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MULTI-OBJECTIVE NEURAL NETWORK MODELING FOR IMPROVING STUD ARC WELDING PROCESS JOINING

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Abstract

An effective stud weld algorithm has been developed using a tensile strength response. A multi objectives neural network modeling was used to get higher tensile strength with lower variance. A multi-layer perception (MLP) was trained by back propagation Levenberg-Marquardt (LM) [8:16:2] algorithm using sample testing measures. The result was compared with Taguchi experimental design method. The comparison shows that neural network is an effective method to represent this multi objective target problem. The verification of results shows that the ultimate tensile strength increases by 30.84% and the standard deviation around mean reduces by 30.06%.The results prove that neural network is a powerful tool to represent the multi level eight input parameters with two objectives first is to maximize the ultimate tensile strength and the second is to minimize the standard deviation of tensile strength with almost negligible error (4.96×10^{-10}) for representing data.

Keywords: Multi-objective neural network, Optimization, Stud arc welding process.

1. Introduction

A process may be defined as the combination of inputs (such as materials, machines, manpower, measurement, and environment) and methods that results in various outputs which are measures of performance [1]. The inputs X_1, $X_2 \ldots X_n$ are input factors, such as welding time, welding current, types of materials, and other process variables are transformed to a finished part that has several quality characteristics. It is usually necessary to model the relationship between the influential input variables and the output quality characteristic [2, 3].

The purpose of this paper is to demonstrate the evaluation of optimizing manu-

Nomenclatures

$L_{16}2^7 1^8$	Design of experiments matrix array of 16 run for 7 parameters with two levels and 1 with eight levels
N	Sample size
OA	Orthogonal Array
R^2	Sum of square error model
S	Standard deviation of ultimate tensile strength samples N/mm^2
X_n	Processes variables or parameters
$\overline{x}$	Mean of ultimate tensile strength samples N/mm^2
Greek Symbols	
β_n	Main effects terms in equation
ε	All the random variation that can't be explained by all other terms.

facturing process for stud arc welding parameters based on an Artificial Neural Network (ANN) which can represent complex input/output relationship. The neural networks learn by repeatedly trying to match the set of input data to the corresponding output target values. After a sufficient number of learning iterations, the network creates an internal modal that can be used to predict for new input conditions, in which the natural network recognizes the correlative patterns between the inputs and output for the corresponding process [4-11].

2. Artificial Neural Network (ANN)

Multi Layer Perception (MLP) is a popularly used neural network structure. In the MLP neural network, the neurons are grouped into layers. The first and the last layers are called input and output layers, respectively, and the remaining layers are called hidden layers. Typically, an MLP neural network consists of an input layer, one or more hidden layers, and an output layer. The inputs are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the first hidden layer. Within the first hidden layer, they get summed, and then processed by a nonlinear function (usually the hyperbolic tangent). As the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer. Finally the data is multiplied by interconnection weights and then processed one last time within the output layer to produce the neural network output. Neural networks can easily represent non-linear relationships between input data and output data. Even if the data is incomplete, neural networks are able to correctly classify the different data classes captured from the network or other sources [12].

The training algorithm

Levenberg-Marquardt (LM) algorithm supervised learning was used in this study. In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. In other words, it must calculate how the error changes as each weight is increased or decreased slightly, i.e., the neuron in the network learns by changing the weights and the bias.

The following steps take place when each neuron is activated [13]:

a) Various signals are received from other neurons.
b) A weighted sum of these signals is calculated.
c) The calculated sum is transformed by a function (knowing as activation function).
d) The transformed result is send to other neurons.

3. Experimental Work

This work employs eight parameters affect ultimate tensile strength of stud welding. These parameters are (Welding Time, Sheet Thickness, Sheet Material, Welding Current, Stud Design, Stud Material, Preheating, and Surface Cleaning). The levels for welding time are shown in Table 1, and the list of seven control parameters and their levels are shown in Table 2. The selection of a number of levels depends on how the outcome (tensile strength) is affected due to different level settings.

Table 1. Levels of Welding Time Control Parameter.

Parameter	Parameter label	Unit	Level							
Welding time (s)	X_1	s	1	2	3	4	5	6	7	8
			0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5

Table 2. Control Parameters and Levels for the Experiments.

