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Multi-objective Optimization in Drilling Kevlar Fiber Reinforced Polymer Using Grey Fuzzy Analysis and Backpropagation Neural Network–Genetic Algorithm (BPNN–GA) Approaches

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Abstract

An integrated approach has been applied to predict and optimize multi-performance characteristics, such as optimum thrust force (F_z), torque (M_z), hole surface roughness (R_a), delamination (D) and hole roundness (R), in drilling process of Kevlar fiber reinforced polymer. The experiments were performed by varying drill point geometry and drilling process parameters, i.e., drill point angle, feed rate, and spindle speed. The quality characteristics F_z, M_z, R_a, D, and R were the smaller the better. Taguchi orthogonal array (OA) L_{18} was used as the design of experiments. Grey fuzzy analysis was first applied to obtain a rough estimation of the optimum drill point geometry and drilling process parameters. Backpropagation neural network (BPNN) model was developed and utilized to predict the optimum F_z, M_z, R_a, D, and R. Genetic algorithm (GA) was performed to search for global optimum of drilling process parameters combinations. The analysis of the effect of drill point angle, as well as drilling process parameters, on the individual performance characteristics was conducted by examining both the percentage contribution of drill point geometry and drilling process parameters on the total variance of three responses individually, and the response graphs. The results of the confirmation experiment showed that the BPNN based GA optimization method could accurately predict and also significantly improve the multiple performance characteristics.

Keywords BPNN–GA · Drilling process · KFRP · Multi performance optimization · Grey fuzzy analysis

List of Symbols

y_i	Measured characteristic value of the response
$X_i^*(k)$	Normalization value of the k response
$\min X_i(k)$	The smallest value of $X_i(k)$ for the kth response
$\max X_i(k)$	The largest value of $X_i(k)$ for the kth response
ζ	Distinguishing coefficient
$\xi_i(k)$	GRG value of the kth response
$\Delta_{0,i}(k)$	Deviation sequence of reference for the kth response
Δ_{min}	Smallest value of $\Delta_{0,i}$
Δ_{max}	Largest value of $\Delta_{0,i}$

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1 Introduction

Kevlar has been widely used as a reinforcing fiber in producing composite materials due to its specific tensile modulus which is greater than glass and aluminum. However, they are not as stiff as graphite or boron fibers. Kevlar fiber reinforced polymer (KFRP), or also often called aramid fiber reinforced polymer (AFRP), is one of the composite types which have several beneficial properties, such as high tensile strength, high hardness, low density, heat and corrosion resistant, strong and lightweight [1]. KFRP is usually used in the automotive industry, tank industry, aircraft, military equipment and spacecraft. In the manufacturing industry, drilling is one of the machining processes commonly applied in producing hole for components assembly using bolt and rivet. There is a difference in the drilling process of this material from the metal materials because of its nonhomogeneous and anisotropic properties. While drilling composite materials, the two phases namely filler and matrix behave differently than when they are separate, because composite contains the soft epoxy matrix and hard fibers.

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The performance of the drilling process on composite materials can be measured based on several performances or quality characteristics such as delamination (D), hole surface roughness (R_a) and hole roundness (R) [2–4]. Delamination is initiated by thrust force, which is affected by feed rate and tool geometry significantly [2]. Therefore, the aforementioned quality characteristics, including responses such as thrust force (F_z) and torque (M_z), should be minimized. The minimum multiple quality characteristics could be achieved by determining the optimal drilling parameters using the multiple quality characteristics optimization methods. Currently, the multiple quality or performance characteristics optimization methods are developed based on statistical and meta-heuristic methods. Response surface methodology (RSM) is commonly used to explore the relationships between machining or explanatory variables and performance characteristics or response variables, as well as to predict the response. The popular statistical based optimization methods include RSM combined with desirability function, Taguchi method combined with grey relational analysis (GRA), fuzzy logic, utility, a technique for order performance by similarity to ideal solution (TOPSIS) and weighted principal component analysis (WPCA). Palanikumar et al. conducted an optimization of multiple performance characteristics in turning of glass fiber reinforced polymer composite material using grey-fuzzy analysis [5]. The optimized responses were tool wear and surface roughness. Fiber orientation, cutting speed, feed, depth of cut and machining time was considered as the turning parameters. An optimization of multiple performances using grey-fuzzy analysis in the drilling of hybrid metal matrix composites has been performed [6]. The drilling parameters used in the optimization were spindle speed, feed rate and percentage weight of SiC. The optimized multiple performance characteristics were thrust force, surface roughness, and burr height. Krishnamoorthy et al. have also used grey-fuzzy analysis to optimize five different performance characteristics (thrust force, torque, entry delamination, exit delamination, and hole surface roughness) in the drilling of carbon fiber reinforced plastic (CFRP) [3]. The drilling parameters which considered affected the performance characteristics were spindle speed, point angle, and feed rate. Pandey and Panda have applied the grey-based fuzzy algorithm to conduct an optimization of multiple performance characteristics in the drilling of bone [7]. The objective of the multiple performance optimization were reducing the temperature and force during the drilling process and surface roughness of the hole. The drilling parameters considered were spindle speed and feed rate. Sakthivel et al. have also used grey-fuzzy logic in the optimization of cutting parameters in the drilling of glass fibre reinforced stainless steel mesh polymer composite [8]. The optimized responses were thrust force, torque, delamination and diameter deviation. The varied drilling parameters were point angle, spindle speed, and feed rate.

Artificial neural network (ANN) has gained popularity for modeling very complex nonlinear systems and predicting the responses. The meta-heuristic methods for single or multiple objectives optimizations commonly used are a genetic algorithm (GA), ant colony optimization (ACO), harmony search, simulated annealing (SA), particle swarm optimization (PSO) and gravitational search algorithm (GSA). Jayabal and Natarajan conducted an optimization of three different responses (thrust force, torque, and tool wear) in the drilling of coir fiber reinforced composites using Nelder-Mead and GA methods [9]. The varied drilling parameters were drill bit diameter, spindle speed, and feed rate. Saravanan et al. applied GA based multi objective optimization in drilling carbon fibre reinforced plastic (CFRP) [10]. The input parameters were spindle speed and feed rate, while the output were metal removal rate (MRR) and hole eccentricity or hole roundness. Kannan et al. performed a study to improve hole quality (surface roughness), to increase productivity (drilling time) and to reduce thrust force in drilling copper by applying the integration of ANN with GA and PSO [11]. Spindle speed and feed rate were the varied drilling parameters. The relationships between the drilling parameters and surface roughness, drilling time and thrust force were developed by using ANN. GA and PSO were utilized for minimizing surface roughness, drilling time and thrust force. Shunmugesh and Panneerselvam conducted a multi objective optimization in drilling of CFRP using ANN which is linked with particle swarm optimization gravitational search algorithm (PSO GSA) and GA [4]. Cutting speed, feed rate and drill bit type were the varied drilling parameters, while thrust force, torque and surface roughness were the minimized responses. In the past, Wan et al. experimented with multi-objective optimization in small scale resistance spot welding of titanium alloy [12]. Grey relational analysis was used for rough estimation of the optimum welding parameters. BPNN based GA was applied to search the global optimum parameters.

