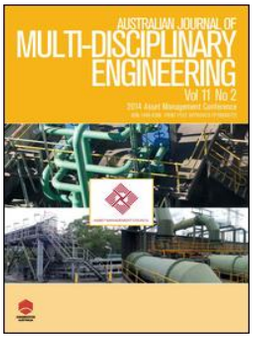

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ARTICLE

Study on prediction of experimental machining response data using artificial neural network

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ABSTRACT
The drilling is one of the most rigorous machining processes in the case of Fibre Reinforced Polymer (FRP) materials due to its promoting characteristic by which components can be assembled easily. As it is common in the case of all composite drilling, delamination that gets induced is directly influenced either by thrust force or twisting force/torque. The present empirical study deals with twisting force/torque attribute obtained based on Taguchi's Design of Experiments (DOE) leading to an influence of the machining parameters (feed rate, cutting speed, tool material) while drilling hybrid composite laminate and the same was validated using Artificial Neural Network (ANN) Back Propagation algorithm approach on training/testing experimental data-set. The output response obtained through ANN was found to be nearest to the experimental results with the least output error.

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KEYWORDS
Drilling parameters; twisting force; DOE; ANN

1. Introduction

Fibre-reinforced polymers (FRPs) being one of the most attractive material is replacing most of the metals nowadays in various applications-oriented industries due to its interesting properties. Since the FRPs may be produced of any shape, it has to be subjected to the final machining process which does not yield the same result as that of metals due to their inhomogeneous nature. Due to its strong anisotropic and inhomogeneous nature, the machining process yields fibre pullout, delamination, and surface damage. Along with the experimental approach, An Artificial Neural Network (ANN) is been used as a suitable tool to predict the experimental data as they can solve the problems in a faster way compared to other tools. ANN is categorised by several features that decide its suitability and learning capability to gain knowledge (Rajesh Mathivanan and Mouli 2012). The Experimental data are trained up directly through learning capability to build a nonlinear relationship between inputs and output in a simple or complex way that can be adapted easily. Among various methods, a predictive approach like ANN can be replaced with an empirical statistical approach on training and test data basis to obtain the minimum error in case of the hole to damage ratio while drilling laminate (Mathew, Ramakrishnan, and NaiK 1999). The relationship between machining input and output variables can be easily understood on applying Multiple Regression Analysis (MRA) in comparison with a selective neural network to derive the near-net results which may depend upon the type of drilling and material (Lin, Bhattacharyya, and Kecman 2003; Tsao and Hocheng 2008; Tsao 2008). Apart from the comparative statistical tool results, Finite Element Analysis (FEA) plays a vital role to extract a predictive reduction in output error in comparison with multi-layer neural networks through consideration of neurons (Budan et al. 2008). Among different response variables, delamination damage is considered a critical issue, and it was observed through their work that results obtained through the ANN approach were found to be in close agreement with experimental data (Mishra, Malik, and Singh 2010). In few cases, the experimental effect of control factors on delamination induced torque was studied in resemblance with artificial neural network results to identify the effective and efficient tool for optimising response variables error while drilling laminates (Athijayamani, Natarajan, and Thiruchitrambalam 2010; Krishnamoorthy, Rajendra Boopathy, and Palanikumar 2011). Another research work indicates that hybrid predictive models were used in estimating drilling-induced damage results in comparison with empirical values on training and testing basis (Malik, Mishra, and Singh 2011). One more attempt revealed that the specimen stiffness which depends upon bearing strength was found to reduce while analysing through ANN and MRA approach (Khashaba et al. 2013). As per the Analysis of Variance (ANOVA) study made on surface roughness and delamination output attributes, ANN results

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indicate that a deviation was comparatively less (Sreenivasulu Reddy 2013). The integration of efficient hybrid approaches has been proposed to overcome limitations on delamination free machining which was found to be a difficult task (Kumar, Datta, and Mahapatra 2015). Also, it was observed that optimum speed, low rate of feed and minimum diameter leads to better surface roughness as per ANN validation in comparison with experimental results (Palanikumar et al. 2013). The end milling can also be considered as a part of the drilling process which includes a study on the delamination factor influenced by the rate of feed analysed through ANOVA and ANN prediction models (Erkan Ömer et al. 2013). The literature scan indicates that ANN was able to predict the minimisation of selected output parameters while the proposed hybrid algorithm was found to perform well compared to the Genetic Algorithm (Shunmugesh and Panneerselvam 2016). In one of the recent studies, out of various algorithms used, performance evaluation of the LM algorithm was found to be better while training and testing output variables (Sathish and Raj Rodrigues 2018). Out of two approaches, it was reported that the traditional Taguchi approach failure can be overcome by integration of the Principal Component Analysis (PCA) fuzzy – Taguchi approach (Kumar et al. 2015). The study also indicates that tool speed and rate of feed which affects the machining force, as well as peel-up delamination, were observed to be optimum and in the case of push-out delamination factor, later parameter was found to be a predominant factor (Shunmugesh and Kavan 2017). With this regard, composite materials and structures are accounted for as complex engineering systems, the analysis and modelling of which requires the application of efficient and robust techniques from a computation time and accuracy perspectives (N Rajesh Mathivanan, Manjunatha Babu, and Vijaya Kumar 2018; Vikas et al. 2016a)

From the Literature Survey, it was observed that the final machining process on unique FRP materials has been carried using various cutting control factors on applying distinctive Statistical and ANN approaches leading to distinctive concluding remarks. Hence, the present investigation involves 1. The experimental approach which includes Specimen Fabrication and Drilling Characterisation 2. Results and Discussion made based on Taguchi Based Approach and ANN Based Approach on a response data using Minitab 17 and MATLAB 15 software respectively.

2. Methodology

The succeeding flow chart shown in Figure 1 Indicates the Detailed Sequential steps to be carried out before and

