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Prediction of Fatigue Life of Fiber Glass Reinforced Composite (FGRC) using Artificial Neural Network

Abstract-*The present work studies the mechanical properties of composite materials, experimentally and analytically, that are fabricated by stacking 4-layers of fiberglass reinforced with polyester resin. This plies are tested under dynamic load (fatigue test) in fully reversible tension-compression (R=-1) to estimate the fatigue life of the composite where fatigue performance of fiberglass reinforced composed is an increasingly important consideration especially when designing wind turbine blades. In order to predict fatigue life (Number of cycles to failure), conventional analytical techniques are used in the present work. In addition, Artificial Neural Network (ANN) is a reliable and accurate technique that is used for predicting fatigue life. The used networks are; Feed Forward Neural Network (FFNN), Generalized Regression Neural Network (GRNN) and Radial Bases Function Neural Network (RBFNN). Based on the comparison of the results, it is found that the ANN techniques are better than conventional methods for prediction. The results shows that (RBNN2), where stress load and angle of orientation are input to the network and number of cycles to failure as output, is an efficient tool for prediction and optimization the fatigue life of fiberglass reinforced composite.*

Keywords- *Prediction, FGRC, ANN, FFNN, GRNN, RBFNN.*

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1. Introduction

I. Typical of rotor blades fatigue loads

The load on the rotor blade is in two extreme ways. This is illustrate in Figure 1, which first, shows the applications of composite materials (bicycles, cars, airplanes, helicopters, bridges, wind turbines), with the No. of load cycles that experienced; during the life of structure, and on the vertical, the degree of variations in load cycles. Rotor blades of Wind turbine are subjected to a wide No. of loads during their lifetime of twenty years.

Prediction of the No. of load cycles were up to 10^8 or 10^9 cycles [1]. Second, high variability are showed by this loads. The variation of loads on rotor blades is a result of the random nature of the wind. This is in spite of the fact, that there is indeed regular component of fatigue loading.

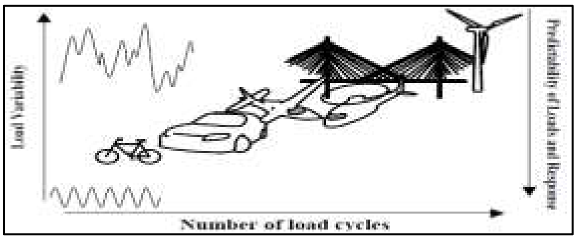

Figure 1: Wind turbine loading regime [1].

II. Materials of Rotor blade

Typically, rotor blade is constructed from fiber-reinforced polymer, because of its high stiffness, ratio of high (stiffness to density) and good toughness of fracture [2]. Typically, continuous fiberglass composite is used, although designer is moving toward employing fiberglass because of its stiffer fiber and is slowly becoming available for wind industries. In this case, the materials used in wind turbine, relative to composite of aerospace, is characterize by relatively coarsely.

The fibers are contained in polymer matrix, which provide a resistance to the compression load, but mainly serve to fix and align the fibers geometrically. Wide of blades are made from polyester but epoxy is also used. Both densities; are the same but better performance of fatigue is attributed to composite with the epoxy matrix, enable of lighter design. Moreover, the advantage of epoxy is the absence the vapor of toxic styrene during manufacturing. Essentially, each blade is made with resin.

III. The Aim of the work

The aim of the present research is to optimize life predictions of composite under variable stress loads. Ultimately, this research aims to optimize

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life prediction guidelines by enhancement the fatigue life prediction that obtained by the traditional approaches using linear, power law and quadratic polynomial regression in comparison with ANN techniques that considered as an accurate and reliable method

IV. Fatigue of composite

Before the fatigue; has been treated generally, so an introduction of fatigue life must be given. Fatigue loads; are represented by a waveform, typically sinusoidal, cyclic load. The characteristic of this waveform is given in Figure 2, in terms of the quantity *S* and *N*. Typically; stresses are used for homogeneous material, while strain is preferred for composite. For *(N)*, the No. of cycles to failures is used. In addition, half cycle to failure, No. of load sequence to failure, or No. of cycles to predefined stiffness, may be used. The result of fatigue experiments is often plotted in (S-N) diagrams, as shown in Figure 2. In general, fatigue characteristics are calculated by the slope of the (S-N) curve. The flat S-N curve (small slop) often is considered; to represent main fatigue characteristics over the steep S-N curve. The fatigue behavior can be appraised, depend upon; the location of the intersect with the abscissa.

