process Parameters	Unit	Symbol	Level 1	Level 2	Level 3
Tool Type	-	A	HSS-M2	HSS-M35	-
Point angle	°(degree)	B	102	118	134
Feed rate	mm/rev	C	0.04	0.07	0.1
Cutting speed	m/min	D	25	37	50

Table 2. Design of experiment.

No.	A	B	C	D	No.	A	B	C	D
1.	1	1	1	1	10.	2	1	1	3
2.	1	1	2	2	11.	2	1	2	1
3.	1	1	3	3	12.	2	1	3	2
4.	1	2	1	1	13.	2	2	1	2
5.	1	2	2	2	14.	2	2	2	3
6.	1	2	3	3	15.	2	2	3	1
7.	1	3	1	2	16.	2	3	1	3
8.	1	3	2	3	17.	2	3	2	1
9.	1	3	3	1	18.	2	3	3	2

Normalization of data is performed because the data has values of different magnitudes. The normalization process aims to facilitate convergence, so the input and output of BPNN are converted at intervals between −1 to 1. Normalization of input and output data can be calculated using Eq. 1 [18].

$$y = 2\frac{(p - p_{min})}{(p_{max} - p_{min})} - 1 \tag{1}$$

where y is the result of normalizing the input data (process parameters) and output data (response parameters), and p is the process and response parameter data from the experiment.

2.4 Firefly Algorithm

A metaheuristic algorithm named the firefly algorithm (FA) is an algorithm based on the phenomenon of light emitted by fireflies with the assumption that all artificial fireflies are unisexual. Here, the brightness level of fireflies is their main attraction. The closer the distance between the fireflies, the higher the attraction. When the distance between fireflies increases, the firefly's attraction decreases [13]. In addition, the attractiveness of fireflies and their brightness have a proportional relationship. Fireflies move to a place

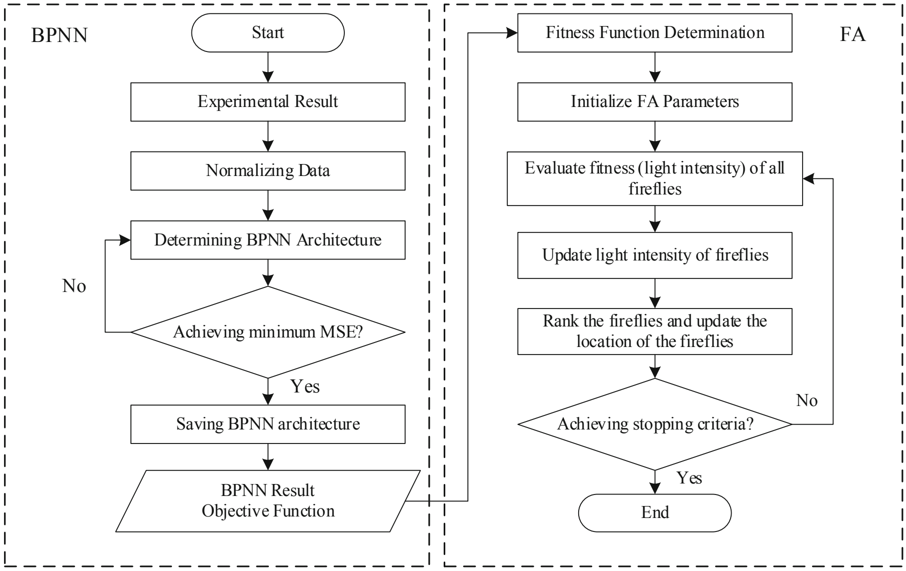

Fig. 1. Flowchart of the BPNN-FA.

that has a brighter and more attractive light intensity. The idea behind this behavior can be linked to the objective function of efficiently determining the most appropriate solution. The movement of the less attractive fireflies to the other most attractive fireflies makes the FA parameter can be updated [13, 19]. Figure 1 shows the flowchart of the BPNN-FA hybrid method for multi-objective optimization.