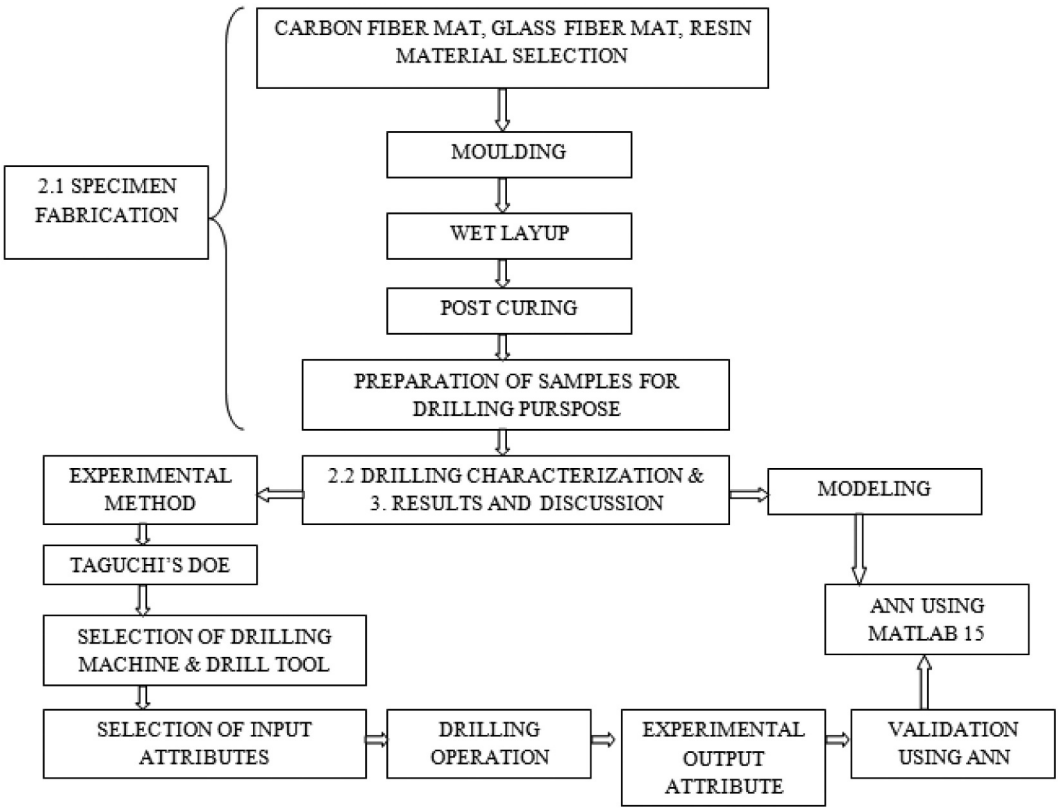


Figure 1. Detailed Methodology.

during the drilling process: (1) Specimen Fabrication (2) Drilling Characterisation which is followed by Taguchi Based Approach and ANN Based Approach.

2.1. Specimen fabrication

As the quality of hybrid laminate depends upon the selection of a feasible moulding process, the wet layup process being chosen as an initial process it meets the standards of the required specimen. Here, the hybrid specimen was made by making use of 12 Layers of 200 GSM (Grams/m^2) Bi-directional Carbon Fibre (20%) interleaved in 18 Layers of 360 GSM Bi-directional Glass Fibre mats (60%) in order to achieve 12 mm thickness. During this period, few parts of epoxy resin LY556 were mixed with hardener HY951 in terms of 100:10 Ratio (20%) and left for curing at 22°C room temperature to improve its brittleness and final trimmed product of 500 mm x 500 mm was obtained as shown (refer Figure 2(a)) (Rajesh Mathivanan, Manjunatha Babu, and Vijaya Kumar 2018).

2.2. Drilling characterisation

The sample of size 288 mm x 88 mm was cut from 500 mm x 500 mm Laminate (refer Figure 3) through

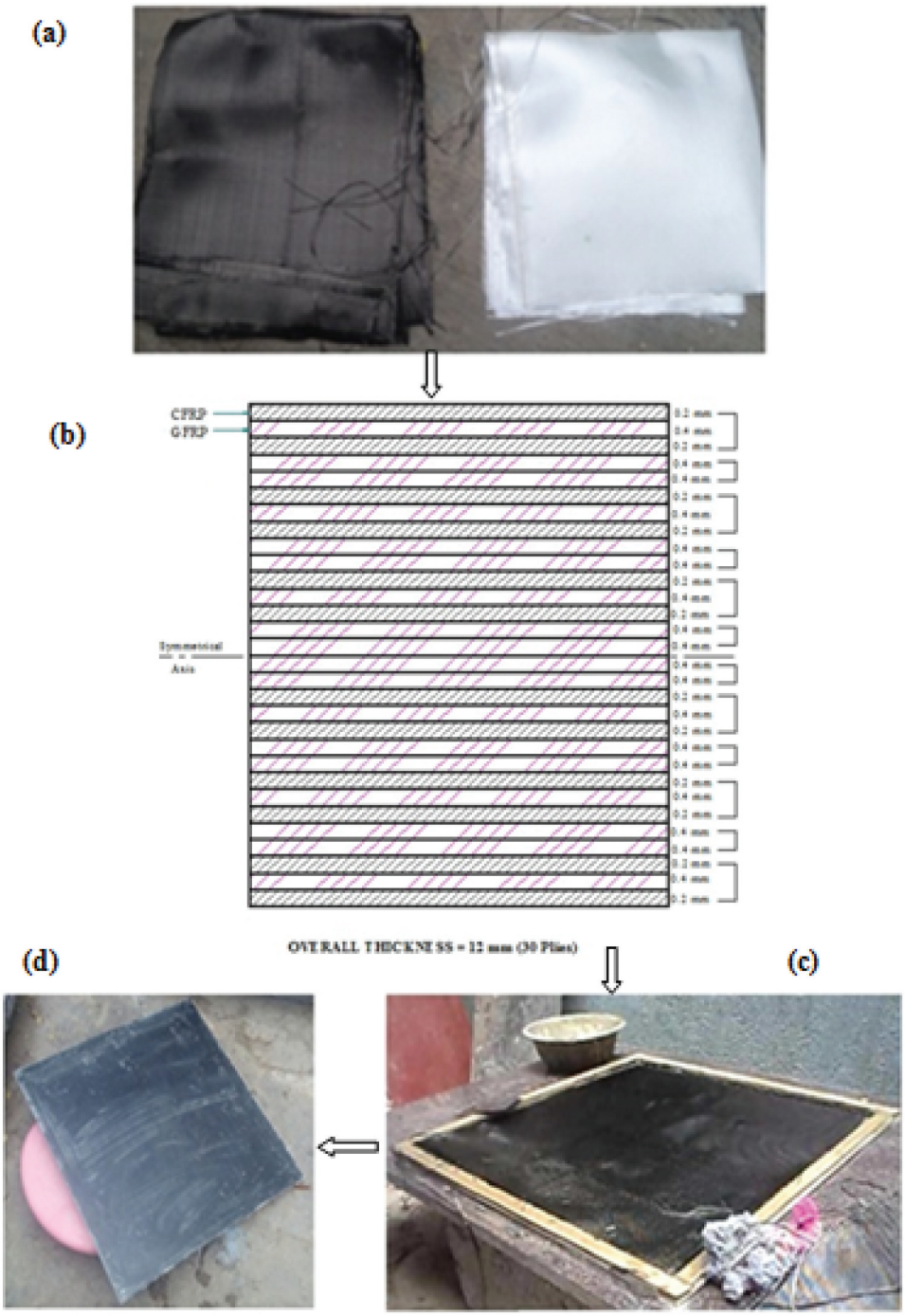


Figure 2. (a) Carbon & Glass fibre mat (b) Layup sequence (c) Mould for fibre layup (d) Laminate of Size 500 mm x 500 mm.