The usage of grey fuzzy analysis and BPNN based GA for the minimization of thrust force, torque, hole surface roughness, delamination and hole roundness simultaneously in drilling composites was very limited. This research has taken KFRP as working material and applying the combination of grey fuzzy analysis and BPNN-based GA for determining the optimal parameters in the drilling process. Grey fuzzy analysis has been used for obtaining a rough estimation of optimum parameters combination in drilling KFRP. The multiple performance characteristics were predicted and improved by BPNN-based GA optimization method.

2 Optimization Methodologies

2.1 Grey-Fuzzy Optimization

Taguchi's method has been carried out for analyzing the experimental results. Taguchi method uses the design of orthogonal arrays to study the variables and its interactions using a small number of experiments. The steps used to perform an optimization using grey-fuzzy analysis are shown in Fig. 1.

2.1.1 Calculation of S/N Ratio

The signal-to-noise (S/N) ratio is a measure of the data set relative to the standard deviation. If the S/N is large, the magnitude of the signal is large relative to the noise, as measured by the standard deviation. There are three S/N ratios available, depending on the type of the performance characteristics; lower is better (LB), higher is better (HB) and nominal is better (NB). In drilling process, lower thrust force, torque, hole surface roughness, delamination and hole roundness are indications of better performance. Therefore, for obtaining minimum machining performance, the "LB" ratio was selected for all of these responses. The S/N ratios for LB characteristic can be calculated as follows [13]:

$$\text{S/N ratio} = -10 \log \left[\sum_{i=1}^{n} \frac{y_i^2}{n} \right], \tag{1}$$

where n is the number of measurements and y_i^2 is the measured characteristic value. Regardless the category of performance characteristics, the greater S/N ratio corresponds to the better performance characteristic.

2.1.2 Calculation of S/N Ratio

In the grey relational analysis method, data preprocessing is used to normalize the initial data. The experimental results of thrust force, torque, hole surface roughness, delamination and hole roundness have been converted into values in the range between zero and one by using linear normalization. The normalization of S/N ratio of the responses were calculated using Eq. (2) [14, 15].

$$X_i^*(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)}, \tag{2}$$

where $X_i^*(k)$ is the normalization value, $\min X_i(k)$ is the smallest value of $X_i(k)$ for the kth response and $\max X_i(k)$ is the largest value of $X_i(k)$ for the kth response.

2.1.3 Grey Relational Coefficient

Grey relational analysis is used to measuring the two systems or two sequences relevancies. The sequences used in the grey relational analysis are called grey relational coefficient (GRC), which shows the relationship between the ideal condition and the actual condition of the normalized response. The calculation of GRC $\xi_i(k)$ conducted by using Eq. (3) [14, 15].

$$\xi_i(k) = \frac{\Delta_{\min} + \xi \Delta_{\max}}{\Delta_{0,i}(k) + \xi \Delta_{\max}}, \tag{3}$$

where $\Delta_{0,i}(k)$ is the deviation sequence of the reference sequence, ζ the distinguishing coefficient ($\zeta = 0.5$ is generally used), $\Delta_{\min}$ is the smallest value of $\Delta_{0,i}$ and $\Delta_{\max}$ is the largest value of $\Delta_{0,i}$.

2.1.4 Fuzzification and Defuzzification

The GRC of each quality characteristic converted into one multi-response output which is called grey fuzzy reasoning
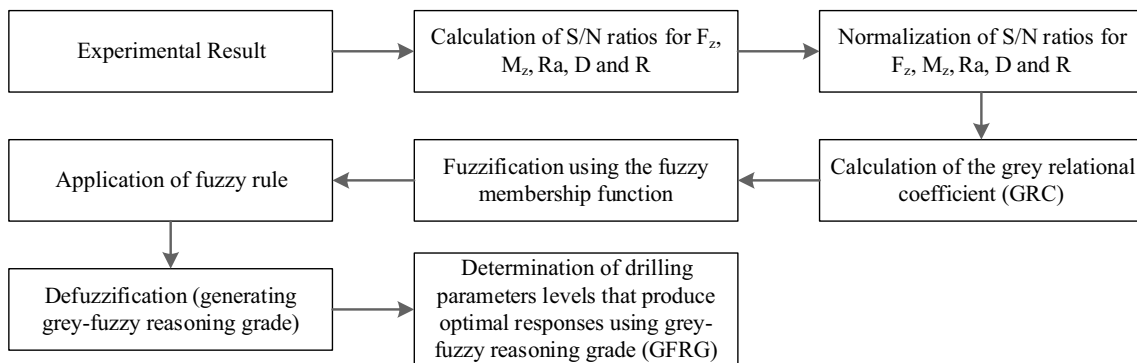

Fig. 1 Steps for optimization using grey-fuzzy

grade (GFRG). The fuzzy logic analysis which uses membership function, fuzzy rule and defuzzification are used to perform the GRC conversion.

2.1.5 Analysis of Variance (ANOVA)

The purpose of ANOVA is to evaluate the significance of the factor effect on an experiment. The factor effect is not cited in the prediction formula until its significance has reached a certain level. The percentage contribution of machining parameters or factors on the desired quality measures value indicates the relative power of a factor and/or interaction for reducing the total variance [16]. If the factor or/and interaction levels could be controlled precisely, then the total variation could also be reduced by the amount indicated by the percentage contribution. This tool has been used by several researchers [15–18].

2.2 Back Propagation Neural Network (BPNN)

Artificial neural network (ANN) is an information processing system that has certain work-related characteristics that resemble biological neural networks [19]. ANN has been developed as a generalization of mathematical models of the cognitive aspects of human or biological nerves, that is based on the assumptions that:

1. Information processing occurs on elements called neurons.
2. Signals propagate between neurons through the interconnection.
3. Each interconnection has a corresponding weight that on most neural networks serves to multiply the transmitted signal.

Each neuron implements an activation function, which is not linear usually, on the network input to determine its output signal. One of the architectures of artificial neural networks that has a high accuracy and speed is the back-propagation neural network (BPNN). BPNN was first introduced in 1986 [20]. BPNN is commonly applied to multi-layer perceptrons. Perceptron has at least an input section, an output section and several layers that are between input and output. This middle layer, also known as hidden layers, can be one, two, three layers or more. The last layer output from the output layer is directly used as the output of the neural network.

