PREDICTION OF DELAMINATION SIZE IN DRILLING FIBER REINFORCED POLYMERIC COMPOSITE MATERIALS USING ARTIFICIAL NEURAL NETWORKS TECHNIQUE

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ABSTRACT

Delamination is a well-recognized problem associated with drilling fiber reinforced composite materials (FRCMs). The most noted problems occur as the drill enters and exits the FRCM. A method based on the artificial neural networks (ANNs) technique was used to predict delamination size resulting from drilling glass fiber reinforced epoxy (GFRE) laminates at both drill entry and exit sides of the hole. The experimental work that was performed to provide the data used to develop the required ANNs was presented in [1]. From the statistical analysis, using correlation coefficients between the target and the output values from the ANN, it is concluded that the obtained ANNs can be used effectively to model and predict delamination size at both drill entry and exit sides.

يعتبر انفصال الطبقات من أهم المشاكل التي تظهر عند عملية ثقب المواد المركبة البوليميرية. في هذا البحث تم استخدام تقنية الشبكات العصبية الاصطناعية للتنبؤ بقيمة انفصال الطبقات نتيجة عملية ثقب عينات من الإيبوكسي المدعم بالألياف الزجاجية عند موضع دخول و خروج البنطة. لإنشاء الشبكات العصبية المطلوبة، تم استخدام بيانات التجارب العملية الناتجة من البحث [1]. عند اختبار أفضل الشبكات المستخدمة في التنبؤ باستخدام معامل الارتباط بين القيم الفعلية لانفصال الطبقات و القيم الناتجة من الشبكة وجد أن قيم معامل الارتباط تقترب من الواحد مما يدل على إمكانية استخدام الشبكات العصبية المنشأة بكفاءة للتنبؤ بقيم انفصال الطبقات الناتجة من عملية الثقب.

Keywords: Prediction, Delamination size, Drilling, Composite Materials, Artificial Neural Networks (ANNs).

1. INTRODUCTION

Machining composite materials is a rather complex task owing to its heterogeneity, heat sensitivity, and to the fact that reinforcements are extremely abrasive. Conventional machining methods should be adapted in such a way that they diminish thermal and mechanical damage. Drilling is a frequently practiced machining process in industry owing to the need for component assembly in mechanical pieces and structures. The drilling of laminate composite materials is significantly affected by the tendency of these materials to delaminate and the fibers to bond from the matrix under the action of machining forces (thrust force and torque). The presence of delamination reduces the stiffness and strength of a laminate and hence its load carrying capacity. Delamination can often be the limiting factor in the use of composite materials for structural applications, particularly when subjected to compressive, shear and fatigue type of loads and when exposed to moisture and other aggressive environments over a long period of time.

Artificial neural networks (ANNs) have recently been introduced into the field of polymer composites. Inspired by the biological nervous system, ANNs can be used to solve a wide variety of complex scientific and engineering problems. Like their biological counterparts, ANNs can learn from examples, and therefore can be trained to find solutions of the complex non-linear, multi-dimensional functional relationships without any prior assumptions about their nature; further, the network is built directly from experimental data by its self-organizing capabilities [2].

Ho-Cheng and Dharan [3] presented an analysis of delamination during drilling of composite materials using fracture mechanics approach. The analysis predicts an optimal thrust force (defined as the minimum force above which delamination is initiated) as a function of drilled hole depth and material properties. Jain and Yang [4] proposed an analytical model based on fracture mechanics to predict critical thrusts and feed rates at which the delamination crack begins to propagate at different ply levels for unidirectional laminates. Jain and Yang [5] demonstrated that the critical thrusts and feed rates obtained for unidirectional laminates can be conservatively used for multi-directional laminates.