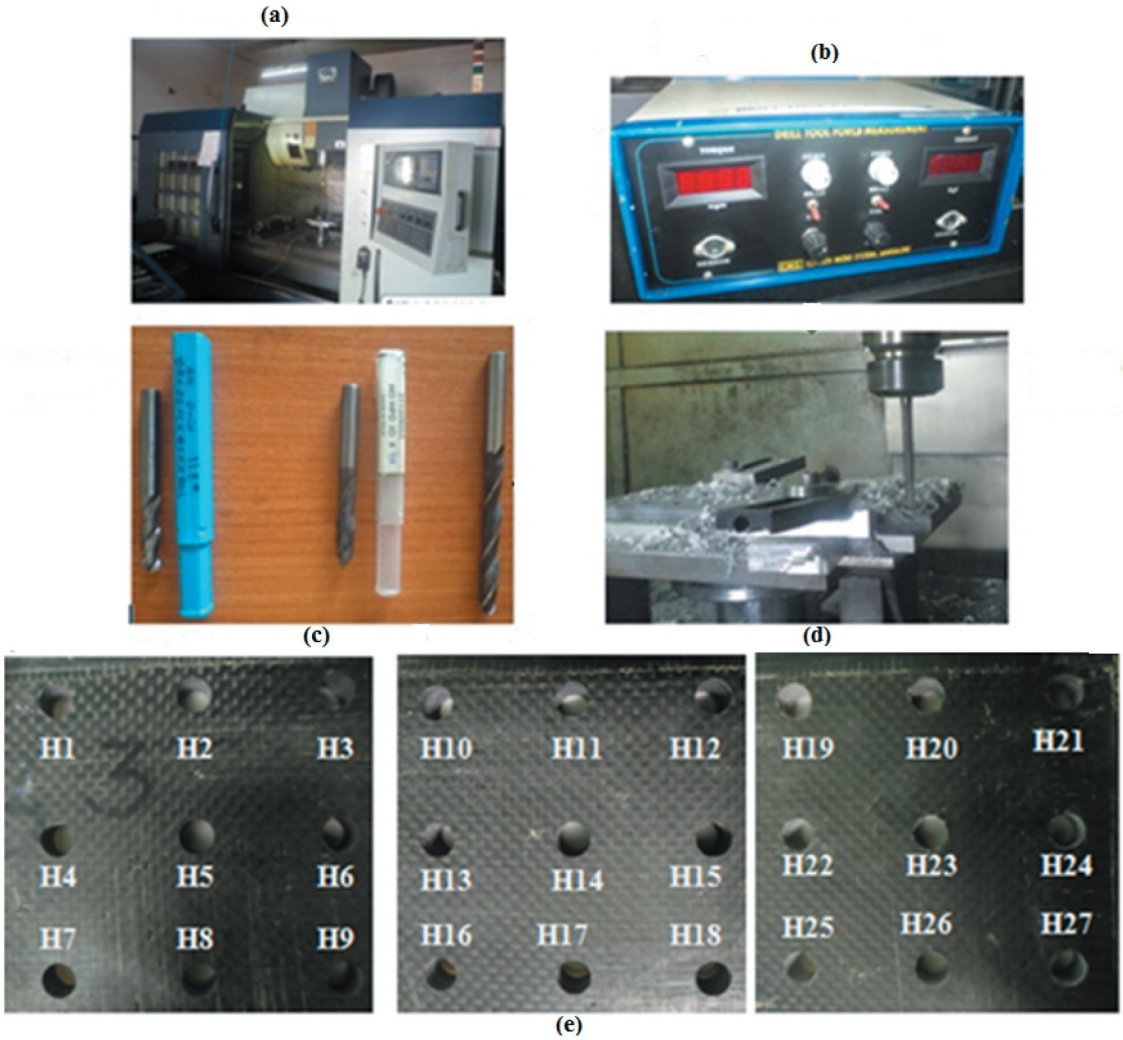


Figure 3. Drilling process includes; (a) CNC Drill centre (b) Dynamometer (c) Drill tools (d) Sample drilling (e) Drill Sample as Per L_{27} array.

the fabrication process was clamped firmly on CNC drilling machine integral with drill tool dynamometer to acquire twisting force value as shown (refer Figure 3). The drilling process was carried out on a trial basis using Solid Tungsten Carbide (STC 90° Point angle & STC 118° Point angle) and High-Speed Steel (HSS 90° Point angle) with uniform drill diameter of 8 mm at 3 levels of control factors (Tool Material, Feed Rate, and Cutting Speed) to acquire response factor (twisting force) as per Taguchi's Design of Experiments which embraces L_{27} array obtained through multilevel factorial design as shown in Tables 1 & 2 while ANN approaches was used as an alternative predictive tool on using output and input attributes with which is explained in succeeding sections through constructional design and indicative results showed (refer Figure 7 through 8).

2.3. Taguchi-based approach

Among various existing statistical techniques, Taguchi's DOE is been considered an important tool while analysing simple or complex problems (Sreenivasulu Reddy 2013). This technique helps in generating a standard combination of relevant factors and their levels to study the obtained results on assumed test conditions. The main reason for using this technique is to separate the various control factors based upon the significance level in resemblance with a delta ranking on a particular response variable to be analysed. The twisting force or torque values obtained at Specimen entrance have been analysed with the help of MINITAB 17 user-friendly software on preparing required Taguchi's L_{27} (3^3) DOE based on the multilevel factorial design for 27 runs as shown in Table 2. The significant effects of drill tool material, cutting speed, and rate of feed on twisting

Table 1. Control factors.

Tool Material	Feed Rate (mm/min)	Cutting Speed (rpm)
Solid Tungsten Carbide 90°	50/60/70	800/900/1000
Solid Tungsten Carbide 118°	50/60/70	800/900/1000
High-Speed Steel	50/60/70	800/900/1000

Table 2. Taguchi's L_{27} array.