3 Result and Discussion

3.1 Experimental Result

Experiments were carried out based on a combination of these parameter levels to produce eighteen data for each response, including F_t, T, and SR. Each experiment combined process parameters such as tool type, point angle, feed rate, and cutting speed, as shown in Table 2. The results of F_t, T, and SR measured during the drilling experiment are represented in Fig. 2. From the graph in Fig. 2, the response of F_t, T, and SR reached the lowest value in the 10th, 16th, and 7th experiments, respectively. The minimum value of F_t was obtained as 575.8 N during the experiment with the combination of tool type HSS-M2 with a point angle of 102°, feed rate of 0.04 mm/rev, and cutting speed of 50 m/min. Likewise, the minimum value of T was obtained as 1.676 Nm during the experiment with the combination of tool type HSS-M35 with a point angle of 134°, feed rate of 0.04 mm/rev, and cutting speed of 50 m/min. Whereas the minimum value of SR was obtained as 2.48 µm during the experiment with the combination of tool type HSS-M2 with a point angle of 134°, feed rate of 0.04 mm/rev, and cutting speed of 37 m/min. From the results of this experiment, it was found that the lower the feed rate, the smaller the F_t, T, and SR. Similar results were also found in the previous study [20].

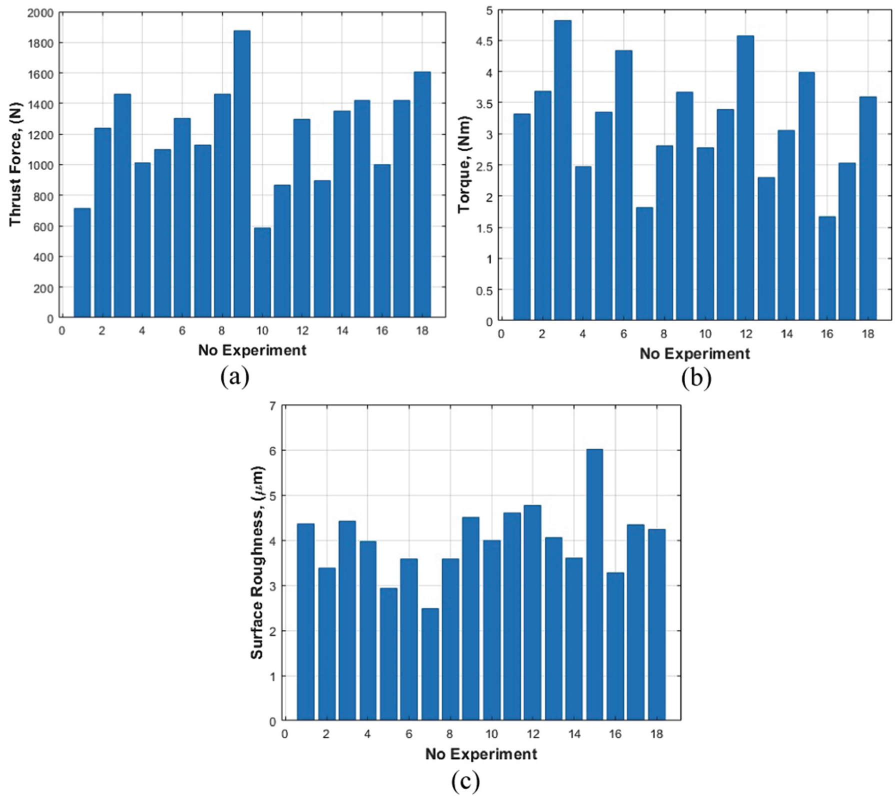

Fig. 2. Experiment value for response (a) F_t, (b) T, and (c) SR.