Knowledge of the damage mechanisms and their progression is to understand the fatigue behavior of composite materials, these damage mechanisms are abundant, they occur at many unpredictable locations throughout the laminate. There are five major damage mechanisms: cracking of matrix, breaking of fiber, crack coupling, beginning of delamination and growth of delamination.

Figure 3 shows the state of damage versus percent1 of life for three phase's progression of damage. Phase ***I***, cracking of matrix; Phase ***II***, fracture of fiber, crack coupling and beginning of delamination; Phase ***III***, growth of delamination and final fracture1 [4].

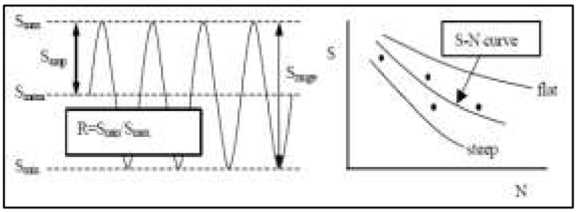

Figure 2: General fatigue terminology [3].

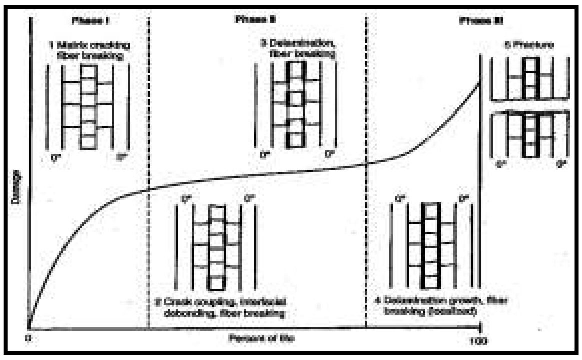

Figure 3: Schematic representation of the three phases of damage during the fatigue Life of a multidirectional composite laminate [4]

2. Methodology

I. Fabricating mold

The mold was manufactured from two steel plates in the workshop. It has dimensions of 30*30 cm^2 area with thickness of 3mm as shown in Figure 4, with some weights to make the fibers tighten and strung.

II. Fatigue test Specimen

The specimens are cut out of 30*30 cm^2 panels and the cut edge is polished in two stages in order to remove the flaws and the additional fibers and to obtain surfaces. Emery papers of grade *434* and *1000* were used for this purpose. According to ASTM D 3479/D 3479M–96, standard test method, the specimens are prepared for fatigue of composite materials [5]. A set of five specimens of unidirectional laminate [0_4] and a set of five specimens of angle-ply [45/-45/45/-45] at 0^o, 30^o and 45^o cut angle are prepared. These specimens of composite materials are chosen as they showed promising strength characteristics in the tensile test compared with other types. Suitable dimension for fatigue specimens to satisfy the section the machine that suited for flat plate specimens. Figure 5 shows the geometry of the specimens with its dimension, Figure 6 shows the fatigue specimens.

Figure 4: fabricating mold
The frame was manufactured to produce multi-ply unidirectional laminates ($0^°/0^°/0^°/0^°$), angle ply laminates [±45], with thickness range (2.3-3.5) mm.

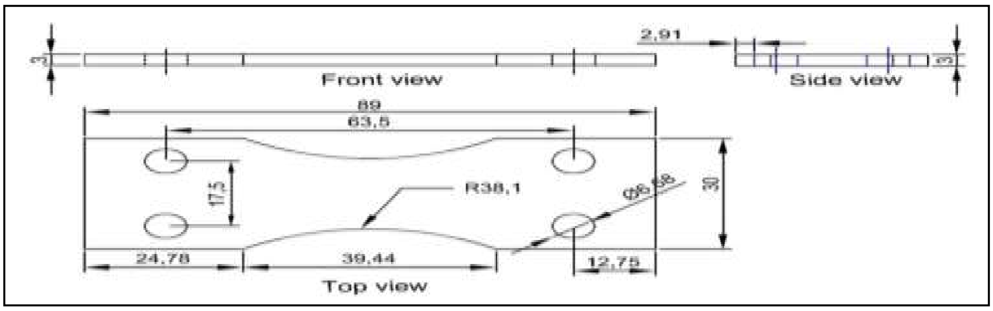

Figure 5: fatigue specimens (all dimension in *mm*)

Figure 6: fatigue test specimens

Figure 7: Fatigue test machine.