Std Order	Run Order	Ptype	Blocks	Feed Rate (mm/min)	Cutting Speed (rpm)	Tool Material	Torque Result (N-m)	Hole Location
1	1	1	1	50	800	STC1	1.962	H1
2	2	1	1	60	800	STC1	1.962	H2
3	3	1	1	70	800	STC1	0.981	H3
4	4	1	1	50	900	STC1	1.962	H4
5	5	1	1	60	900	STC1	1.962	H5
6	6	1	1	70	900	STC1	0.981	H6
7	7	1	1	50	1000	STC1	1.962	H7
8	8	1	1	60	1000	STC1	1.962	H8
9	9	1	1	70	1000	STC1	1.962	H9
10	10	1	1	50	800	STC2	0.981	H10
11	11	1	1	60	800	STC2	1.962	H11
12	12	1	1	70	800	STC2	2.362	H12
13	13	1	1	50	900	STC2	0.981	H13
14	14	1	1	60	900	STC2	1.962	H14
15	15	1	1	70	900	STC2	1.472	H15
16	16	1	1	50	1000	STC2	0.981	H16
17	17	1	1	60	1000	STC2	1.962	H17
18	18	1	1	70	1000	STC2	1.962	H18
19	19	1	1	50	800	HSS	29.92	H19
20	20	1	1	60	800	HSS	31.13	H20
21	21	1	1	70	800	HSS	31.39	H21
22	22	1	1	50	900	HSS	29.58	H22
23	23	1	1	60	900	HSS	31.26	H23
24	24	1	1	70	900	HSS	31.07	H24
25	25	1	1	50	1000	HSS	29.43	H25
26	26	1	1	60	1000	HSS	31.39	H26
27	27	1	1	70	1000	HSS	32.18	H27

Table 3. Response table for S/N ratio and means (smaller the better).

k : $controlfactor; k = 1, ToolMaterial; k = 2, Cuttingspeed; k = 3, Feedratej$: $Levelintheselectedcontrolfactor;$
$yisobserveddataj = 1isL1; j = 2isL2andj = 3isL3nisnumberofruns = 9; Similarnotationssreusedforothercontrolfactors$

	S/N Ratio			Means		
Level	Feed Rate (mm/min)	Cutting Speed (rpm)	Tool Material	Feed Rate (mm/min)	Cutting Speed (rpm)	Tool Material
1	−11.702	−12.619	−4.908	10.84	11.231	1.799
2	−13.869	−12.957	−4.12	11.728	11.379	1.702
3	−13.177	−13.172	−29.721	11.568	11.526	30.636
Delta	2.167	0.554	25.601	0.888	0.295	28.934
Rank	2	3	1	2	3	1

force have been studied using relevant main effects response (refer Table 3) as shown. The main reason for the S/N ratio consideration was to build a noiseless process.

2.4. ANN based approach

The ANN started its initiation through human brain topology and neural biology which lead to a relevant mathematical model that is characterised by numerous elements with adjustable weights. The recently developed model was observed to be influenced by a few input parameters studied through the artificial neural network, ANFIS and fuzzy logic result in comparison with empirical data (Jenarthanan, Ramesh Kumar, and Jeyapaul 2016). Here, in the present work, the training data was considered based on a supervised learning principle for the neural network. The predicted ANN output data are matched with the real-time experimental values only after feeding the input data by adjusting the interconnecting weights between layers. The network could be operated on data fed in the training set for justification to obtain a converging network through the different learning algorithms considered in neural network models. In one of the research work, feed-forward back propagation neural network (BPNN) with the Levenberg–Marquardt learning algorithm is considered as a superior tool to optimise the number of expensive and time-saving experiments (Mishra, Malik, and Singh 2010; Vikas et al. 2016a; Jenarthanan, Ramesh Kumar, and Jeyapaul 2016; Vikas et al. 2016a, 2016b; Rao Sudarshan, Varadarajan, and Rajendra 2014) and among the various algorithms available, Levenberg–Marquardt (LM) algorithm (TrainLM) is expected to reach the nearest convergence. The present work highlights how the TrainLM is able to obtain the least output errors than any of the other algorithms tested. This back propagation network works on multilayer architecture which includes neurons as the main processing elements that are interconnected with each other by variable weights that need to be determined. In the network, the input layer receives information from the external source and passes this information to the succeeding network for processing. The hidden layer works based on data transfer through an input

layer leading to all information processing. The output layer receives processed information from the network and sends the results to an external receptor. The complete network structure is as shown in Figure 7. Based on the experimental constraint, the important input parameters such as the tool material, cutting speed, and rate of feed is fed as input parameters to the present Artificial Neural Network (ANN) model (refer Figure 7). The output parameter selected here is the twisting force or torque.

3. Results and discussion

3.1. Taguchi effect of control factors on the response variable (Twisting force)

Since the statistical software works on loss function, its role is to indicate the variation between the experimental value and value to be obtained. Again the loss function needs to be transmuted into a Signal-to-Noise (S/N) ratio as indicated in Equation 1. Among the distinctive S/N ratios, based on the type of characteristics; 'Smaller is Better' (SB) was preferred to minimise the desired results. In drilling, the minimisation of twisting force leads to better execution. Therefore, the 'SB' for the twisting force was been picked out to attain the enrich improvement in machining performance characteristics.

$$\frac{S}{N}(\eta) = -10\log\left(\sum^{Y^2}/n\right) \tag{1}$$

Where, η = observed data (dB),

Y = experimental value

n = number of observations

The degrees of freedom were determined as per the equation provided:

$$Degrees\ of\ freedom\ (DF) = Number\ of\ observations - 1 \tag{2}$$

For this experiment, the number of experiments considered was 26 based on the degrees of freedom as per Equation 2.

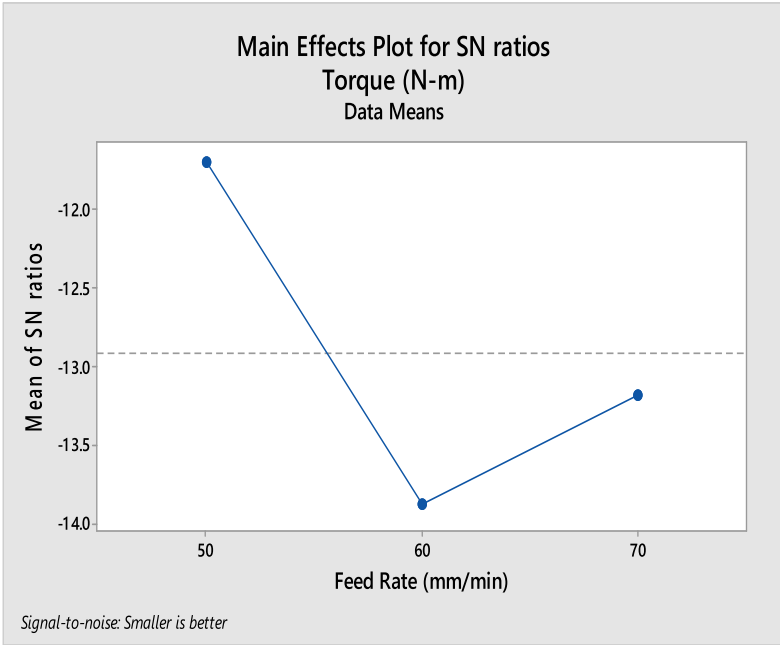
The individual main effect of the S/N ratio and means response for twisting force was plotted and the same can be observed from Figure 4 through Figure 6. According to the S/N ratio main effect plot, it can be monitored that the twisting force was found to be efficient at an optimised level of individual effect of input factors which are said to be as the rate of feed 50 mm/min, speed of 800 rpm, and tungsten carbide 118° tool T2. Whereas, moderate level parameters were noticed to be 70 mm/min, tungsten carbide tool (T1), 900 rpm followed by lower level parameters as 60 mm/min, tungsten carbide tool (T3), 1000 rpm. Table 3, indicates that all the control factors have been given equal prominence depending upon their individual performance categorised by delta rank, respectively, leading to the behaviour of twisting force with respect to tool material followed by other factors. In the case of overall response (Table 3), it indicates that the S/N ratio effect was observed to be minimised at T2, 800 rpm, 50 mm/min. The S/N Ratio and means main effects plot of feed rate and tool material was also drawn individually to clearly observe the variation in twisting force.