Stone and Kishnamurthy [6] developed a thrust force controller to minimize the delamination associated

with drilling in graphite-epoxy laminate. A neural network control scheme was implemented which required a neural network identifier to model the drilling dynamics and a neural network controller to learn the relationship between feed rate and the desired thrust force. The robustness of the controller was demonstrated by varying some of the drilling parameters, spindle speed and drill diameter. Sadat [7] used an analytical approach to predict the delamination load (the trust force that causes delamination at a given ply location) in a drilling of graphite/ epoxy multilayered (angle-ply) composite laminates. In his work, it was assumed that delamination was caused by the thrust force of the drill, and a relation for delamination load as a function of material properties and uncut plies thickness was determined. Enemuoh et al [8] used an intelligent sensor fusion technique based on artificial neural network to predict on-line delamination during drilling of an advanced fiber composite beam (AS4/PEEK). The fusion model included two drilling parameters (feed rate and cutting speed), two drilling conditions (tool material and tool geometry) and two sensors (thrust force and acoustic emission).

Chakraborty [9] aimed at developing an artificial neural network model for detection of extent of delamination, its shape and location in a graphite/epoxy composite laminate using natural frequencies as inputs and corresponding size, shape and location of delamination as outputs of the network. Hundreds of finite element models have been run to generate natural frequencies up to ten modes for various combinations of size, shape and location of an embedded delamination in a laminate and these data have been used to train a back propagation neural network for future prediction of delamination in the laminate.

Sardiñas et al [10] proposed a multi-objective optimization of the drilling process of a laminate composite material. Two mutually conflicting objectives are optimized: material removal rate, which represents the productivity; and delamination factor, which characterizes the superficial quality. A micro-genetic algorithm was implemented to carry out the optimization process. An a posteriori approach was used to obtain a set of optimal solutions. Finally, the obtained outcomes were arranged in graphical form (Pareto's front) and analyzed to make the proper decision for different process preferences.

Srinivasa Rao et al [11] used the multi-variable linear regression analysis to make the correlation between the delamination factor and the drilling parameters; feed rate, spindle speed and drill diameter, when drilling glass/epoxy woven mat cross-ply laminates. Karnik et al [12] predicted the delamination factor at the entrance side of drilled CFRP plates, using the multilayer feed forward ANN model trained by error-back propagation training algorithm, with spindle speed, feed rate and point angle as the inputs to the developed ANN. Drilling experiments are conducted as per full factorial design using cemented carbide (grade K20) twist drills that serve as input-output patterns for ANN training.

This paper summarizes an approach for prediction of delamination size, both at drill entry and exit sides, resulting from drilling GFRE specimens, using the feed-forward artificial neural networks (ANNs) technique trained with the back-propagation routine. The inputs to the neural network were drill diameter, spindle speed, feed, drill pre-wear, thrust force, and torque.

2. DATA FOR DEVELOPMENT OF ANNs

Artificial neural network algorithms are regarded as multivariate nonlinear analytical tools capable of recognizing patterns from noisy complex data and estimating their nonlinear relationships. Their major advantages include superior learning, noise suppression, and parallel data processing capabilities [13]. Further, the network is built directly from experimental data by its self-organizing capabilities [2].

Experimental work was performed in order to obtain the data required to train, validate and test the developed ANNs. E-glass fiber reinforced epoxy (GFRE) woven roving composite specimens were manufactured using hand lay-up technique [14]. Specimens were machined using cemented carbide drills with two diameters $\Phi8$ and $\Phi13$ mm. The workpieces were drilled with five spindle speeds, five feeds and five drill pre-wear values (fresh drill plus four artificially introduced pre-wear values) with a backing plate has a center hole of 26 mm under dry cutting conditions. The details about the experimental work and the specification of the GFRE specimens were presented in [1]. At the end of the experimental work there were 250 holes (125 holes for each drill diameter) plus 25 holes machined with cutting conditions different from that of the experimental work for the purpose of testing the developed neural networks for generalization.