Training on back-propagation method involves three stages, that is feed forward training pattern, error counting and weight adjustment. After the training, network applications only use the first stage of computing, i.e., feed forward, to perform testing. Although the training phase is slow, the network can produce output very quickly. Back-propagation

method has been varied and developed to improve the speed of the training process. Since a single layer of the network has a very limited capacity in learning, adding layered networks would give more capacity in learning. BPNN architecture consists of many layers (multilayer neural network), namely [21]:

1. Input layer which consists of neurons or input units, from input 1 to input unit n.
2. The hidden layer which consists of hidden units ranging from hidden units 1 to hidden units p.
3. Output layer consists of units of output starting from the output unit 1 to the output unit m.

The symbols n, p and m is each arbitrary integer numbers according to the artificial neural network architecture designed.

2.3 Genetic Algorithm (GA)

Genetic algorithm is a search method of stochastic optimum value based on natural selection mechanism-genetic theory. Genetic algorithms differ from conventional convergence method that are more deterministic [22, 23].The classical optimum search method generally utilizes the convergence of the convergent asymptotic curves to the desired solution. The convergence process is conducted by evaluating a point on the asymptotic curve in each iteration process. In the next iteration process, the evaluation point is shifted towards the valleys/hills that are expected to lead to the convergent point that exists. Point-by-point analysis like this can produce the correct value only if the problem being analyzed has an extreme point that ensures that the local optimum value is also a global optimum value. On the other hand, genetic algorithms perform the process of searching the optimum value at several points simultaneously (one generation). A set of optimized parameters will be used to create a chromosome which defined as a solution candidate for an optimization problem. The chromosome being analyzed can be a binary, integer or decimal code. For the first generation, the initial chromosome is randomly generated from its solution space. A set of good chromosome (parent) is then selected based on its fitness value, whereas a set of bad chromosome will be removed from solution candidate in the next generation. The iteration process is then carried out with a generation-to-evolution approach, but the number of chromosome in each generation is generally maintained. Two parent chromosomes are then selected using selection method (e.g. roulette wheel, ranking and tournament) to produce offspring chromosome through crossover and mutation process for generating and maintaining the population set. A stopping parameter is finally applied to stop iteration and a chromosome with the best fitness is then selected as a
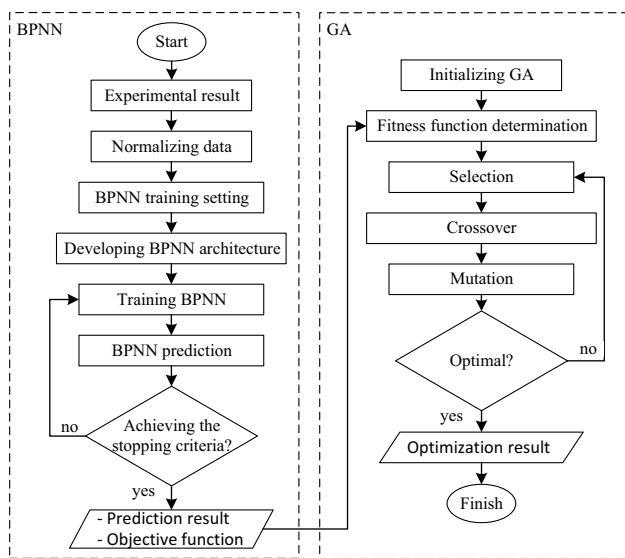
Fig. 2 Optimization using BPNN–GA method

Fig. 3 KFRP drilling process

solution for the optimization problem. Figure 2 shows the flow chart of BPNN–GA based optimization method.

3 Experimental Design and Result

3.1 Materials and Equipment

A CNC Milling Machine YCM MV 86A is used to conduct the experimental study. The drilling process of KFRP composite was conducted without coolant as shown in Fig. 3. A KISTLER 4-component dynamometer Type 9272 was used to measure the thrust force and torque as shown in Fig. 4. Table 1 shows the levels of drill point geometry, point angle, feed rate and cutting speed that were used in the experiment. The levels of parameters used in the study adapted to the levels interval recommended by the manufacturer of the cutting tool. The drill bits used in this experiment were two flute straight twist drill having a diameter of 10 mm. Two drill point geometries were selected, i.e., S-type and X-type as shown in Fig. 5. While the first type was made of HSS, the other was made of HSS-cobalt. KFRP composite with a dimension of 200 mm (length) × 30 mm (width) × 6 mm (thickness) was used as workpiece material. The matrix material is an epoxy resin, while the fiber is kevlar/aramid. The composite was manufactured by PT. Dirgantara Indonesia, an aircraft manufacturer. It has a tensile strength of 515 MPa, a tensile modulus of 25 GPa, the density of 1.35 g/cm3 and shear modulus of 8.45 GPa. The hole surface roughness values were measured using a Mitutoyo Surftest SJ-310. The hole roundness values were measured using a Roundtest Roncorder EC-3D. The value of delamination

Fig. 4 Schematic of thrust force and torque measurement

Table 1 Drilling parameters and their levels

Parameters	Unit	Level		
		1	2	3
Drill point geometry (PG)	–	S type	X type	–
Drill point angle (PA)	Degree	100	118	140
Feed rate (V_f)	mm/min	50	115	180
Cutting speed (V_c)	m/min	47.1	62.8	78.5

is represented by delamination factor which is calculated as the ratio between maximum diameter (D_{max}) in the delamination area and the nominal diameter (D_0) of the drill (10 mm), or [24]:

$$D = \frac{D_{max}}{D_0},$$

(4)

Fig. 5 Drill point geometry for **a** S-type, **b** X-type

3.2 Design of Experiments

An experiment was designed using Taguchi method which uses an orthogonal array to study the entire parametric space with a limited number of experiments [14]. Design of experiments and Taguchi's method have been used to accomplish the objective of the experimental study. To select an appropriate orthogonal array for the experi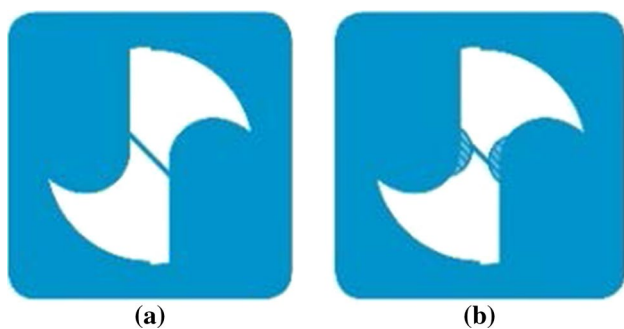ments, the total degrees of freedom had to be computed. There were 7 degrees of freedom due to one two-level machining parameter and four three-level machining parameters in the drilling process. Hence, an L_{18} orthogonal array was selected for the experiment and shown in Table 2. To preserve the randomness of the experiment, a random order was also determined for running the experiments. The experiments were replicated three times.