From Table 3, it is observed that feed rate and cutting speed has the least prominent effect on twisting force at all levels in comparison with cutting tool material studied through S/N Ratio and means effect. As per Figure 4 through Figure 6 and Table 3, the progressive variation of twisting force or torque can be observed through respective plots.

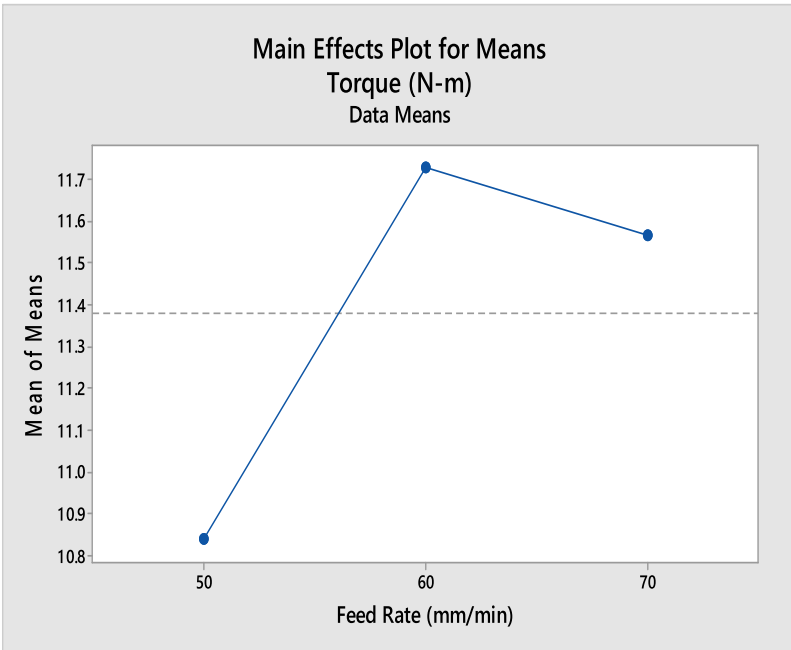
3.2. ANN constructional design with training

The present study leads to; the total number of twisting force values considered was 27 leading to training and testing. The standard multilayer feed-forward Back Propagation Neural Network (BPNN) with the tan-sigmoid function was chosen for the experiment and was simulated through model using MATLAB 15 Neural Network (NN) toolbox as represented in Figures 7 & 8 respectively. Figure 7 indicates that the weight (W) is the product of input signal leading to weighted function which in turn summed up with bias (b) of constant input as 1 as per Equation 6. The construction of a network is categorised into three layers: input, hidden, and output/target layer. Out of many iterations performed, three control attributes in the input layer, 14 neurons in the hidden layer and one response attribute in the output layer (3-14-1-1) architecture were considered and trained with 1000 epochs (iterations) to predict the optimum structure results as shown in Figure 9. The number of iterations (epochs) to be executed is an important parameter in the case of Back Propagation Neural Network (BPNN) algorithm training. The Parameters used for training purposes in the model are indicated in Table 4.

Since the several structures with different numbers of hidden neurons have to be considered to determine the best configuration in the present context, the machinability of Hybrid FRP composites was subjected to training through different architectures by varying the number of neurons in the hidden layer(s). During and after training, it has been denormalised to compare with the experimentally obtained data. The denormalised values (Xi) for each raw output data-set may be calculated as per Equation 3a through 4.



(a)



(b)

Figure 4. Main effects plot for feed rate – (a) S/N Ratio (b) Means.

$$X(i) = [(2X - (X_{Max} + X_{Min}))/(X_{Max} - X_{Min})/2] \quad (3a)$$

$$X(i) = \frac{[(X_n + 1) - (X_{Max} - X_{Min})]}{2} + X_{Min} \quad (3b)$$

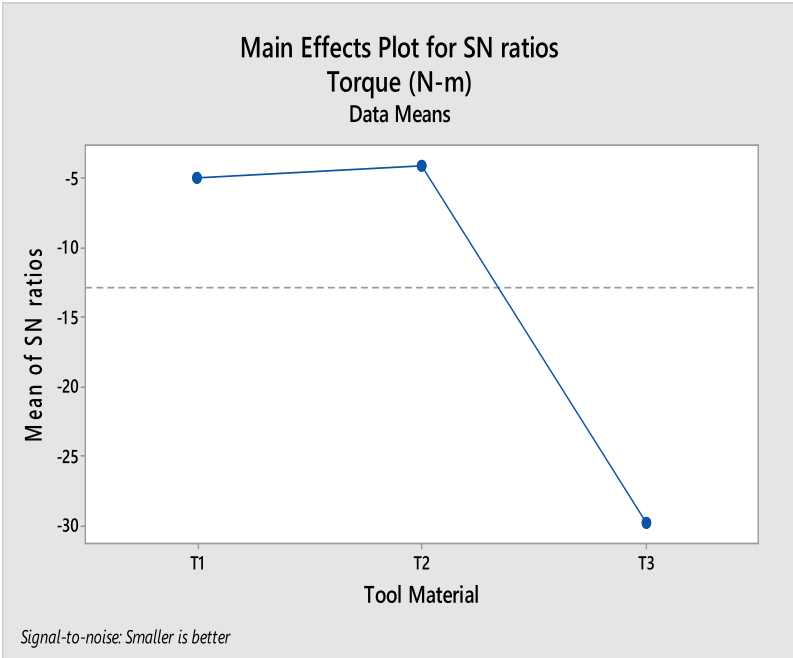
Where, X_{Max} = maximum raw data, X_{Min} = minimum raw data