Parameters	Parameter labels	Unit	Level1	Level 2
Sheet thickness	X_2	mm	1.6	3.175
Sheet material	X_3	None	K52355	K14358
Welding current	X_4	Ampere	350	540
Stud design	X_5	None	Un-flange stud	Flange stud
Stud material	X_6	None	54NiCrMoS6	40CrMnMoS8-6
Preheating	X_7	None	Preheating	No preheating
Surface cleaning	X_8	None	Oil sheet	Clean sheet

3.1. Experimental process run

The experiment was conducted based on the design matrix. The experiments depend on the $L_{16}2^7 1^8$ OA [11]. The value of ultimate tensile strength for each run (from 1-16) was measured by the tensile strength test machine. Five samples were taken for each run. The mean and standard deviation of measured ultimate tensile strength were calculated by equations 1 and 2 respectively, and recorded in Table 3.

Mean:
$$\bar{x} = \sum_{i=1}^{N} x_i / N \tag{1}$$

Standard deviation:
$$S = \sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2 / (N-1)} \tag{2}$$

Table 3 explains the eight parameters level for each run of experiments, for example row 4, number 2 represents the level two for parameters: welding time

(0.2 s), sheets thickness (3.175 mm), sheet material (K14358), welding current (540 ampere), and stud design (Flange stud). While number 1 represents level one for parameters: stud material (54NiCrMoS6), preheat (Preheating), and surface cleaning (oil sheet). At these parameters, the mean of tensile strength for five samples of stud welding was (377.310 N/mm²) and standard deviation was (46.790 N/mm²).

Table 3. Design Matrix Array $L_{16}2^7 1^8$ with Mean and Standard Deviation of Samples Ultimate Tensile Strength.

Run	Welding time	Sheet thickness	Sheet material	Welding current	Stud design	Stud material	Pre-heat	Surface cleaning	Mean N/mm²	Standard deviation N/mm²
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8		
1	1	1	1	1	1	1	1	1	182.302	28.860
2	1	2	2	2	2	2	2	2	280.315	36.946
3	2	1	1	1	1	2	2	2	249.082	32.539
4	2	2	2	2	2	1	1	1	377.310	46.790
5	3	1	1	2	2	1	1	2	237.453	52.977
6	3	2	2	1	1	2	2	1	331.202	77.637
7	4	1	1	2	2	2	2	1	323.375	104.318
8	4	2	2	1	1	1	1	2	348.828	36.095
9	5	1	2	1	2	1	2	1	297.547	68.611
10	5	2	1	2	1	2	1	2	450.352	76.343
11	6	1	2	1	2	2	1	2	395.933	62.388
12	6	2	1	2	1	1	2	1	172.287	40.835
13	7	1	2	2	1	1	2	2	224.283	43.258
14	7	2	1	1	2	2	1	1	220.052	47.705
15	8	1	2	2	1	2	1	1	252.352	62.900
16	8	2	1	1	2	1	2	2	204.927	50.651

4. Surface Response Experimental Design Method

The general $Y=f(X)$ linear equation with multiple X_n is:

$$Y=\beta_0+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\beta_4 X_4+\beta_5 X_5+\ldots+B_n X_n+\varepsilon \tag{3}$$

where Y is the response, X_n are the variables, β_0 is the overall effect, β_1, β_2, β_3, β_n are the main effects terms in equation, and ε is the term that for all the random variation that can't be explained by all other terms.

An empirical model was derived that extended the experimental results into a functional relationship that predicts values at all points in the experimental space with accuracy. Ordinary least-squares regression was used to create empirical models for each of the two-performance measurement (mean and standard deviation). Multiple linear regression models based on the data given in Table 3 were obtained from Minitab 14 package software. These models approximately predict the mean function of tensile strength, Y_1, as shown in Table 4, and standard deviation, Y_2, as shown in Table 5.

Table 4. Tensile Strength Linear Regression Equation, R^2 = 43.5%.