3.2 Modeling Using BPNN

In this study, the modeling of the drilling process on AISI 1045 steel was carried out using BPNN. BPNN modeling requires input data and output data. The data used as input for predictions using BPNN was a combination of process parameters, namely tool type, point angle, feed rate, and cutting speed. The experimental result, including F_t, T, and SR, were used as output data.

Eighteen data collected resulted from experiments. Seventy percent (70%) of the data were used for training, whereas just 15% of each was used for validation and testing. Sixteen data sets were randomly selected for training data. Besides, each of the other two data sets was presented to the network as testing and validation data. The BPNN parameters were set first before being used for the modeling process; the maximum numbers of epochs or iterations of BPNN were set to 1000; the total hidden layers and neurons for each hidden layer varied between 2 and 5; the activation function in each hidden layer used tansig, while the output layer used the activation function purelin. Levenberg-Marquardt (trainlm) can provide a good convergence speed, so it was chosen as the training function of BPNN [21].

Table 3. BPNN architecture.

Response	Total number of hidden layers	Total number of neurons	Activation function	MSE
Thrust Force (F_t)	2	4	Tansig	0.000712
Torque (T)	2	4	Tansig	0.000587
Surface Roughness (SR)	2	4	Tansig	0.000772

The developed BPNN model has been trained and tested based on the input and output data. The desired BPNN architecture was determined using the smallest value of mean square error (MSE). Based on the MSE value generated from BPNN shown in Table 3, a two-hidden-layer structure with a total of four neurons for each hidden layer and activation function tansig can be used to create a decent BPNN architecture. F_t, T, and SR each have MSE values of 0.000712, 0.000587, and 0.000772, respectively. Besides obtaining MSE, there are differences between the target value from experiments and the BPNN prediction outcomes, which are demonstrated in Fig. 3. Based on these results, it was known that the predicted value of BPNN was close to the experimental results. The average error for each response, including F_t, T, and SR, was 0.36%, 0.48%, and 0.45%, successively. The average error between prediction and experiment did not exceed 5% for each response, which indicated that the BPNN model accurately predicted the drilling process [10, 17].

3.3 Optimization Using FA

In this study, the FA approach was applied to simultaneously optimize the F_t, T, and SR based on the drilling process parameters, including the tool type, point angle, feed rate, and cutting speed. BPNN modeling, which has produced a network architecture with the smallest MSE, was used for the FA optimization process. Before applying the FA method, parameters such as light absorption coefficient, attractiveness value, and randomness factor was determined first. The appropriate FA tuning parameter values, such as randomness reduction, randomness factor (α), attractiveness value (β_0), and absorption coefficient (γ), were 0.98, 0.91, 1, and 1, successively. The number of fireflies was 30. While the maximum number of iterations was taken as 50 to terminate the iteration process. This FA parameter was applied by previous researchers to get the most appropriate solution [13, 14, 19, 22].

The fitness function was used during the optimization process to obtain the minimum value from the response. The fitness function applied in this study was calculated by combining all objective functions. The objective function was determined based on the BPNN model. The fitness function was stated in Eq. 2.

$$minimize f(x) = Obj_F + Obj_T + Obj_{SR} \tag{2}$$

where Obj_F, Obj_T, and Obj_{SR} were the objective function of thrust force, torque, and surface roughness, respectively.