$$Node(i) = \sum^{(} W_i X_i) \quad (4)$$

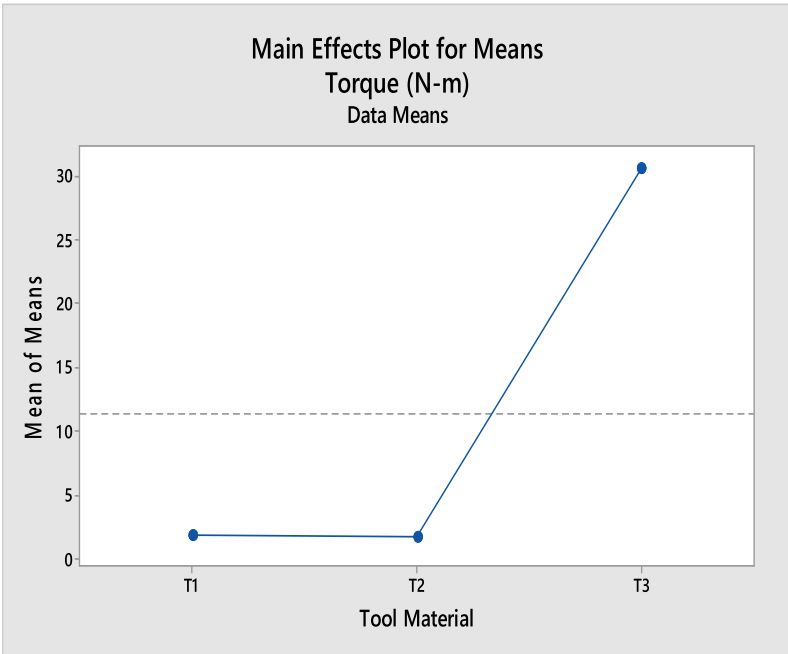
Predictive error in each output node has been verified through calculation according to Equation 5 & 5a in order to predict the feasible model.

$$OutputError\% = \left[\frac{Actualvalue - PredictedValue}{ActualValue}\right] x100 \quad (5)$$

$$OutputError = [Actualvalue - PredictedValue] \quad (5a)$$



(a)



(b)

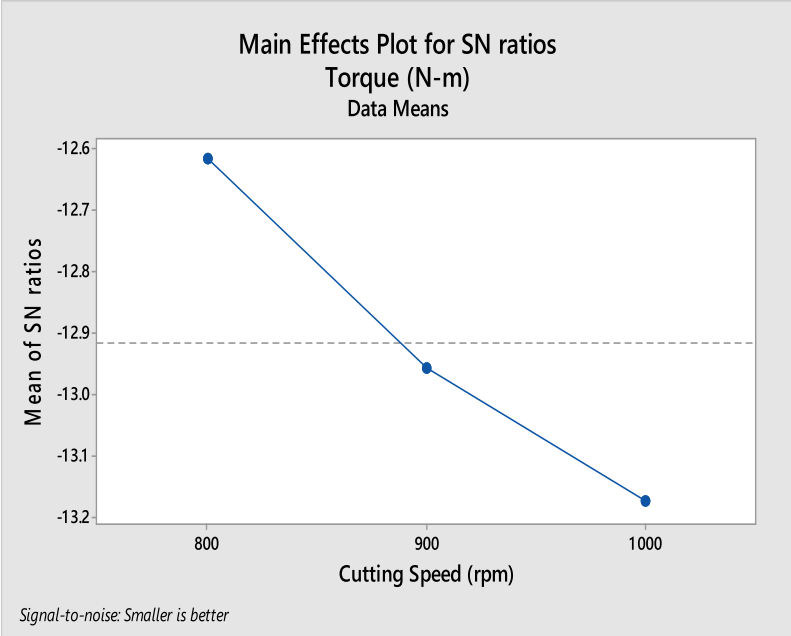
Figure 5. Main effects plot for tool material – (a) S/N ratio (b) Means.

$$fNode(i) = \sum^{(} Wx + b) \tag{6}$$

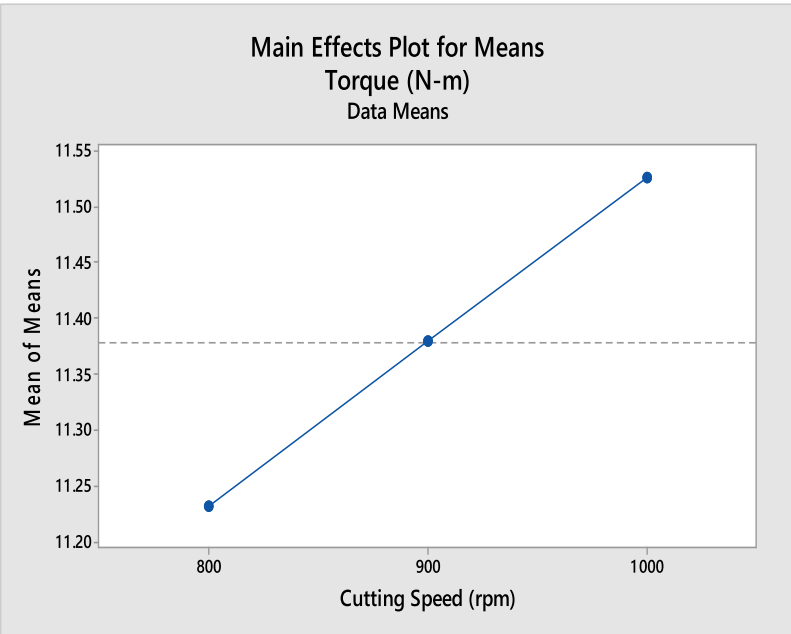
3.3. ANN performance prediction

In the present work, the performance of each network has been tested and examined based on the erratum and convergence of entire data-set within specified error range between the network predictions and the experimental values as mentioned in Table 5 which was extracted as per validation plot shown in Figure 9.

In order to decide the optimum structure of the neural network, the rate of error convergence was checked by changing the number of hidden neurons and a number of hidden layers. By increasing neurons in the single hidden layer (beyond 14), the error distribution was noticed to be non – uniform. Hence, it



(a)



(b)

Figure 6. Main effects plot for cutting speed – (a) S/N Ratio (b) Means.

has been decided to select one hidden layer and a varied number of neurons to yield an optimum one structure. As observed through Table 5, the network with 14th neuron in hidden layer has produced the best performance in contrast to other neurons considered for the output attribute (3–14-1-1). It was also observed that the other combination of architectures (3-1-1-1, 3-2-1-1, 3-3-1-1, 3-4-1-1, 3-5-1-1, 3-6-1-1, 3-7-1-1, 3-8-1-1, 3-9-1-1, 3–10-1-1, 3–11-1-1, 3–12-1-1, 3–13-1-1) does not yield expected results, since the mean prediction error, as well as the error distribution, maximum value of error and minimum value of error were observed to be high. From Table 5, as per ANN prediction, it can also be noticed that relative error exceeds beyond the expected limit at hole location 3 which indicates that hole quality needs an refinement. Here, the input parameters which leads to maximum error were noticed to be 70 mm/min feed rate, tungsten carbide 90° (T1), 800 rpm cutting speed. Whereas, the validation plot indicates that the obtained results through training and testing lies within the confidence level of 95%. From Figure 8, it indicates that maximum number of iterations or epoch considered to run ANN model was around