3. RESULTS AND DISCUSSION

In order to develop the required neural networks, from all of the holes that were machined in the experimental work, holes were selected randomly as; 200 holes for training patterns, 50 holes for cross validation patterns (which were used as a training stoppage criterion [15]), and 25 holes were used as test patterns.

All of the developed ANNs are of multi-layer perceptron type and trained using the back-propagation routine [16,17]. A NeuroSolutions software (version 5) [18] was used in the training,

validating and testing process of the developed neural networks. For training, a value of 0.7 was selected for the momentum term, a starting value of 1.0 was assigned for the learning rate, and maximum epochs of 40,000 were chosen with batch weight update method.

3.1 ANNs for Thrust Force and Torque Prediction

Among the inputs to the ANNs for delamination size prediction, there are thrust force and torque. Thus, before using the developed networks, thrust force and torque generated during the drilling process should be predicted in order to eliminate the need for measuring each of thrust force and torque at every prediction process of delamination size.

To obtain the best neural network structure, nineteen neural networks were developed by changing both of the number of hidden layers and the number of hidden units within each hidden layer.

(1) ANNs for thrust force prediction

Figure 1 shows the schematic diagram of the neural net for predicting the thrust force (F_t). Four inputs were fed to the network; spindle speed, feed, drill pre-wear and drill diameter.
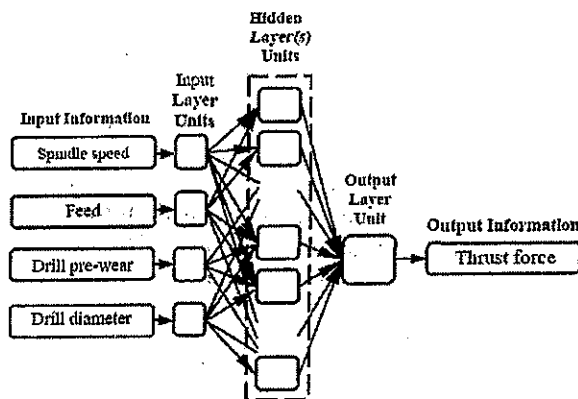

Fig. 1 Schematic diagram of the neural network for predicting thrust force.

Table 1 represents the tried neural networks that were used for the prediction of F_t. From the Table it can be seen that the best neural network for predicting F_t is the net which has the structure of 4 input units, 4 hidden units in first hidden layer, 6 hidden units in second hidden layer and one output node (F_t) where its test data set error is the lowest value (685.92 N^2). Fig. 2 shows the relationship between the measured and the predicted values of F_t for this best net, including the results of training, validation and test data sets.

(2) ANNs for Torque Prediction

Figure 3 shows the schematic diagram of the neural net for predicting the torque (T). Four inputs were fed to the network; spindle speed, feed, drill pre-wear and drill diameter.

Table 1 Trials for the ANNs for predicting thrust force

| No.	Network Structure	Training Set MSE (N^2)	Validation Set MSE (N^2)	Test Set MSE (N^2)
1	4-2-1	3064.43	4215.79	2046.56
2	4-4-1	852.80	1641.96	3766.13
3	4-6-1	413.93	1093.04	1260.83
4	4-8-1	311.79	870.57	1349.23
5	4-10-1	225.76	764.06	2869.18
6	4-12-1	163.20	663.40	3501.07
7	4-2-2-1	1891.31	3110.48	6460.15
8	4-2-4-1	1893.41	3107.27	4484.77
9	4-4-2-1	635.94	1040.81	1130.97
10	4-4-4-1	519.75	870.50	1246.73
11	4-4-6-1*	440.94	1090.87	**685.92**
12	4-6-4-1	285.34	864.77	1223.04
13	4-6-6-1	304.80	760.32	939.15
14	4-6-8-1	307.11	653.40	1071.55
15	4-8-6-1	277.69	550.78	1654.97
16	4-8-8-1	257.96	643.75	3948.74
17	4-8-10-1	191.12	702.85	1275.64
18	4-10-8-1	230.48	510.98	2408.76
19	4-10-10-1	133.48	449.47	4481.59