III. Fatigue test procedure

Fatigue test is a procedure type of cyclic bending2 loading. The aim of the fatigue test is to produce S-N curve (applied stress versus No. of cycles to failure) for each fatigue test specimen. For this test, the AVERY Fatigue Testing Machine Type-*7305* is designed to apply loads with or without initial static loads, as shown in Figure 7. The grip is provided for the cyclic load where3 the load is applied on one4 end of the fatigue specimen by an oscillating1 spindle by a connection means such as a crank, connecting rod and double eccentric attached. The eccentric attachment can be adjusted to provide the necessary range of bending angle.

At the opposite end of the specimen, the applied load is measured by means of a Torsion Dynamometer. The angle of twist can be registered by horizontal rod on a Dial gage. The relationship between the reading of dial gage and the imposed torque by using the calibration curves. From the applied torque and the deflection angle, the applied stress can be calculated. In order to record the number of cycles, a revolution counter is fitted to the motor. The cycling rate is *1420 rpm* (*24 Hz*).

The test machine is adjusted at stress ratio *R=-1* refers to that the cyclic bending load stress means tension- compression stress. Each set of specimens have been tested by changing the moment each time and recording the number of cycle to failure".

IV. Artificial Neural Network (ANN)

The history of AI (Artificial Intelligence) is begun in 1956 as a term by John McCarthy first academic conference (Dartmouth). After five years, Alan Turing gave a proposal about the machines that can be able to simulate the human brain and can3 do intelligent things [6]. AI becomes important area of research in many fields; "engineering, science, education, medicine, business, accounting, finance, marketing, economics and stock market" [7].

The intelligent machines are nearly similar to the humans brain and it follow that one could achieve AI by simulating the function of the humans brains on the computer. The artificial neural network can be characterized by several features: "large number of simple neuron-like processing elements; large number of weighted connections between the elements in which the weights on the connections encode the networks knowledge; highly parallel; distributed control and emphasis on learning internal representations automatically" [8]. An input of neural network determines the net input signals to neuron that coming from the inputs with activation functions that calculate the activation; level of the neuron as a function of its summation input signals and (perhaps) of its previous situation. The output signals are emitted through output of the neuron [9].

V. Feed Forward Back Propagation Neural Network (FFNN) [10]

FFNN is one of the most popular structures in ANNs, which are widely used to solve many complex problems by creating a relationship between input and output. In many applications, BPNN widely used method for FFNN learning because it has good advantage with simple implementation. The structure of BBNN is shown in Figure 8 where the output of neuron is input to the next neuron multiplied by its weights [11]. The input values converted to output values by calculation of activation functions, which is sigmoid activation, function because it is differentiable:

$$f(x) = \frac{1}{1+e^{-\lambda x}} \quad (1)$$

Where λ is a constant parameter, and x is the input to the activation function **[12]**.

BPNN is widely used in diverse applications like performance evaluation, location selection, prediction and optimization.

$$a^1 = f^1(IW^{1,1} \times p + b^1) \quad (2)$$
$$a^2 = f^2(LW^{2,1} \times a^1 + b^2) \quad (3)$$

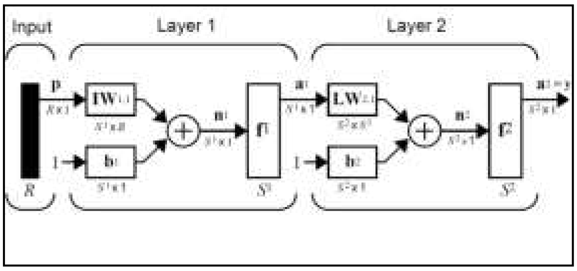

Figure 8: Feed forward neural network [13]

VI. Generalized Regression Neural Network (GRNN)

GRNN has a certain characteristics which are used to solve a complex problem because it is fast learning and good approximate with a large number of training data. It consist of three layers, in other research four layers; input, pattern, summing and output layer as shown in figure (9). Normal distribution function is the probability density function that is used in GRNN [14].