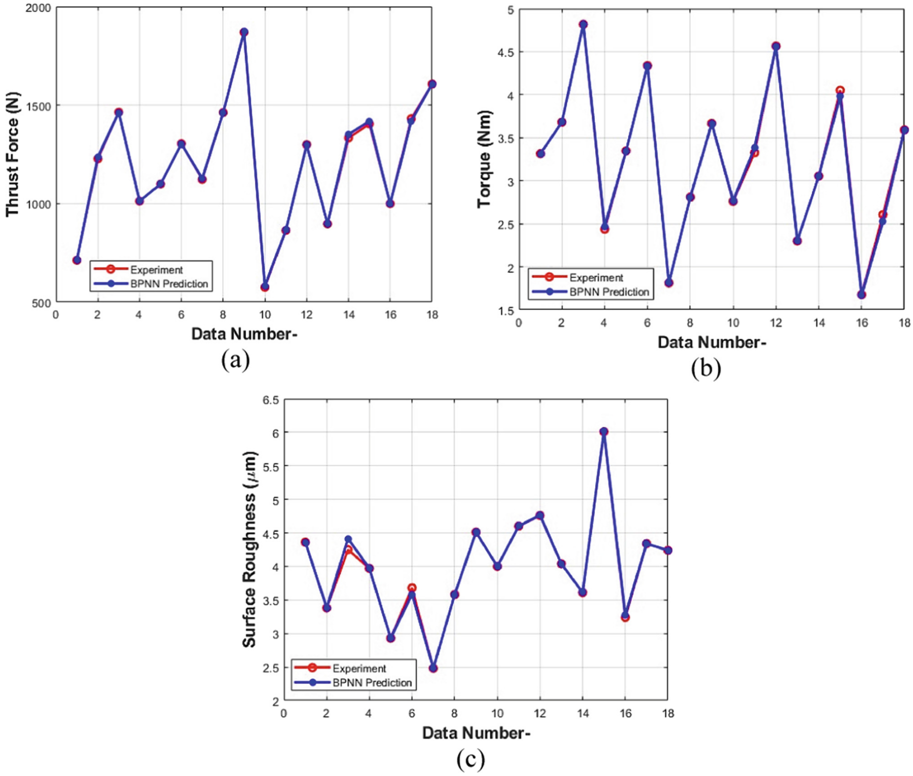

Fig. 3. Comparison of BPNN prediction and data of experiment for (a) F_t, (b) T, and (c) SR.

Figure 4 displays the result of the iteration of the FA method. According to this result, the fitness value was convergent within 50 iterations. Moreover, the multi-objective optimization result using FA are shown in Table 4. According to the Table 4, the HSS-M2 tool type with a point angle of 131°, feed rate of 0.04 mm/rev, and cutting speed of 32.5 m/min achieved the optimum performance for F_t, T, and SR. The predicted value of F_t, T, and SR were 770.897 N, 1.731 Nm, and 2.501 μm, successively.

3.4 Confirmation Experiment

The best parameter prediction results from FA were then validated by performing confirmation experiments. The confirmation experiments were conducted three times. Table 4 summarizes the results of the confirmation experiment. According to the Table 4, the confirmation experiment's results indicate that the FA prediction was close to the experiment. The average for the confirmation experiment for F_t, T, and SR were 776.433 N, 1.747 Nm, and 2.581 μm, respectively. Moreover, the errors between prediction and the average of confirmation experiments for F_t, T, and SR were 0.71%, 0.92%, and 3.11%, respectively. The error between prediction and experiment was small, less than 5%, demonstrating the remarkable similarity between the predicted and measured F_t, T, and SR [14].

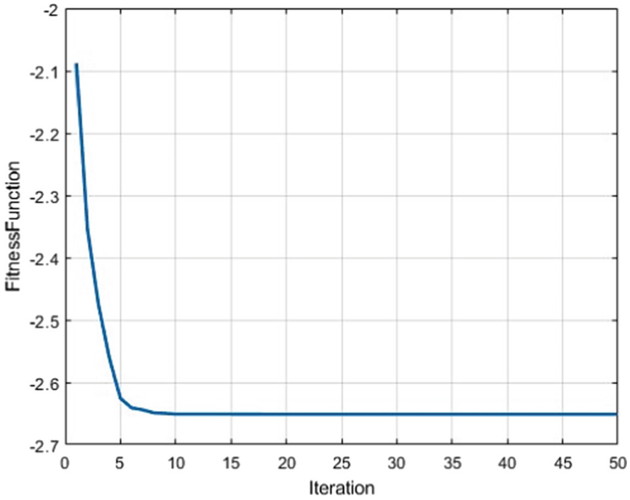

Fig. 4. FA method iteration process.