Predictor	Coefficient of Parameter	T	P
Constant	**79.6**	**0.45**	**0.667**
X_1	-5.198	-0.55	0.598
X_2	27.87	0.65	0.539
X_3	58.49	1.36	0.217
X_4	10.98	0.25	0.806
X_5	15.78	0.37	0.725
X_6	57.22	1.33	0.226
X_7	-47.70	-1.11	0.305
X_8	29.34	0.68	0.518

Table 5. Standard Division Regression Equation, R^2 = 47.0%.

Predictor	Coefficient of Parameter	T	P
Constant	12.81	0.28	0.786
X_1	1.874	0.78	0.463
X_2	-5.36	-0.48	0.643
X_3	0.05	0.00	0.997
X_4	7.49	0.68	0.520
X_5	8.99	0.81	0.443
X_6	16.59	1.50	0.177
X_7	5.09	0.46	0.659
X_8	-10.81	-0.98	0.361

The regression equations for the mean tensile strength and standard deviation are as follows:

Tensile strength:

$$Y_1=80-5.20X_1+27.9X_2+58.5X_3+11.0X_4+15.8X_5+57.2X_6-47.7X_7+29.3X_8 \quad (4)$$

Standard deviation:

$$Y_2=12.8+1.87X_1-5.4X_2+0.0X_3+7.5X_4+9.0X_5+16.6X_6+5.1X_7-10.8X_8 \quad (5)$$

where X_1 is welding time, X_2 is sheet thickness, X_3 is sheet material, X_4 is welding current, X_5 is stud design, X_6 is stud material, X_7 is preheat sheet and X_8 is surface cleaning.

The significant factor is the square error root R^2 of the response data from the entire solution space. The value of R^2 of the model must be 80 percent or higher that can be confident to represent the data, while the unexplained variation ε accounts for the remaining 20 percent or less. The 1st and 2nd model to response data were evaluated the values of R^2. The R^2 for the two models are low (47.0% for the mean model and 43.5% for the standard deviation model, respectively). This problem may be solved by many ways; the first one is to take the higher order of model representation. However this will make the model very complex as there are many coefficients for the factors. The second method is by eliminating some factors that have a small effect on the process by stepwise, but this method will loose some parameters in the model. Other method is neural networks which has learning model characteristics. These characteristics support the neural networks as a competitive tool in processing multivariable input-output implementation.

5. Neural Network Model Development

The first step toward developing a neural model is the identification of inputs (x) and outputs (y). Artificial neural networks are employed commonly in the prediction of output parameters by training the network with the experimental results obtained [14].The output parameters are determined based on the purpose of the neural-network model. The flow chart of program is shown in Fig. 1 and the input variables, output variables, number of nodes and exciting function are shown in Table 6. Non-linear Artificial Neural Network architecture of developed program is shown in Fig. 2.

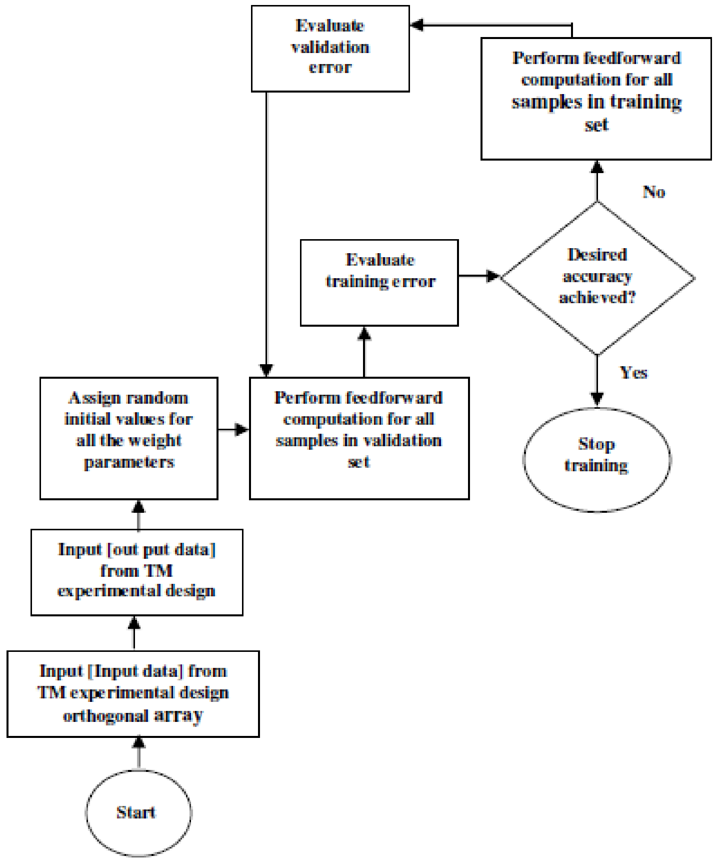

Fig. 1. Flowchart Demonstrating Neural-Network Training Neural Model Use of Training Data Sets in ANN Model Approach.