3.3 Experimental Results

Table 3 shows the experimental result for thrust force, torque, hole surface roughness, delamination and hole roundness. The S/N ratios for all response parameters were calculated using Eq. (1).

4 Optimization Results

4.1 Grey-Fuzzy Optimization

The normalization of S/N ratio of the responses was calculated using Eq. (2). The calculation of GRC $\xi_i(k)$ was conducted using Eq. (3). The GRC of each response was converted into one multi-response output which is called grey fuzzy reasoning grade (GFRG) as shown in Table 4. The conversion was conducted by using fuzzy logic analysis which uses membership function, fuzzy rule and defuzzification.

In this research, three fuzzy subsets are assigned in the GRC of thrust force, torque, hole surface roughness, delamination and hole roundness as shown in Fig. 6a, b shows that there are nine fuzzy subsets assigned in the GFRG. For both figures, S is small, VS is very small, M is middle, SM is smaller middle, LM is larger middle, L is large, VL is very large and H is huge. The GFRG from all 18 experiments with three replications were predicted by evaluating the fuzzy inference system (FIS), which was activated by a set of rules that have been written.

The optimum condition of the parameter levels can be chosen by using average analysis from the response graph. The procedure of response table is used to group GFRG by parameter levels and then to calculate the average. The average GFRG value for each factor levels is then plotted in Fig. 7 to attain the optimum parameter setting that would reduce the total variance of the responses simultaneously. Based on Fig. 7, for minimizing all of the responses in drilling of KFRP composite drill point geometry, drill point angle, feed rate and cutting speed are set at level 2 (type X), level 1 (100°), level 1 (50 mm/min), level 1 (50 mm/min) and level 2 (62.8 m/min) respectively. This setting is selected from the drilling parameters which have the greatest GFRG.

Table 5 shows the ANOVA table of the GFRG which includes the percentage contribution of each drilling parameters. The application of grey-fuzzy optimization is useful in determining the levels of drilling parameters for

Table 2 Experimental Layout Using L_{18} Orthogonal

No.	PG	PA	V_f	V_c	No.	PG	PA	V_f	V_c
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

Table 3 Result of experiments

No.	Thrust force (F_z) (N)			Torque (M_z) (Nm)			Hole surface roughness (R_a) (µm)			Delamination (D)			Hole roundness (R) (µm)		
	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
1	32.16	31.89	31.23	0.749	0.891	0.787	1.988	1.812	1.954	1.093	1.185	1.016	170	175	195
2	67.84	68.65	68.23	1.038	1.091	1.105	2.219	2.094	2.134	1.085	1.076	1.109	220	215	225
3	97.81	97.93	98.89	0.916	1.088	0.924	2.945	2.792	2.888	1.327	1.399	1.27	260	255	265
4	76.35	77.12	74.98	0.558	0.558	0.408	3.112	3.112	3.19	1.31	1.371	1.243	250	240	230
5	46.73	45.75	47.11	0.362	0.488	0.386	2.96	3.077	2.921	1.168	1.171	1.159	290	300	310
6	129.10	129.52	129.28	2.049	1.957	1.991	3.763	3.735	3.713	1.423	1.475	1.365	400	395	405
7	46.15	45.66	45.14	0.662	0.732	0.682	1.9	1.968	1.889	1.277	1.217	1.361	260	285	295
8	167.00	167.24	168.26	1.065	1.057	0.983	3.358	3.36	3.299	1.43	1.498	1.338	390	380	370
9	210.70	211.52	211.38	1.601	1.574	1.538	3.045	3.066	3.081	1.495	1.536	1.478	400	405	395
10	83.40	83.11	84.59	0.103	0.187	0.094	2.227	2.139	2.222	1.047	1.074	1.005	190	205	205
11	53.13	53.81	51.55	1.621	1.532	1.635	2.376	2.456	2.389	1.178	1.156	1.2135	220	210	230
12	72.27	71.54	72.10	1.695	1.735	1.73	2.133	2.034	2.139	1.152	1.194	1.095	210	195	195
13	58.09	58.97	57.96	0.416	0.417	0.256	1.955	2.075	1.955	1.081	1.075	1.0945	190	175	175
14	108.55	108.72	107.63	0.924	1.055	0.952	3.044	2.994	2.974	1.291	1.288	1.2865	270	285	285
15	96.75	97.54	96.71	1.616	1.461	1.612	2.839	2.996	2.802	1.335	1.364	1.3135	330	300	330
16	124.47	123.39	124.44	0.522	0.524	0.583	2.047	1.932	2	1.254	1.258	1.229	210	220	230
17	173.87	173.22	173.41	0.38	0.385	0.312	2.578	2.678	2.64	1.242	1.239	1.224	260	265	255
18	166.83	167.54	167.23	1.324	1.334	1.377	2.026	1.969	1.921	1.3	1.374	1.2455	290	275	275