$$y(x) = \frac{\sum_i^n y_i \exp\left(-D_i^2 / 2\sigma^2\right)}{\sum_i^n \exp\left(-D_i^2 / 2\sigma^2\right)} \quad (4)$$

Where: D is distance and $(D^2 = (x - x_i)^t (x - x_i)$, x_i is the mean input and σ is the smoothness parameter (can be arbitrarily chosen to.$\sigma = 0.1$) and t is the number of alteration

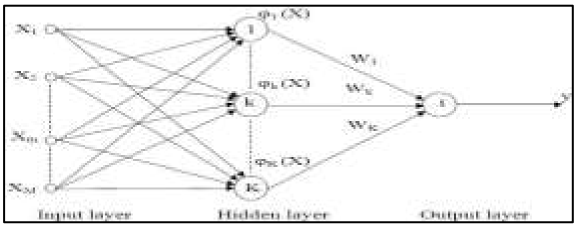

Figure 9: Architecture of GRNN [15].

VII. Radial Basis Function Neural Network (RBFNN)

RBFNN can be used as a replacement of many networks that have flexibility transfer function (sigmoid activation function) and it is considered as powerful method for regression and approximation. It consists of three layers; input, hidden that has the nonlinear (RBF) and output layer with linear activation function; as shown in Figure 10. The technique of (RBF) provides better generalization ability to avoid unnecessary lengthy calculations. The (RBF) represented as:

$$\varphi(x, \mu) = e^{\frac{\|x-\mu\|^2}{2d^2}} \quad (5)$$

Where: μ is the mean value of the data, d is the distance of the data from the mean value and x is the input data.

VIII. Design of ANN

The ANN consists of elements that are analogue to the neuron in the brain. The processing contains of many computational1 elements that are arranged in layer. Several advantages of ANN including the ability to learn compared to the conventional techniques. For designing the ANN models, the first step is the characterize of the problems that have to be solved, this will calculate the selection of suitable topology of the network. Next step is to identify the input data which can be binary or real values input. In the last step, determination of the input1, hidden and output layers to give a best performance. "To evaluate the performance of each models, the performance criteria formula are defined as:

$$Mean\ square\ error = \frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2 \quad (6)$$

$$Root\ mean\ square\ error = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2} \quad (7)$$

$$Mean\ absolute\ error = \frac{1}{n}\sum_{i=1}^{n}(|t_i - a_i|) \quad (8)$$

Where t_i and a_i are observed and predicted values respectively. n Is the number of input data".

In ANN, all records of different orientation are used. 75% of records are training, 10% are cross validation and 15% are testing. Three steps are used in each network; first with one input parameter (stress load), second with two parameters (stress load and angle of orientation) and third with three input parameters (stress load, angle of orientation and thickness of ply) in (FFNN1, 2, 3), (GRNN1, 2, 3) and (RBNN1, 2, 3) respectively.

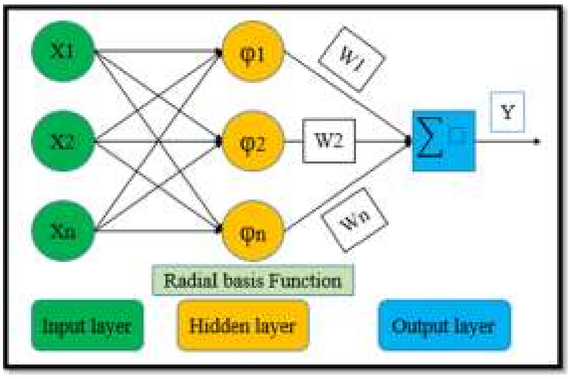

Figure 10: Architecture of (RBFNN) [16]

3. Results and Discussion

Stress load and number of cycles to failure are calculated for each type of fiberglass. The results of fiberglass reinforced composites at orientation of unidirectional $(0^o/0^o/0^o/0^o)$ and cross-angle $(45^o/-45^o/45^o/-45^o)$, $(15^o/-75^o/15^o/-75^o)$ and $(0^o/90^o/0^o/90^o)$ plies. The results of (FGRC) of all orientations are listed in Tables 1, 2, 3 and 4.