* The best network structure.
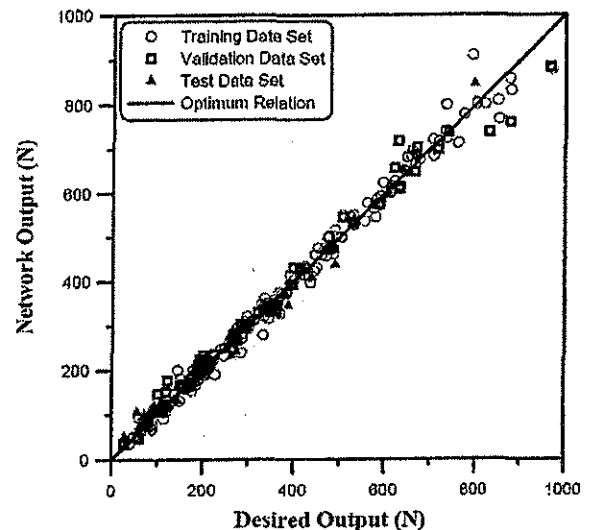
Fig. 2 Relationship between actual (desired) and predicted (output) values of the best obtained network for predicting thrust force.

Table 2 represents the tried neural networks that were used for the prediction of T. From the Table it can be seen that the best neural network for predicting T is the net which has the structure of 4 input units, 2 hidden units in first hidden layer, 2 hidden units in second hidden layer and one output node (T) where

its test data set error is the lowest value $(0.0094$ $(N.m)^2)$.

Fig. 4 shows the relationship between the measured (target) and the predicted (output) values of T for this best net, including the results of training, validation and test data sets.
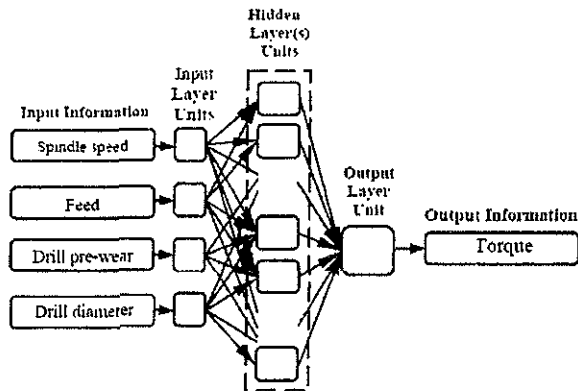

Fig. 3 Schematic diagram of the neural network for predicting torque.

Table 2 Trials for the ANNs for predicting torque

No.	Network Structure	Training Set MSE $(N.m)^2$	Validation Set MSE $(N.m)^2$	Test Set MSE $(N.m)^2$
1	4-2-1	0.0171	0.0133	0.0184
2	4-4-1	0.0049	0.0053	0.0116
3	4-6-1	0.0054	0.0058	0.0216
4	4-8-1	0.0054	0.0056	0.0265
5	4-10-1	0.0067	0.0056	0.0202
6	4-12-1	0.0042	0.0059	0.0210
7	4-2-2-1*	0.0066	0.0057	**0.0094**
8	4-2-4-1	0.0060	0.0062	0.0116
9	4-4-2-1	0.0067	0.0058	0.0220
10	4-4-4-1	0.0044	0.0055	0.0126
11	4-4-6-1	0.0055	0.0056	0.0220
12	4-6-4-1	0.0025	0.0057	0.0250
13	4-6-6-1	0.0026	0.0053	0.0162
14	4-6-8-1	0.0027	0.0048	0.0135
15	4-8-6-1	0.0011	0.0040	0.0208
16	4-8-8-1	0.0008	0.0050	0.0186
17	4-8-10-1	0.0016	0.0049	0.0194
18	4-10-8-1	0.0007	0.0049	0.0205
19	4-10-10-1	0.0028	0.0057	0.0278

* The best network structure.