Table 6. Parameter Optimization Settings for Artificial Neural Network.

Input variables	welding time, sheet thickness, sheet material, welding current, stud design, stud material, preheat sheet and surface cleaning
Output variables	mean tensile strength value, standard deviation value
Testing data	16 sets experimental data
Input nodes	8
Output nodes	2
Hiding nodes	16
Exciting function	sigmoid activation function hyperbolic tangent
	Levenberg-Marquardt method (LM)

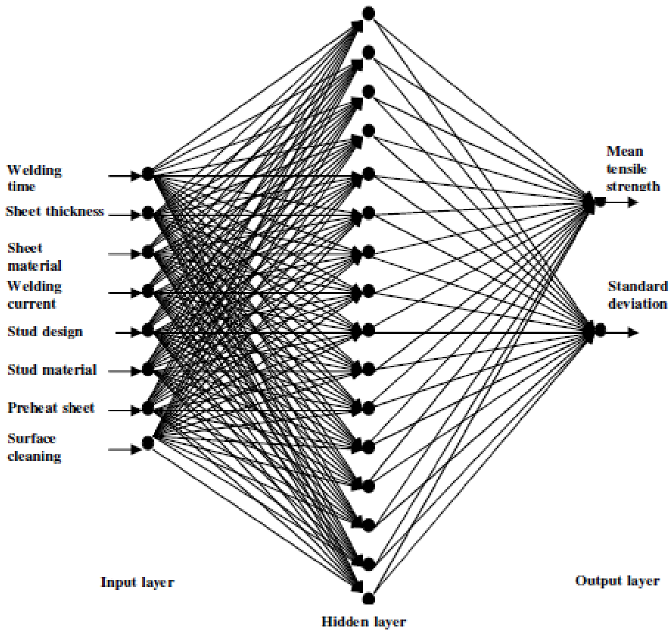

Fig. 2. Non-Linear Artificial Neural Network Architecture Program.

Neural-Network Model Training

The neural-network weight parameters, *w*, are initialized so as to provide a good starting point for training (optimization). The artificial neural network program input and output are shown in Table 7. The initialization of the weights is performed with small random value (0.01) and then by changing the number of hidden nodes (the initial assumption number is five), and by trial and error for the number of nodes and the value of error, the optimum performance of training is shown in Fig. 3.

Table 7. Input and Output of Artificial Neural Network Program.

Input	Output	
1 1 1 1 1 1 1 1	182.302	28.86
1 2 2 2 2 2 2 2	280.315	36.946
2 1 1 1 1 2 2 2	249.082	32.539
2 2 2 2 2 1 1 1	377.31	46.79
3 1 1 2 2 1 1 2	237.453	52.977
3 2 2 1 1 2 2 1	331.202	77.637
4 1 1 2 2 2 2 1	323.375	104.318
4 2 2 1 1 1 1 2	348.828	36.095
5 1 2 1 2 1 2 1	297.547	68.611
5 2 1 2 1 2 1 2	450.352	76.343
6 1 2 1 2 2 1 2	395.933	62.388
6 2 1 2 1 1 2 1	172.287	40.835
7 1 2 2 1 1 2 2	224.283	43.258
7 2 1 1 2 2 1 1	220.052	47.705
8 1 2 2 1 2 1 1	252.352	62.900
8 2 1 1 2 1 2 2	204.927	50.651