Table 4 GRC of responses and GFRG

| No.	Grey relational coefficient (GRC)					GFRG	No.	Grey relational coefficient (GRC)					GFRG
	F_z	M_z	R_a	D	R			F_z	M_z	R_a	D	R	
1	1.0000	0.4270	1.0000	0.7789	1.0000	0.8475	10	0.4943	1.0000	0.7113	1.0000	0.7912	0.8183
2	0.5533	0.3921	0.7457	0.8010	0.6655	0.6453	11	0.6505	0.3526	0.5949	0.5913	0.6655	0.5869
3	0.4563	0.4035	0.4517	0.4272	0.5206	0.4198	12	0.5366	0.3459	0.7845	0.6559	0.7912	0.6338
4	0.5200	0.4992	0.4038	0.4464	0.5812	0.4825	13	0.6090	0.5687	0.8944	0.8257	1.0000	0.7932
5	0.7127	0.5403	0.4297	0.6203	0.4387	0.5612	14	0.4357	0.4034	0.4264	0.4631	0.4747	0.4052
6	0.4029	0.3333	0.3333	0.3713	0.3333	0.338	15	0.4590	0.3545	0.4509	0.4231	0.4097	0.3877
7	0.7231	0.4488	0.9984	0.4666	0.4747	0.6305	16	0.4101	0.4874	0.8968	0.5051	0.6655	0.5987
8	0.3629	0.3967	0.3756	0.3709	0.3482	0.3537	17	0.3581	0.5713	0.5131	0.5187	0.5206	0.5044
9	0.3333	0.3540	0.4159	0.3333	0.3333	0.3362	18	0.3632	0.3688	0.9231	0.4472	0.4747	0.4795
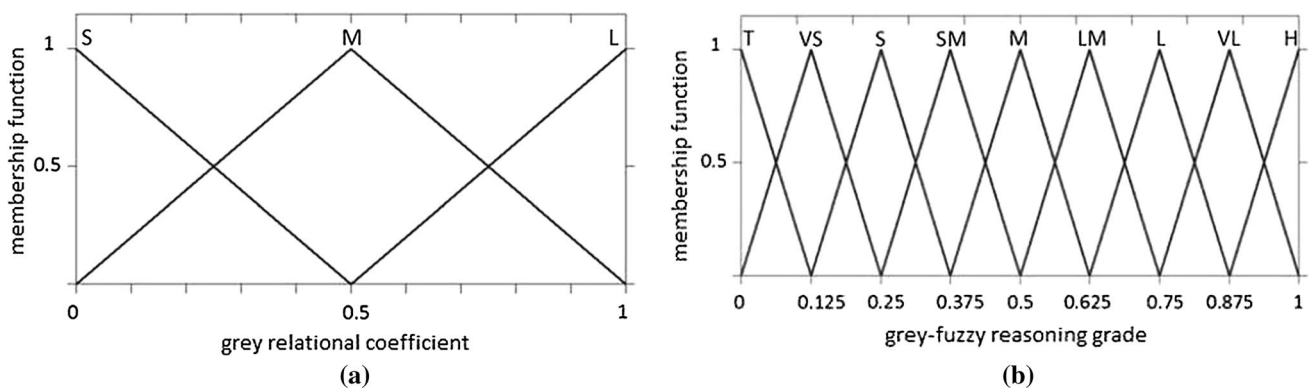
Fig. 6 Membership function of **a** GRC for all responses, **b** GFRG
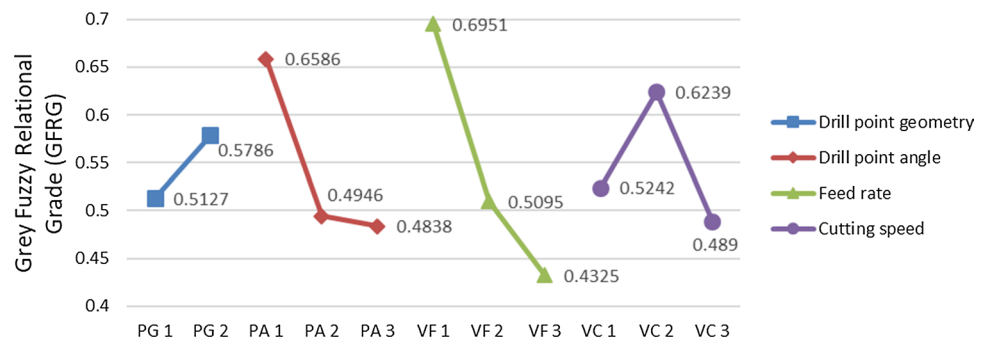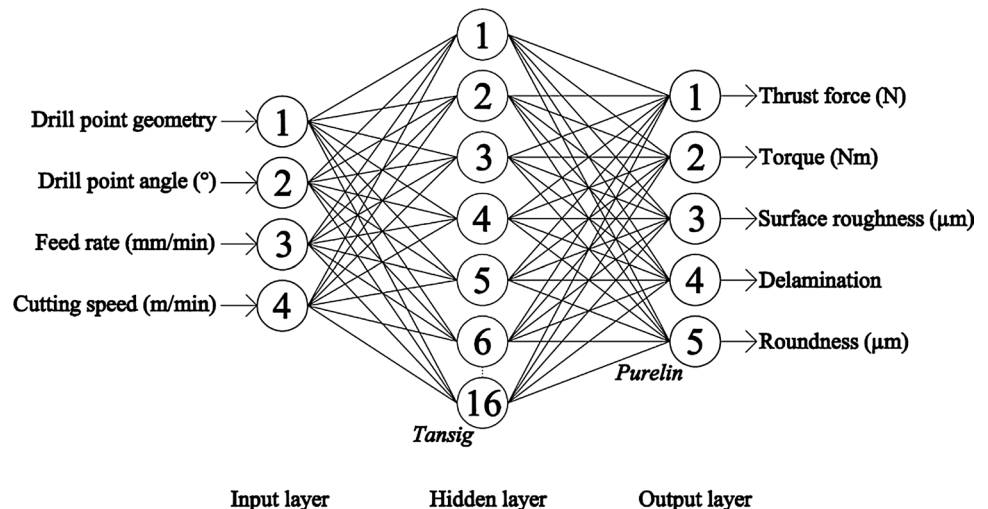
Fig. 7 Response graph for GFRG

Table 5 ANOVA and percentage contributions of drilling parameters for GFRG

Source	DF	SS	MS	F	SS′	% con.
PG	1	0.019536	0.019536	5.05	0.015671	3.48
PA	2	0.11509	0.057545	14.89	0.10736	23.82
V_f	2	0.218722	0.109361	28.3	0.210992	46.8
V_c	2	0.058804	0.029402	7.61	0.051074	11.33
Error	10	0.038649	0.003865			14.57
Total	17	0.450801				100

Fig. 8 BPNN architecture

multiple-performance optimization. However, the obtained levels of the drilling parameters are considered as rough estimations. Therefore, further analysis is conducted for searching the global optimum drilling parameters by using the combine methods of BPNN and GA.

4.2 BPNN–GA Based Optimization

4.2.1 BPNN

The numbers of neurons of input and output layers were the same as the numbers of drilling parameters and responses. Therefore, there are four neurons of input layers and five neurons of output layers. Trial and error method was performed to obtain the minimum value of mean square error (MSE) in determining the number neuron of the hidden layer, as well as the number of hidden layers. The result showed that the number of neurons in the hidden layer was 16, which meant that the optimum architecture of BPNN used in this study was 4–16–5 as seen in Fig. 8. This architecture produces MSE training and testing values of 0.019 and 0.015 respectively, which are the minimum values from trial and error calculation. The activation functions for hidden layers and output layers were tansig and purelin respectively. Levenberg–Marquardt (trainlm) was applied as the training function. The stopping criteria in training the data is shown in Table 6. The percentage of data used for training and testing were 70% and 30% respectively from 54 total

Table 6 The stopping criteria in training

Name	Values
Max. epoch	10,000
Performance goal	0.001
Min. performance gradient	0.00001
Max. validation failure	1000

data. Table 7 shows the overall data of BPNN that compare the predicted and experimental results of each combination for all of the responses. It can be seen that the average error between experimental and predicted results did not exceed 10%, which verified that the prediction of the responses close to the experimental data [25].