3.2 ANNs for Delamination Size Prediction

Figure 5 shows the schematic diagram of the neural net for predicting the delamination size at drill entrance and drill exit. For each output, six inputs were fed to the network (drill diameter, spindle speed, feed, drill pre-wear, thrust force, and torque). The value of the thrust force and torque that is fed to the ANNs is the average value of the maximum five peaks in drilling process of the hole.
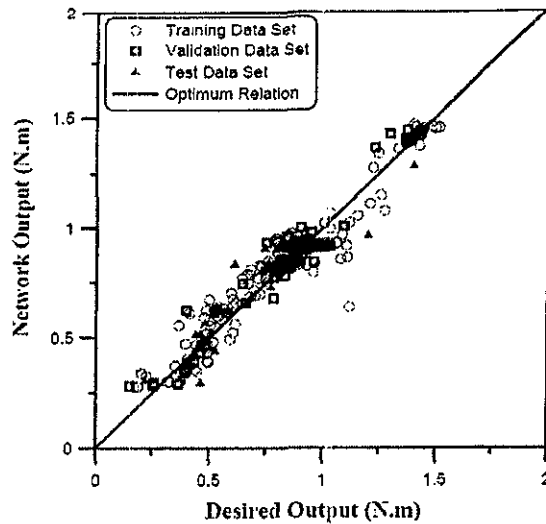

Fig. 4 Relationship between actual (desired) and predicted (output) values of the best obtained network for predicting torque.

To obtain the best neural network structure, twenty-seven neural networks were developed by changing both of the number of hidden layers and the number of hidden units within each hidden layer. Tables 3 and 4 represent the tried networks for predicting delamination at drill entry and exit sides respectively. Actually, each network in the Table was obtained by training five times (runs) starting with five different initial weight values, the run and epoch numbers which gave the minimum mean square error (MSE) of the validation sets were chosen as the required net. The criterion of selecting the best net from the tried networks is the minimum mean square of the differences between the measured and the predicted values obtained from the net (MSE), applied for the test data sets. So, from Tables 3 and 4 the best network structures for predicting delamination size at hole entry and exit sides are 6-18-1 (with a MSE of 0.1194 mm2) and 6-6-6-1 (with a MSE of 0.2557 mm2) respectively.
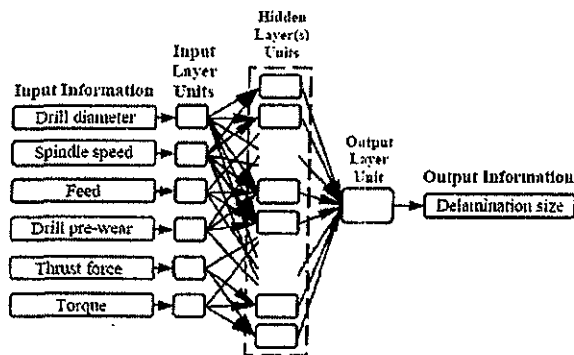

Fig. 5 Schematic diagram of the neural network for predicting delamination size at drill entrance and exit sides.

Figures 6 and 7 illustrate the relationships between the actual (desired) and predicted (network output) values of the best obtained neural network structures for predicting delamination at hole entry and exit respectively. In order to investigate the performance of the best obtained networks, correlation coefficients between the targets and the corresponding network outputs (actual-predicted relationship) were estimated. Correlation coefficient is a measure of how well the variation in the outputs is explained by the targets, if the number is equal to 1, it means that there is a perfect correlation between the targets and the ANNs outputs.

Table 5 shows the values of the correlation coefficients for each of training, validation and test data sets for the developed ANNs. From this Table, it is clear that the values of the correlation coefficients approach to 1 which give strong indication that the obtained ANNs can be used effectively to model and predict thrust force, torque as well as delamination size at both drill entrance and exit sides.