Table 4. Results of the confirmation experiment and the prediction.

Process Parameters				Prediction			Confirmation Experiment		
Tool Type	Point Angle	Feed rate	Cutting speed	Ft (N)	T (Nm)	SR	Ft (N)	T (Nm)	SR (μm)
							780.966	1.759	2.660
HSS-M2	131	0.04	32.5	770.897	1.731	2.501	771.267	1.747	2.558
							777.065	1.736	2.526
Average							776.433	1.747	2.581
Error (%)							0.71	0.92	3.11

Additionally, one sample t-test was carried out to check the results of the confirmation experiment were statistically the same as the predictions of BPNN-FA [12]. The P-values were 0.188, 0.130, and 0.183 for F_t, T, and SR, respectively. The P-value of the three responses was higher than the significance level (α) of 0.05. These results statistically show that the BPNN-FA prediction and confirmation were the same. Consequently, it can be declared that the prediction of BPNN-FA was acceptable and valid.

4 Conclusion

Experimental investigations have been executed on the drilling process on AISI 1045 steel with the parameters of the type of tool, cutting speed, feed rate, and point angle. Modeling and multi-objective optimization use hybrid BPNN-FA to obtain the minimum F_t, T, and SR. The final conclusions that can be drawn from this study are as follows:

- The most appropriate BPNN architecture consists of two hidden layers with four neurons for each hidden layer. The BPNN training function used is trainlm while the activation functions for the hidden layers and output layer are tansig and purelin in succession.
- BPNN has effectively predicted the minimal F_t, T, and SR with an average error value of less than 5%.
- The optimum conditions can be achieved by setting the parameters of cutting speed of 32.5 m/min, feed rate of 0.04 mm/rev, using the HSS-M2 cutting tool, and point angle of 131°.
- Hybrid BPNN-FA methods produce a relatively small error between the predictions and the average confirmation experiments, which is less than 5%.

References

1. Vankanti, V.K., Ganta, V.: Optimization of process parameters in drilling of GFRP composite using Taguchi method. Journal of Materials Research and Technology. 3, 35–41 (2014).
2. Desikan, B., Jenarthanan, M.P.: Mathematical Modeling of Surface Roughness during Drilling of Resin Hybrid GFRP Composites. Applied Mechanics and Materials. 854, 18–25 (2016).
3. Adalarasan, R., Santhanakumar, M.: Application of Taguchi based Response Surface Method (TRSM) for Optimization of Multi Responses in Drilling Al/SiC/Al2O3 Hybrid Composite. Journal of The Institution of Engineers (India): Series C. 96, 65–71 (2015).
4. Balaji, M., Venkata Rao, K., Mohan Rao, N., Murthy, B.S.N.: Optimization of drilling parameters for drilling of TI-6Al-4V based on surface roughness, flank wear and drill vibration. Measurement (Lond). 114, 332–339 (2018).
5. Abas, M., Sayd, L., Akhtar, R., Khalid, Q.S., Khan, A.M., Pruncu, C.I.: Optimization of machining parameters of aluminum alloy 6026-T9 under MQL-assisted turning process. Journal of Materials Research and Technology. 9, 10916–10940 (2020).
6. Soepangkat, B.O.P., Suhardjono, Pramujati, B.: Application of Taguchi-grey method to optimize drilling of EMS 45 steel using minimum quantity lubrication (MQL) with multiple performance characteristics. In: AIP Conference Proceedings. American Institute of Physics Inc. (2017).
7. Meral, G., Sarıkaya, M., Mia, M., Dilipak, H., Şeker, U., Gupta, M.K.: Multi-objective optimization of surface roughness, thrust force, and torque produced by novel drill geometries using Taguchi-based GRA. International Journal of Advanced Manufacturing Technology. 101, 1595–1610 (2019).
8. Tan, C.L., Azmi, A.I., Muhammad, N.: Surface Roughness Analysis of Carbon/Glass Hybrid Polymer Composites in Drilling Process Based on Taguchi and Response Surface Methodology. Adv Mat Res. 1119, 622–627 (2015).
9. Han, C., Luo, M., Zhang, D.: Optimization of varying-parameter drilling for multi-hole parts using metaheuristic algorithm coupled with self-adaptive penalty method. Applied Soft Computing Journal. 95, (2020).
10. Kara, F., Aslantas, K., Çiçek, A.: ANN and multiple regression method-based modelling of cutting forces in orthogonal machining of AISI 316L stainless steel. Neural Comput Appl. 26, 237–250 (2015).
11. Anand, G., Alagumurthi, N., Elansezhian, R., Palanikumar, K., Venkateshwaran, N.: Investigation of drilling parameters on hybrid polymer composites using grey relational analysis, regression, fuzzy logic, and ANN models. Journal of the Brazilian Society of Mechanical Sciences and Engineering. 40, (2018).