BPNN training, testing and validation were conducted by using MATLAB R2013a. The graphs between the targets (experimental data) and BPNN output or predicted results for training, testing, validation and all data are shown in Fig. 9. The values of the correlation coefficients for training, testing and all data were 0.99258, 0.96947 and 0.98534 respectively. These results indicating that there was an excellent goodness of fit between the targets (experimental data) and BPNN output or predicted results. The same procedure [26] for examining the correlations between the target and output values in term of training, testing and all data was also applied.

4.2.2 GA

GA parameters are shown in Table 8. By solving the optimization problem using GA, the minimum thrust force, torque, hole surface roughness, delamination and hole roundness could be obtained by using X-type drill point geometry and setting drill point angle, feed rate and cutting speed at 100°, 50 mm/min and 75 m/min respectively.

5 Result and Discussion

5.1 Influence of Drilling Condition on Thrust Force, Torque, Hole Surface Roughness, Delamination and Hole Roundness

The percentage contributions of drilling parameters on the total variance of the multiple responses or GFRG are shown in Table 5. Feed rate has the highest contribution (46.8%), followed by point angle (23.82%), cutting speed (11.33%) and drill point geometry (3.48%). The analysis of the influence of drilling parameters on KFRP was conducted by examining the percentage contribution of drilling parameters on total variance of five responses individually and the response graphs. The percentage

contribution of drilling parameters is shown in Table 9. Regarding the magnitude of the percentage contribution of drilling parameters on the total variance of thrust force, torque, hole surface roughness and delamination, the highest contributor was feed rate, followed by cutting speed, drill point angle and drill point geometry respectively. The same results were also obtained by several researchers [17, 18]. The percentage contribution of cutting speed is the highest for hole roundness, followed by drill point geometry, drill point angle and feed rate respectively. The response graphs for thrust force, torque, hole surface roughness, delamination and hole roundness are presented in Figs. 10, 11, 12, 13 and 14. The results of the optimization using grey fuzzy analysis and BPNN–GA have shown that drill point geometry type X would produce a low value of thrust force, torque, hole surface roughness, delamination and hole roundness.

Figure 10 shows that increasing point angle would increase the thrust force. The increase of feed rate increases the load on the drill and hence increases the thrust force, while the increase of cutting speed reduces the thrust force. The increase of feed rate would enhance the cross-sectional area of the undeformed chip which has a greater resistance to chip formation, consequently needs a greater axial thrust force to cut it through [27]. This figure also indicates that the increase of cutting speed would decrease the thrust force [18, 28]. Several researchers were also obtained the same conclusion regarding the effects of point geometry, point angle, feed rate and cutting speed on thrust force [3, 5, 6, 18].

Figure 11 depicts that only the increase of feed rate would increase the torque, while the increase of the other three drilling parameters would reduce the torque. This corresponds to the empirical equation for calculating the torque during the drilling process, which states that the torque is influenced by the diameter of the workpiece, feed rate and chisel geometry [29]. This finding is in accordance with the results of several researchers [3, 17, 27].

It can be seen in Fig. 12 that low hole surface roughness could be obtained by using small point angle, low feed rate and high cutting speed. Increasing feed rate would increase the thrust force and fracture the composite materials, which finally increasing surface roughness. The use of high cutting speed and low feed rate will lead to a rise in temperature in the composite material. The temperature rise will decrease the hardness of the composite hence composite material will be cut easily, resulting in lower surface roughness. These phenomena are in agreement with literature [27]. Other studies also obtained similar results [5, 6, 17, 18].

From Fig. 13, it can be seen that delamination could be prevented by using small point angle, low feed rate and high cutting speed. Increasing the feed rate will enhance the thrust force, hence leads to increase the delamination

Table 7 Prediction error of BPNN

No.	Thrust force (F_Z)			Torque (M_Z)			Hole surface roughness (R_a)			Delamination (D)			Hole roundness (R)		
	Exp.	Pred.	Error (%)	Exp.	Pred.	Error (%)	Exp.	Pred.	Error (%)	Exp.	Pred.	Error (%)	Exp.	Pred.	Error (%)
1	32.16	29.63	7.86	0.749	0.746	0.34	1.988	1.947	2.06	1.093	1.134	-3.75	170	179	-5.36
2	67.84	68.22	-0.56	1.038	1.036	0.19	2.219	2.159	2.69	1.085	1.067	1.65	220	220	-0.14
3	97.81	97.67	0.15	0.916	1.054	-15.02	2.945	2.885	2.03	1.327	1.352	-1.89	260	262	-0.86
4	76.35	77.18	-1.09	0.558	0.577	-3.35	3.112	3.095	0.55	1.31	1.338	-2.11	250	245	2.07
5	46.73	45.53	2.57	0.362	0.552	-52.46	2.96	3.043	-2.80	1.168	1.184	-1.41	290	297	-2.52
6	129.1	128.01	0.85	2.049	1.988	2.99	3.763	3.751	0.33	1.423	1.397	1.85	400	404	-1.03
7	46.15	47.20	-2.27	0.662	0.620	6.35	1.9	1.898	0.13	1.277	1.315	-2.98	260	283	-8.69
8	167	168.65	-0.99	1.065	1.031	3.19	3.358	3.385	-0.79	1.43	1.441	-0.80	390	384	1.60
9	210.7	215.78	-2.41	1.601	1.630	-1.83	3.045	2.994	1.67	1.495	1.526	-2.08	400	401	-0.28
10	83.4	85.79	-2.87	0.103	0.124	-20.47	2.227	2.162	2.94	1.047	1.050	-0.29	190	199	-4.67
11	53.13	63.65	-19.80	1.621	1.828	-12.78	2.376	2.392	-0.67	1.178	1.313	-11.42	220	257	-16.61
12	72.27	71.73	0.75	1.695	1.712	-1.03	2.133	2.089	2.08	1.152	1.151	0.06	210	210	-0.08
13	58.09	59.14	-1.81	0.416	0.372	10.68	1.955	1.986	-1.61	1.081	1.086	-0.46	190	178	6.29
14	108.55	108.94	-0.36	0.924	1.017	-10.10	3.044	2.967	2.53	1.291	1.287	0.28	270	284	-5.08
15	96.75	98.83	-2.15	1.616	1.611	0.32	2.839	2.858	-0.67	1.335	1.334	0.04	330	329	0.23
16	124.47	128.42	-3.17	0.522	0.458	12.34	2.047	2.069	-1.10	1.254	1.262	-0.60	210	214	-1.98
17	173.87	179.19	-3.06	0.38	0.345	9.34	2.578	2.602	-0.93	1.242	1.238	0.32	260	258	0.63
18	166.83	170.77	-2.36	1.324	1.413	-6.70	2.026	1.904	6.01	1.3	1.295	0.42	290	285	1.72
19	31.89	29.63	7.08	0.891	0.746	16.22	1.812	1.947	-7.46	1.185	1.134	4.31	175	179	-2.35
20	68.65	68.22	0.62	1.091	1.036	5.04	2.094	2.159	-3.11	1.076	1.067	0.83	215	220	-2.47
21	97.93	97.67	0.27	1.088	1.054	3.16	2.792	2.885	-3.34	1.399	1.352	3.35	255	262	-2.83
22	77.12	77.18	-0.08	0.558	0.577	-3.35	3.112	3.095	0.55	1.371	1.338	2.44	240	245	-2.01
23	45.75	45.53	0.49	0.488	0.552	-13.09	3.077	3.043	1.11	1.171	1.184	-1.15	300	297	0.90
24	129.52	128.01	1.17	1.957	1.988	-1.57	3.735	3.751	-0.42	1.475	1.397	5.31	395	404	-2.31
25	45.66	47.20	-3.37	0.732	0.620	15.30	1.968	1.898	3.58	1.217	1.315	-8.06	285	283	0.84
26	167.24	168.65	-0.84	1.057	1.031	2.46	3.36	3.385	-0.73	1.498	1.441	3.78	380	384	-0.99
27	211.52	215.78	-2.01	1.574	1.630	-3.58	3.066	2.994	2.34	1.536	1.526	0.65	405	401	0.96
28	83.11	81.96	1.38	0.187	0.162	13.43	2.139	2.194	-2.57	1.074	1.063	1.00	205	198	3.34
29	53.81	50.05	6.98	1.532	1.628	-6.29	2.456	2.383	2.99	1.156	1.212	-4.85	210	231	-10.21
30	71.54	73.91	-3.32	1.735	1.720	0.85	2.034	2.158	-6.12	1.194	1.101	7.75	195	195	0.23
31	58.97	59.14	-0.29	0.417	0.372	10.89	2.075	1.986	4.27	1.075	1.086	-1.03	175	178	-1.74
32	108.72	108.94	-0.20	1.055	1.017	3.57	2.994	2.967	0.90	1.288	1.287	0.05	285	284	0.45
33	97.54	98.83	-1.32	1.461	1.611	-10.26	2.996	2.858	4.61	1.364	1.334	2.17	300	329	-9.74
34	123.39	117.09	5.10	0.524	0.596	-13.68	1.932	1.946	-0.72	1.258	1.252	0.80	220	218	0.80