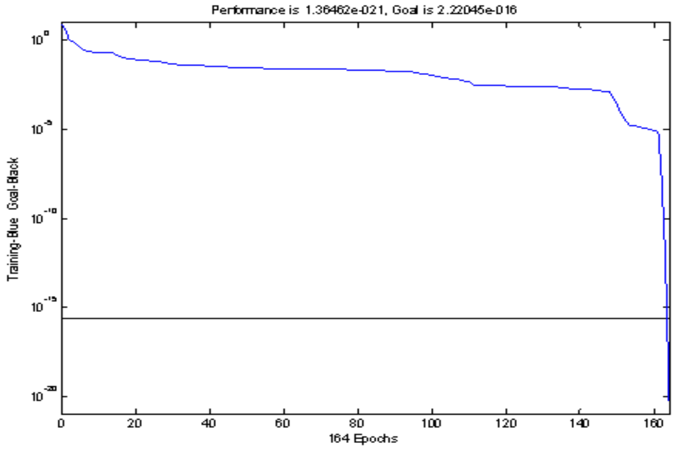

Fig. 3. Neural-Network Data Training.

The output is calculated by determining the difference between given output and the demand output. After finding the relationship between the input and the output, the error between experimental data and the ANN output data for each of the eight parameters is shown in Table 8. The neural network method shows an almost negligible error (4.96×10^{-10}).

Table 8. Represents the Error Value of Each Parameter in Neural Network Function.

Sample	1	2	3	4	5	6	7	8	9	10
Tensile Strength N/mm^2	418.6	441.7	381.2	372.9	462.9	491.8	3835	482.5	368.5	354.5

6. Result Verification

The parameters setting based on ANN are: X_1 level 6: welding time = 0.32 second, X_2 level 2: sheet thickness = 2.93 mm, X_3 level 2: sheet material = non-galvanized (K14358steel) sheet, X_4 level 1: welding current = 430 Ampere, X_5 level 1: stud design = un-flange stud, X_6 level 2: stud material = 40 CrMnMoS8-6 steel stud, X_7 level 1: Preheating, X_8 level 2: Surface cleaning = Clean sheet.

Under these parameters, the sheet thickness of (3.175 mm) and welding current is (540 Ampere), ten samples were produced and the results are shown in Table 9. The mean tensile strength from the confirmation run was 415.87 N/mm^2; and the standard deviation is 50.748 N/mm^2.

Table 9. Tensile Strength of Ten Samples for Stud Welding Input Parameters Based on Neural Network Results.

Parameters	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Percent of error($\times 10^{-10}$)	-0.2	-2	0.5	0.4	0.5	2.3	2.1	-3.2

7. Comparison between Artificial Neural Network and Taguchi Experimental Design Solution

The experimental results from neural network and statistical Taguchi approach was compared and plotted in Fig. 4. Taguchi experimental design is a statistical technique that allows running the minimum number of experiments to optimize the process. Experimental design offers a method of getting the maximum information from the minimum number of tests. In addition, valuable information can be gained on interactions between variables-interactions are often very important, and may be missed when investigations are carried out changing one variable at a time.

The Taguchi technique places a deal of importance on the reduction in variability of products and processes; in other words to make products and processes more robust and less susceptible to changes due to outside influences such as raw material variation, temperature, and changes to machines and operators. Improved robustness can often be achieved without major capital expenditure through the use of these techniques. This figure shows confirm the further improvements with stable quality output when neural network was applied.

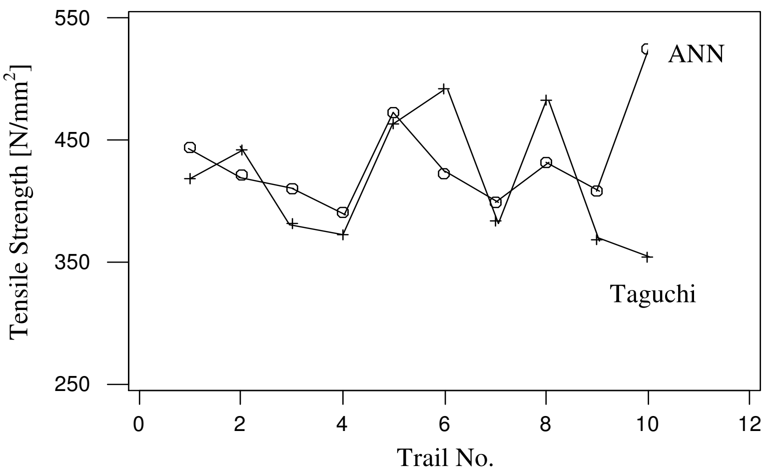

Fig. 4. Comparison between Neural Networks with Taguchi Experimental Design for Tensile Strength Data.