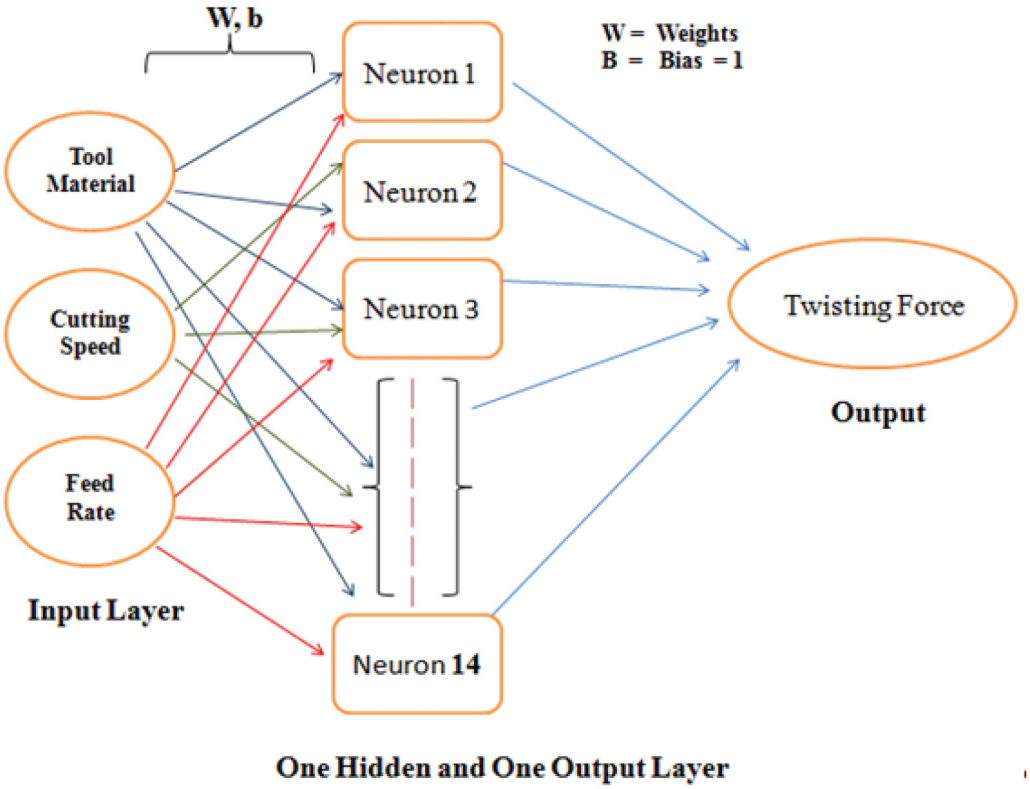


Figure 7. Neural network construction.

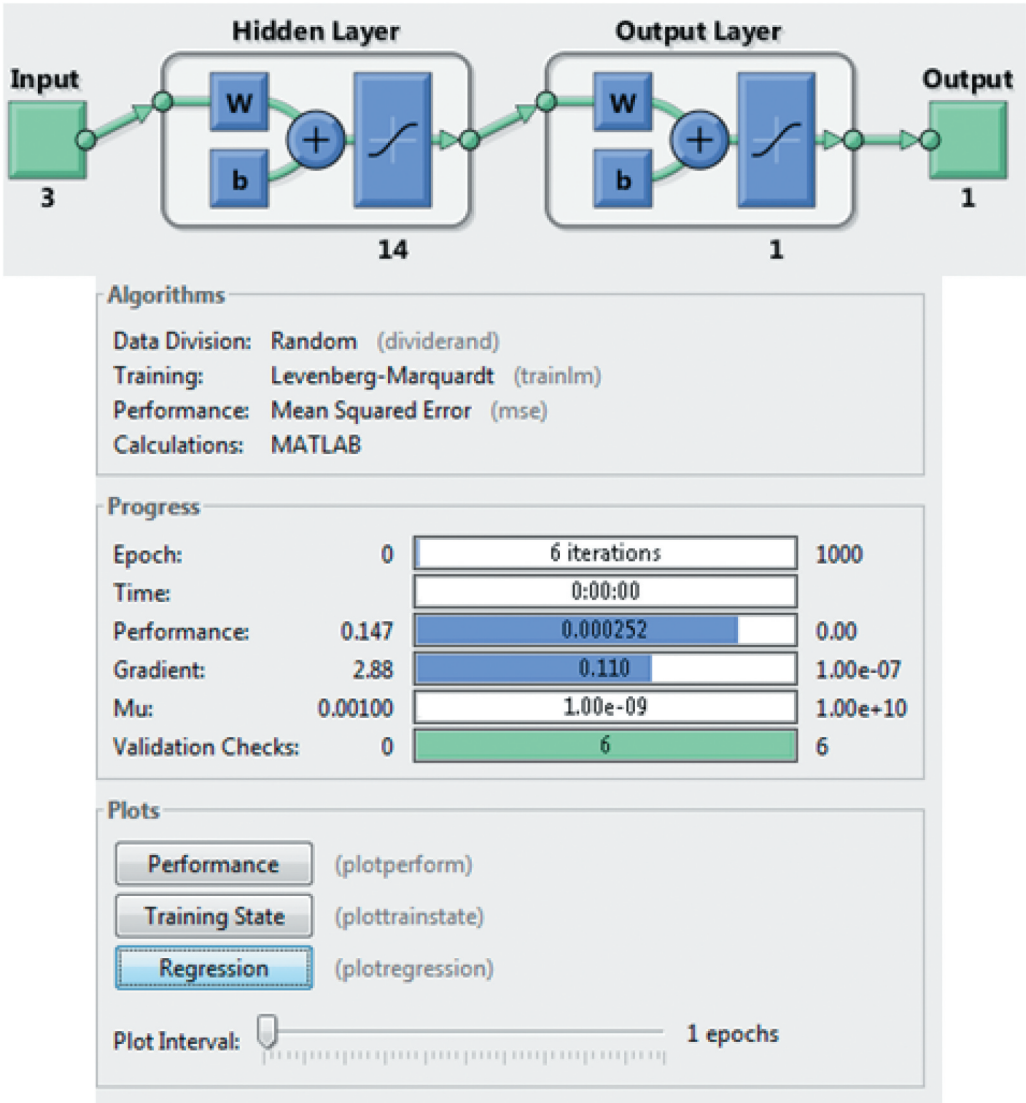


Figure 8. Training and testing algorithm process.