12. Norcahyo, R., Soepangkat, B.O.P., Sutikno: Multi response optimization of thrust force and delamination in carbon fiber reinforced polymer (CFRP) drilling using backpropagation neural network-particle swarm optimization (BPNN-PSO). In: AIP Conference Proceedings. American Institute of Physics Inc. (2018).
13. Gautam, G.D., Mishra, D.R.: Firefly algorithm based optimization of kerf quality characteristics in pulsed Nd:YAG laser cutting of basalt fiber reinforced composite. Compos B Eng. 176, (2019).
14. Effendi, M.K., Soepangkat, B.O.P., Norcahyo, R., Suhardjono, Sampurno: Cutting Force and Surface Roughness Optimizations in End Milling of GFRP Composites Utilizing Bpnn-Firefly Method. International Journal of Integrated Engineering. 13, 297–306 (2021).
15. Bharathi Raja, S., Srinivas Pramod, C. v., Vamshee Krishna, K., Ragunathan, A., Vinesh, S.: Optimization of electrical discharge machining parameters on hardened die steel using Firefly Algorithm. Eng Comput. 31, 1–9 (2015).
16. Chalisgaonkar, R., Kumar, J., Pant, P.: Prediction of machining characteristics of finish cut WEDM process for pure titanium using feed forward back propagation neural network. In: Materials Today: Proceedings. pp. 592–601. Elsevier Ltd (2019).
17. Soepangkat, B.O.P., Norcahyo, R., Pramujati, B., Wahid, M.A.: Multi-objective optimization in face milling process with cryogenic cooling using grey fuzzy analysis and BPNN-GA methods. Engineering Computations (Swansea, Wales). 36, 1542–1565 (2019).
18. Zhang, G., Xia, B., Wang, J.: Intelligent state of charge estimation of lithium-ion batteries based on L-M optimized back-propagation neural network. J Energy Storage. 44, (2021).
19. Shukla, R., Singh, D.: Selection of parameters for advanced machining processes using firefly algorithm. Engineering Science and Technology, an International Journal. 20, 212–221 (2017).
20. Krishnamoorthy, A., Rajendra Boopathy, S., Palanikumar, K., Paulo Davim, J.: Application of grey fuzzy logic for the optimization of drilling parameters for CFRP composites with multiple performance characteristics. Measurement (Lond). 45, 1286–1296 (2012).
21. Wang, H., Li, J., Liu, L.: Process optimization and weld forming control based on GA-BP algorithm for riveting-welding hybrid bonding between magnesium and CFRP. J Manuf Process. 70, 97–107 (2021).
22. Majumder, A.: Comparative study of three evolutionary algorithms coupled with neural network model for optimization of electric discharge machining process parameters. Proc Inst Mech Eng B J Eng Manuf. 229, 1504–1516 (2014).