8. Conclusions

The study has shown a significant improvement (approximately 30.84%) in stud joint strength increase and (approximately 30.06 per cent) decrease in stud joint strength variation. The relationships between multiple level eight input parameters with response of mean tensile strength and standard deviation was conducted, but the sum of square error (R^2) was calculated and found to have a minimum value (47% for mean and 43.5% for standard deviation), while it should be at least 80% for good representation of data. On the other hand the neural network method shows an almost negligible error (4.96×10^{-10}) for representing data. The study proves that effective relation as the table of error values was shown. The paper shows that neural network is effective tool for solving non-linear relation between input parameters and multi output of stud arc welding process.

References

1. Conti, T.; Kondo, Y.; and Watson, G.H. (2003). *Quality into the 21st Century: Perspectives on quality and competitive for sustained performance*. American Society for Quality, USA.
2. Schmidt, S.R.; and Launsby, R.G. (1992). *Understanding industrial designed experiments*. Air Academy Press, Colorado Springs Co.
3. Hamza, R.M.A. (2007). *Evaluation of reducing manufacturing process variability using experimental design technique for stud welding process*. Ph.D. Thesis in industrial engineering, Baghdad University, Iraq.
4. Creech, G.L.; Paul, B.J.; Lesniak, C.D.; Jenkins, T.J.; and Calcatera, M.C. (1997). Artificial neural networks for fast and accurate EM-CAD of microwave circuits. *IRE Transactions on Microwave Theory and Techniques*, 45(5), 794-802.
5. Zaabab, A.H.; Zhang, Q.J., and Nakhla, M.S. (1995). A neural network modeling approach to circuit optimization and statistical design. *IRE Transactions on Microwave Theory and Techniques*, 43(6), 1349–1358.
6. Karsai, G.; Anderson, K.; Cook, G.E.; and Barnett R.J. (1992). Neural network methods for the modeling and control of welding processes. *Journal of Intelligent Manufacturing*, 3(4), 229-235.
7. Viswanathan, V.; Kinsey, B.; and Cao, J. (2003). Experimental impleme-ntation of neural network springback control for sheet metal forming. *Journal of Engineering Materials and Technology*, 125(2), 141-147.
8. Daniel, J.; and Sampaio, B.S. (2006). Quality estimation using generic model parameters and neural network. *ABCM symposium series in mechatronics*, 2, 765-771.
9. Taskin, M.; Dikbas, H.; and Caligulu, U. (2008). Artificial neural network (ANN) approach to prediction of diffusion bonding behavior (shear strength) of NI-TI alloys manufactured by powder metalurgy method. *Mathematical and Computational Applications*, 13(3), 183-191.
10. Assarzadeh, S.; and Ghoreishi, M. (2008). Neural-network-based modeling and optimization of the electro-discharge machining process. *International Journal, Advanced Manufacturing Technology*, 39(5-6), 488–500.
11. Yousif, Y.K.; Daws, K.M.; and Kazem, B.I. (2008). Prediction of friction stir welding characteristic using neural network. *Jordan Journal of Mechanical and Industrial Engineering*, 2(3), 151-155.
12. Ibrahim, L.M. (2010). Anomaly network intrusion detection system based on distributed time-delay neural network (DTDNN). *Journal of Engineering Science and Technology* (*JESTEC*), 5(4), 457-471.
13. Chiu, C.C.; Su, C.T.; and Cheng, N.T. (1997). Selection of optimal parameters in gas-assisted injection molding using a neural network model and the Taguchi method. *International Journal of Quality Science*, 2(2), 106-120.
14. Krishnamoorthy, A.; Boopathy S.R.; and Palanikumar, K. (2011). Delamination prediction in drilling of CFRP composites using artificial neural network. *Journal of Engineering Science and Technology* (*JESTEC*), 6(2), 191-203.