Table 1: stress load and number of cycles to failure of fiber glass at orientation $(0^o/0^o/0^o/0^o)$

Stress (Mpa)	Experimental No. of cycles
50.8	21300
48.69	20200
44.67	36660
44.22	33780
40.7	39800
39.23	51360
37.61	55160
29	44000
25.64	81020
25.6	65300
23.36	92500
19.4	106500
19.12	96000
18.73	133200
12.55	147300
12.36	130200
9.9	247100
7.5	180480

Table 2: stress load and number of cycles to failure of fiberglass at orientation $(45^o/-45^o/45^o/-45^o)$

Stress (Mpa)	Experimental No. of cycles (rpm)
39	33650
38.29	14000
35.29	51000
34.9	4970
30.49	50360
26.38	89300
23.47	64000
23.14	75300
21.63	90880
20.44	122100
17.28	92450
15.91	112500
11	190500
10.8	255600
8	199360

Table 3: stress load and number of cycles to failure of fiber glass at orientation $(15^o/-75^o/15^o/-75^o)$

Stress (Mpa)	Experimental No. of cycles (rpm)
39.38	48250
37.18	49000
32.5	15620
28.55	62480
28.49	71590
28.43	72000
24.55	94360
23.64	89460
20	95500
15.18	125000
13.6	104000
13.59	110000
7.4	197400
6.9	275000
5	277100

Table 4: stress load and number of cycles to failure of fiber glass atorientation $(0^o/90^o/0^o/90^o)$

Stress (Mpa)	Experimental No. of cycles (rpm)
41.38	41180
36.95	58000
35.94	15180
27.63	75770
27.2	48280
25.17	48280
22.26	58220
21.8	90010
18.64	58220
18.21	93720
14.9	100000
11.69	120720
9.78	213000
9.2	161780
8.28	201500

The stress load versus No. of cycles to failure of experimental results of $(0^o/0^o/0^o/0^o)$, $(45^o/-45^o/45^o/-45^o)$,$(15^o/-75^o/15^o/-75^o)$and$(0^o/90^o/0^o/90^o)$ are shown in figures (11), (12), (13) and (14) respectively.

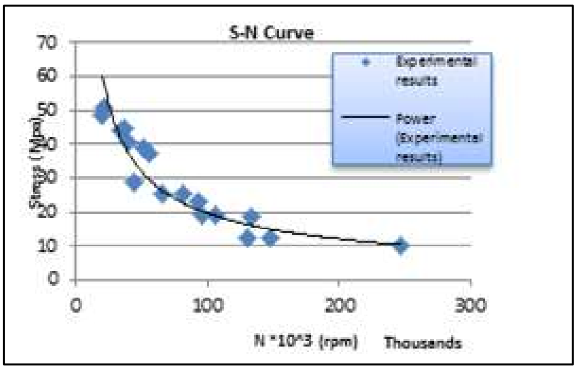

Figure 11: Experimental stress load versus No. of cycles to failure curve of (FGRC) at orientation of (0°/0°/0°/0°) plies.

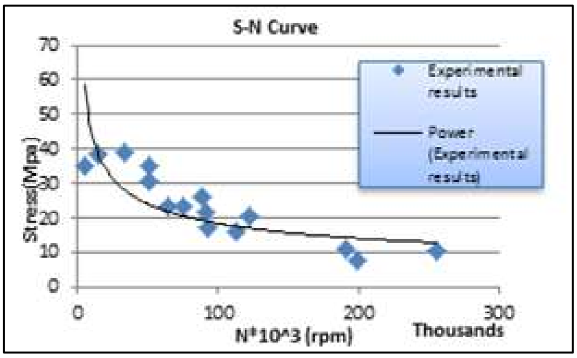

Figure 12: Experimental stress load versus No. of cycles to failure curve of (FGRC) at orientation of (45°/-45°/45°/-45°) plies

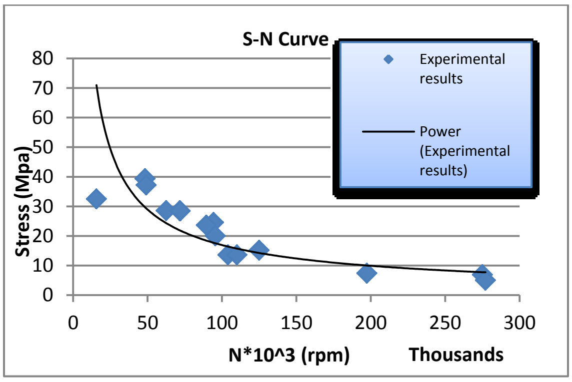

Figure 13: Experimental stress load versus No of cycles to failure curve of (FGRC) at orientation of (15°/-75°/15°/-75°) plies