Table 3 Trials for the ANNs for predicting delamination at drill entrance

No.	Network Structure	Training Set MSE (mm²)	Validation Set MSE (mm²)	Test Set MSE (mm²)
1	6-2-1	0.0196	0.0196	0.1638
2	6-4-1	0.0140	0.0208	0.1411
3	6-6-1	0.0082	0.0210	0.1351
4	6-8-1	0.0055	0.0197	0.1626
5	6-10-1	0.0058	0.0217	0.1612
6	6-12-1	0.0031	0.0169	0.1619
7	6-14-1	0.0026	0.0189	0.1221
8	6-16-1	0.0028	0.0143	0.1680
9	6-18-1*	0.0018	0.0152	**0.1194**
10	6-20-1	0.0018	0.0137	0.1723
11	6-2-2-1	0.0175	0.0276	0.1216
12	6-4-4-1	0.0106	0.0243	0.1286
13	6-4-2-1	0.0101	0.0237	0.1397
14	6-2-4-1	0.0186	0.0302	0.1596
15	6-5-5-1	0.0080	0.0243	0.1824
16	6-4-6-1	0.0128	0.0239	0.1405
17	6-6-4-1	0.0071	0.0243	0.1484
18	6-6-6-1	0.0063	0.0216	0.1781
19	6-6-8-1	0.0048	0.0175	0.1455
20	6-8-6-1	0.0035	0.0172	0.1317
21	6-8-8-1	0.0029	0.0164	0.1655
22	6-10-8-1	0.0025	0.0190	0.1522
23	6-8-10-1	0.0029	0.0187	0.1753
24	6-10-10-1	0.0021	0.0157	0.1495
25	6-12-10-1	0.0017	0.0141	0.1698
26	6-10-12-1	0.0024	0.0187	0.1979
27	6-12-12-1	0.0026	0.0185	0.1230

* The best network structure

Table 4 Trials for the ANNs for predicting delamination at drill exit

| No.	Network Structure	Training Set MSE (mm²)	Validation Set MSE (mm²)	Test Set MSE (mm²)
1	6-2-1	0.1657	0.0911	0.3899
2	6-4-1	0.1108	0.0623	0.3978
3	6-6-1	0.1170	0.0639	0.4225
4	6-8-1	0.1075	0.0647	0.4052
5	6-10-1	0.1115	0.0629	0.2851
6	6-12-1	0.0750	0.0610	0.4552
7	6-14-1	0.0932	0.0562	0.3296
8	6-16-1	0.0974	0.0599	0.3315
9	6-18-1	0.0899	0.0603	0.4750
10	6-20-1	0.0798	0.0596	0.4670
11	6-2-2-1	0.1366	0.0831	0.3143
12	6-4-2-1	0.0882	0.0627	0.3337
13	6-2-4-1	0.1169	0.0680	0.3414
14	6-4-4-1	0.0778	0.0619	0.3587
15	6-5-5-1	0.0996	0.0605	0.2872
16	6-4-6-1	0.1287	0.0565	0.3838
17	6-6-4-1	0.1131	0.0711	0.3818
18	6-6-6-1*	0.1005	0.0605	**0.2557**
19	6-6-8-1	0.0904	0.0580	0.4711
20	6-8-6-1	0.0958	0.0590	0.3078
21	6-8-8-1	0.1010	0.0614	0.2928
22	6-8-10-1	0.0849	0.0533	0.2990
23	6-10-8-1	0.0712	0.0540	0.4015
24	6-10-10-1	0.0811	0.0515	0.3850
25	6-12-10-1	0.0857	0.0567	0.5438
26	6-10-12-1	0.0935	0.0545	0.2822
27	6-12-12-1	0.0821	0.0624	0.4401