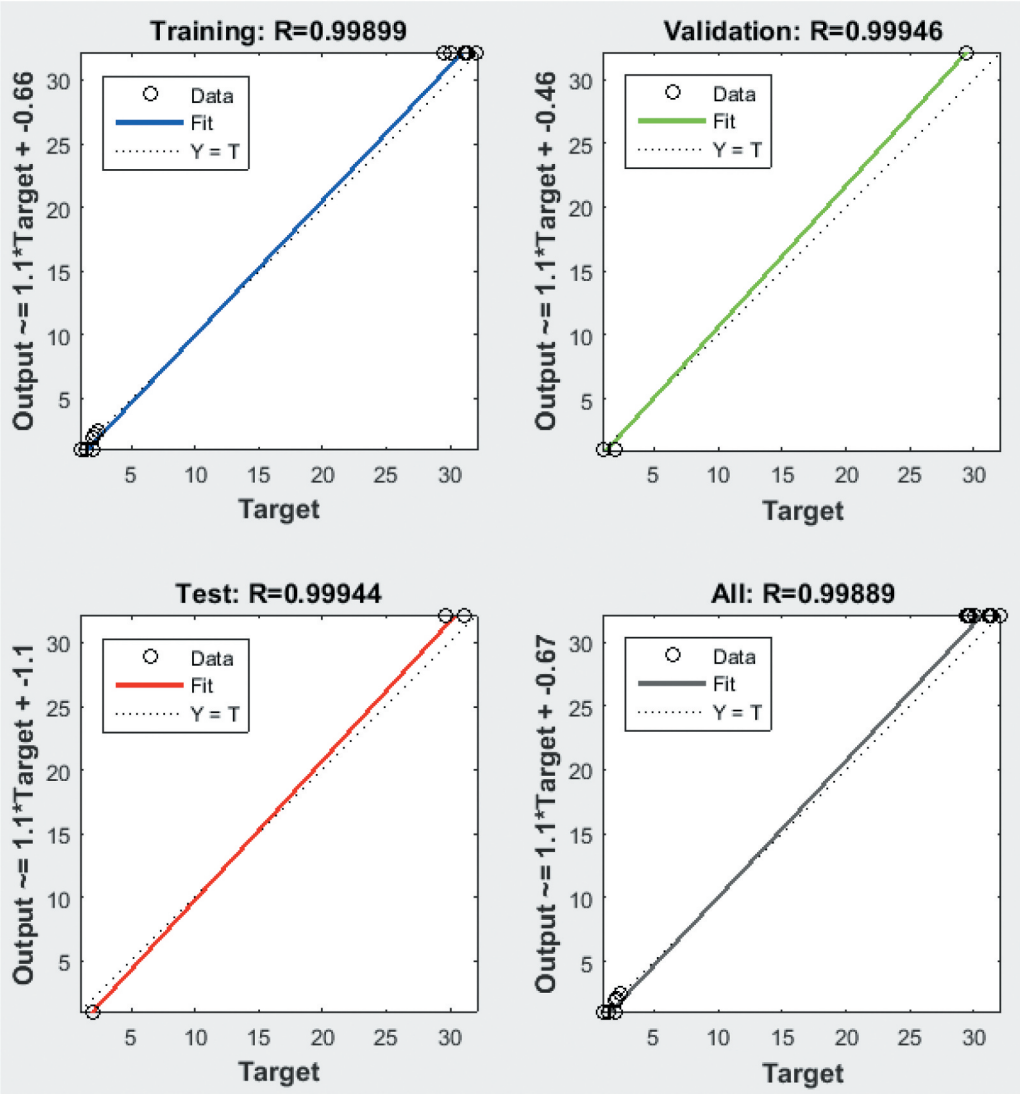


Figure 9. Validation plot for optimum structure 3–14-1-1.

Table 4. Number of neurons and layers.

Number of Neurons used for training & testing	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Input (3 x 27 array)	Tool Material, Cutting Speed, Feed Rate													
Hidden Layer	14 Neurons													
Output (1 x 27array)	Twisting Force													

1000. As, the number of output data or readings was less, the mean square error curve converged at 6 epochs concerning Taguchi DOE L_{27} readings, which indicate the minimal predicted output error.

4. Conclusion

The Statistical analysis for minimisation of twisting force was performed using Minitab 17 based on Taguchi's L_{27} DOE and results indicate that the tool material was found to be a predominant factor because of its distinct effect on the outcome as per means and S/N ratio plot and response table. It was also observed that the response variable was found to be improvised at an optimum feed rate of 50 mm/min, cutting speed of 800 rpm and Tool Material 2 (Tungsten Carbide 118°). Here, through correlation coefficient and convergence, different Backpropagation Neural Network (BPNN) architectures were trained and tested on changing number of neurons in hidden layer using the experimental data until an optimum structure is identified. In one of the paper, they revealed that, out of three approaches, second one was yielding a better results compared to other two approaches (Vikas et al. 2016a) while here in the present findings, for different multi-layer back propagation neural network architectures, (3-14-1-1) structure trained with LM algorithm was found to be the optimum network model. A feasible performance was observed with the obtained neural network model, and it indicates a good correlation between the predicted values of the optimum neural network model and the experimental data for prediction of

Table 5. Predicted results with error – based on optimum structure.

Hole Location	Experimental Output Data	BPNN Predicted Output Data	Relative Output Error
3–14-1-1 – Optimum Structure			
1	1.962	1.920	0.0420
2	1.962	2.143	−0.1810
3	0.981	2.400	−1.4190
4	1.962	1.926	0.0360
5	1.962	2.077	−0.1150
6	1.472	1.270	0.2020
7	1.962	1.947	0.0150
8	1.962	1.995	−0.0330
9	1.962	1.966	−0.0040
10	0.981	0.981	0.0000
11	1.962	2.044	−0.0820
12	2.362	3.199	−0.8370
13	0.981	0.981	0.0000
14	1.962	1.476	0.4860
15	2.162	2.249	−0.0870
16	0.981	0.982	−0.0010
17	1.962	1.952	0.0100
18	1.962	1.968	−0.0060
19	29.72	29.719	0.0010
20	31.13	31.128	0.0020
21	30.02	30.018	0.0020
22	29.58	29.572	0.0080
23	31.26	31.257	0.0030
24	31.07	31.066	0.0040
25	29.43	29.771	−0.3410
26	31.39	30.604	0.7860
27	32.12	32.081	0.0390

twisting force using the entire dataset by setting confidence level as 95% (=R^2). On whole, the prediction of twisting force from ANN (which includes BPNN) was observed to be in good agreement with the experimental results for chosen cutting tool parameters. Also, the ANN models which were able to predict the twisting force response in the drilling of Hybrid FRP composites lies within acceptable error limits.

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No potential conflict of interest was reported by the author(s).

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