Table 7 (continued)

| No.	Thrust force (F$_Z$)			Torque (M$_Z$)			Hole surface roughness (R$_a$)			Delamination (D)			Hole roundness (R)		
	Exp.	Pred.	Error (%)	Exp.	Pred.	Error (%)	Exp.	Pred.	Error (%)	Exp.	Pred.	Error (%)	Exp.	Pred.	Error (%)
35	173.22	166.23	4.04	0.385	0.342	11.29	2.678	2.609	2.56	1.239	1.228	0.91	265	257	3.13
36	167.54	164.57	1.77	1.334	1.313	1.54	1.969	2.016	−2.38	1.374	1.313	4.40	275	278	−1.18
37	31.23	34.09	−9.15	0.787	0.931	−18.35	1.954	1.909	2.32	1.016	1.045	−2.81	195	183	6.30
38	68.23	77.22	−13.17	1.105	1.244	−12.56	2.134	2.049	3.98	1.109	1.049	5.37	225	216	3.89
39	98.89	100.37	−1.50	0.924	0.846	8.40	2.888	2.880	0.28	1.27	1.290	−1.57	265	255	3.69
40	74.98	77.18	−2.94	0.408	0.577	−41.35	3.19	3.095	2.98	1.243	1.338	−7.61	230	245	−6.44
41	47.11	45.53	3.36	0.386	0.552	−42.98	2.921	3.043	−4.17	1.159	1.184	−2.19	310	297	4.09
42	129.28	128.01	0.99	1.991	1.988	0.17	3.713	3.751	−1.01	1.365	1.397	−2.32	405	404	0.22
43	45.14	46.37	−2.72	0.682	0.701	−2.77	1.889	1.900	−0.60	1.361	1.311	3.64	295	271	8.12
44	168.26	163.41	2.88	0.983	1.039	−5.66	3.299	3.250	1.48	1.338	1.398	−4.50	370	373	−0.85
45	211.38	208.51	1.36	1.538	1.488	3.27	3.081	3.151	−2.26	1.478	1.485	−0.45	395	398	−0.69
47	51.55	50.05	2.90	1.635	1.628	0.41	2.389	2.383	0.27	1.2135	1.212	0.12	230	231	−0.63
48	72.1	73.91	−2.52	1.73	1.720	0.57	2.139	2.158	−0.91	1.095	1.101	−0.59	195	195	0.23
49	57.96	59.14	−2.04	0.256	0.372	−45.15	1.955	1.986	−1.61	1.0945	1.086	0.77	175	178	−1.74
50	107.63	108.94	−1.22	0.952	1.017	−6.86	2.974	2.967	0.23	1.2865	1.287	−0.07	285	284	0.45
51	96.71	98.83	−2.19	1.612	1.611	0.07	2.802	2.858	−2.00	1.3135	1.334	−1.59	330	329	0.23
52	124.44	117.09	5.90	0.583	0.596	−2.17	2	1.946	2.70	1.229	1.252	−1.90	230	218	5.11
53	173.41	166.23	4.14	0.312	0.342	−9.46	2.64	2.609	1.16	1.224	1.228	−0.31	255	257	−0.67
54	167.23	164.57	1.59	1.377	1.313	4.61	1.921	2.016	−4.94	1.2455	1.3135	−5.46	275	278	−1.18
Average error			−0.45			−5.34			0.18			−0.52			−0.68
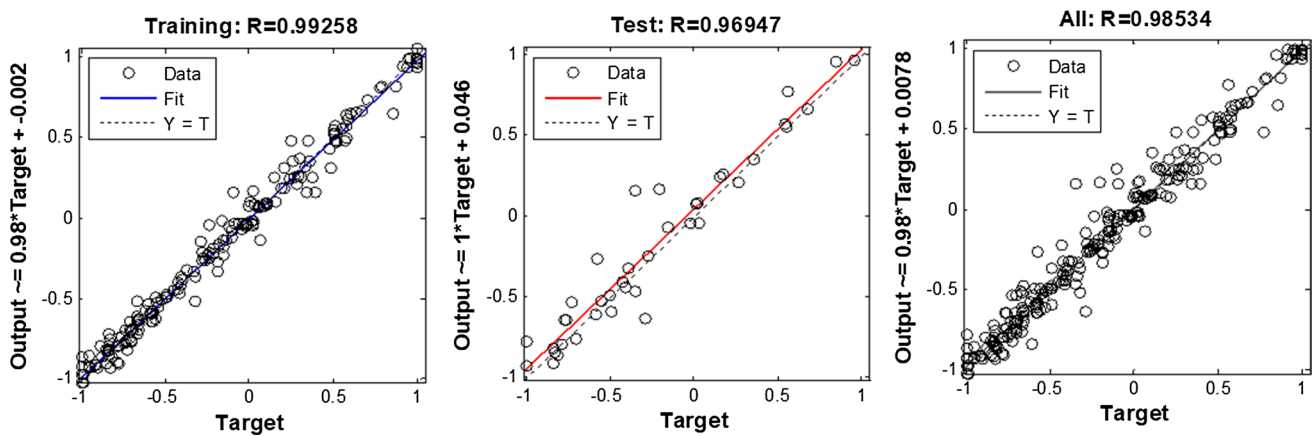
Fig. 9 Comparison between experimental data and prediction data of BPNN