* The best network structure
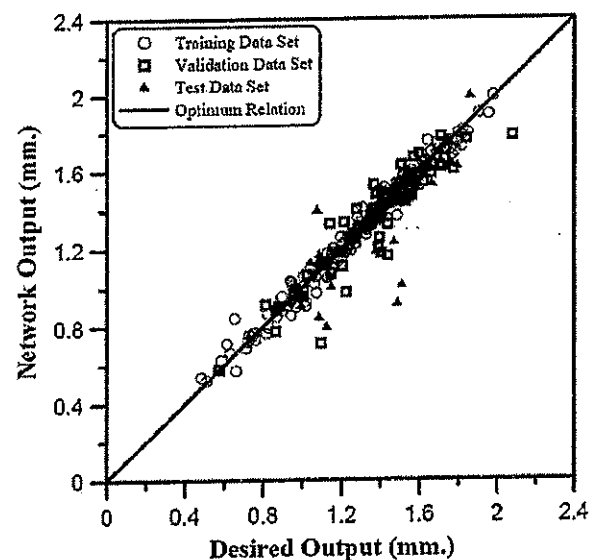
Fig. 6 Relationship between actual (desired) and predicted (output) values of the best obtained network for predicting delamination size at drill entrance.
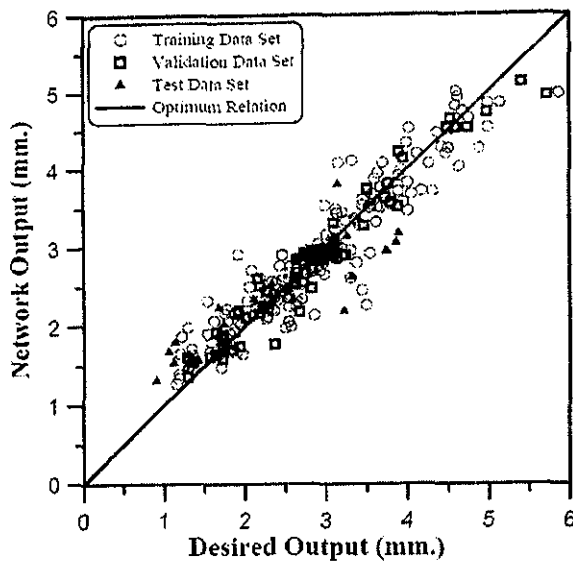
Fig. 7 Relationship between actual (desired) and predicted (output) values of the best obtained network for predicting delamination at drill exit

Table 5 Correlation coefficients for training, validation and test data sets

Correlation coefficients			
Best Networks	Training Data Set	Validation Data Set	Test Data Set
Thrust force (4-4-6-1)	0.995	0.992	0.992
Torque (4-2-2-1)	0.97	0.96	0.92
Drill Entry (6-18-1)	0.99	0.92	0.78
Drill Exit (6-6-6-1)	0.94	0.98	0.87

4. CONCLUSIONS

In this work the artificial neural networks technique, with back-propagation training routine, was used for the prediction of delamination size, resulting from drilling GFRE specimens, at drill entrance and exit sides. Secondary ANNs were developed to predict the generated thrust force and torque instead of measuring them every time a delamination prediction process was performed. Several attempts were made to obtain the best structure of these networks. The results obtained lead to the following conclusions;

- The best obtained network structure for predicting thrust force was 4-4-6-1. With a mean-squared error of 685.92 N^2 for the test data set.

- The best obtained network structure for predicting torque was 4-2-2-1. With a mean-squared error of 0.0094 $(N.m)^2$ for the test data set.

- The best obtained network structure for predicting delamination size at drill entry side was 6-18-1. With a mean-squared error of 0.1194 mm^2 for the test data set.

- The best obtained network structure for predicting delamination size at drill exit side was 6-6-6-1. With a mean-squared error of 0.2557 mm^2 for the test data set.

- As the correlation coefficients for each of training, validation and test data sets for the developed networks approach to 1, the best obtained ANNs can be effectively used to model and predict thrust force, torque as well as delamination size at both drill entrance and exit sides.

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