Table 8 Parameters of GA

Parameters	Name/value
Population size	100
Generation size	100
Selection function	Roulette wheel
Mutation function	Uniform
Crossover function	Two point
Crossover fraction	0.8
Mutation fraction	0.05

at drilled hole. This observation is similar to the results of several researcher [3, 18, 27, 28, 30, 31].

Based on Fig. 14, small hole roundness could be produced by drilling using small point angle, low feed rate and high cutting speed. These phenomena are in agreement with other studies [3, 17, 27].

5.2 Confirmation Experiment

Table 10 shows the results of the confirmation experiments using the optimal drilling parameters obtained by using grey

fuzzy and BPNN–GA optimization methods. Both optimization methods recommended the same type of drill point geometry (type X), drill point angle (100°) and feed rate (50 mm/min). However, BPNN–GA optimization method yielded a higher cutting speed, i.e., 75 m/min. The confirmation experiments of both optimization methods were replicated three times and the averages are also presented in Table 10. Since grey fuzzy analysis does not predict the responses, the given responses values were obtained from the confirmation experiment. It can be seen that all of the predicted responses of BPNN–GA are lower than the results of the experimental confirmation of grey fuzzy, but still higher than the results of the experimental confirmation of BPNN–GA. Therefore, the minimum thrust force, torque, hole surface roughness, delamination and hole roundness could be obtained by applying the optimal drilling parameters which were determined by using BPNN–GA.

Table 9 Percentage contributions of drilling parameters for individual response

Sources	Thrust force (F_Z)		Torque (M_Z)		Hole surface roughness (R_a)		Delamination (D)		Hole roundness (R)	
	Rank	Cont. (%)	Rank	Cont. (%)	Rank	Cont. (%)	Rank	Cont. (%)	Rank	Cont. (%)
Drill point geometry										
(PG)	4	15.55	4	10.37	4	9.47	4	10.85	2	19.82
Drill point angle (PA)	3	21.30	3	13.46	3	10.18	3	19.73	3	20.67
Feed rate (V_f)	1	37.35	1	23.87	1	42.43	1	40.24	4	11.29
Cutting speed (V_c)	2	22.43	2	50.9	2	33.75	2	26.01	1	45.07
Error	–	3.37		1.40	–	4.17	–	3.17	–	3.15
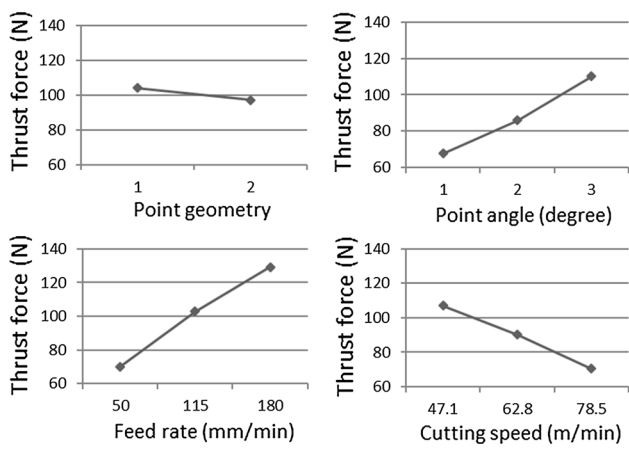
Fig. 10 Response graph for thrust force

Fig. 11 Response graph for torque

Fig. 12 Response graph for hole surface roughness
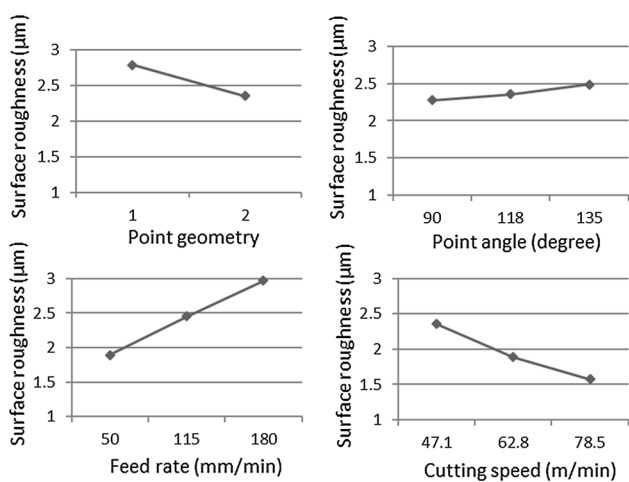

Fig. 13 Response graph for delamination

Fig. 14 Response graph for hole roundness

6 Conclusions

In this study, a multi-objective prediction and optimization of multiple performance characteristics were investigated in drilling KFRP. Grey fuzzy logic was applied first to determine a rough estimation of the optimum drilling parameters. The most influential drilling parameters on multiple performance characteristics were feed rate, followed by point angle, cutting speed and drill point geometry. Next BPNN model was developed and used to predict the minimum thrust force, torque, hole surface roughness, delamination and hole roundness. Afterwards, GA was utilized to search for global optimum drilling parameters combinations. In the end, the analysis of the influence of drilling parameters on the individual performance characteristics was conducted by examining the percentage contribution of drilling parameters on total variance of five responses individually and the response graphs. The results of the experimental confirmation showed that

Table 10 Comparison between confirmation experiment for five responses by grey fuzzy analysis and BPNN–GA methods

Method	Optimal parameters				Response				
	Drill point geometry	Drill point angle (°)	Feed rate (mm/min)	Cutting speed (m/min)	F_Z (N) Pred./exp.	M_Z (Nm) Pred./exp.	R_a (µm) Pred./exp.	D pred./exp.	R (µm) pred./exp.
Grey-Fuzzy	X type	100	50	62.8	± 35.02	± 0.144	± 1.886	± 1.032	± 180
BPNN–GA	X type	100	50	75	22.56/25.65	0.132/0.136	1.787/1.756	0.962/0.922	177.66/170.24

BPNN based GA optimization method could accurately predict and also significantly improve the multiple quality characteristics.

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