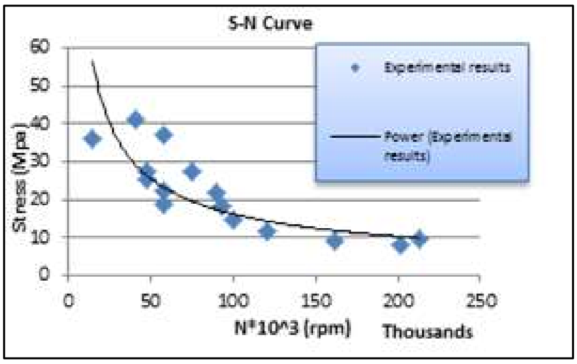

Figure 14: Experimental stress load versus No of cycles to failure curve of (FGRC) at orientation of (0°/90°/0°/90°) plies

I. Prediction of fatigue life (FGRC) using Artificial Neural Network (ANN)

Many mathematical models are discussed in the previous section in order to predict the fatigue life of different orientations of (FGRC) using traditional models (linear, power law, quadratic polynomial regression models). Very efficient tool is used which are (ANN) in order to approximate the output of the networks to the experimental results. ANN is used in many architectures for prediction of fatigue life.

In ANN, all records of different orientations are used. 75% of records are training, 10% are cross validation, and 15% are testing.

II. Prediction of fatigue life using feed forward neural network (FFNN)

FFNNs are used to predict the fatigue life of (FGRC) of all orientations with many models. These networks work with hyperbolic (log-sigmoid) activation function in three strategies: Firstly, one parameter, which is stress load, as an input variable to the network and one output, which is No. of cycles to failure, as an output variable of the network (FFNN1). Secondly, two parameters, which are stress load and angle of orientation, as an input variables to the network and one output, which is No. of cycles to failure, as an output variable of the network (FFNN2). Thirdly, three parameters, which are stress, angle of orientation and the thickness of the ply, as the input to the network and one output, which is No. of cycles to failure, as an output variable of the network (FFNN3). The test results of (FFNN1), (FFNN2) and (FFNN3) after training are listed in Tables 5, 6 and 7.

Table 5: Prediction of fatigue life using FFNN1 with one input parameter

Stress (Mpa)	Experimental No. of cycles (rpm)	Modeling No. of cycles (rpm) by FFNN1

28.43	71590	64663.43
24.55	94360	79143.28
13.59	104000	138581.7
5	277100	216653.8
35.94	15180	41306.87
25.17	48280	76669.09
18.64	58220	104272
11.69	120720	174576.4
8.28	201500	207916.3

Table 6: Prediction of fatigue life using FFNN2 with two input parameters

Stress (Mpa)	Angle of orientation θ^o	Experimental No. of cycles (rpm)	Modeling No. of cycles (rpm) by FFNN2
28.43	75^o	71590	61842.66
24.55	75^o	94360	78127.79
13.59	75^o	104000	130368
5	75^o	277100	231411.6
35.94	90^o	15180	52915.57
25.17	90^o	48280	68808.33
18.64	90^o	58220	89495.61
11.69	90^o	120720	157397.1
8.28	90^o	201500	182553.2

Table 7: Prediction of fatigue life using FFNN3 with three input parameters

Stress (Mpa)	Angle of orientation θ^o	Thickness of ply (mm)	Experimental No. of cycles (rpm)	Modeling No. of cycles (rpm) by FFNN3
28.43	75^o	3.3	71590	92409.05
24.55	75^o	2.9	94360	53106.45
13.59	75^o	2.9	104000	257841.5
5	75^o	3.1	277100	131283.3
35.94	90^o	3.3	15180	41526.69
25.17	90^o	3.3	48280	91129.76
18.64	90^o	2.7	58220	121669.5
11.69	90^o	2.75	120720	161797.6
8.28	90^o	2.3	201500	161779.9

The fatigue life of both experimental No. of cycles and the output of the (FFNN1, 2, 3) are shown respectively in figures 15, 16 and 17.

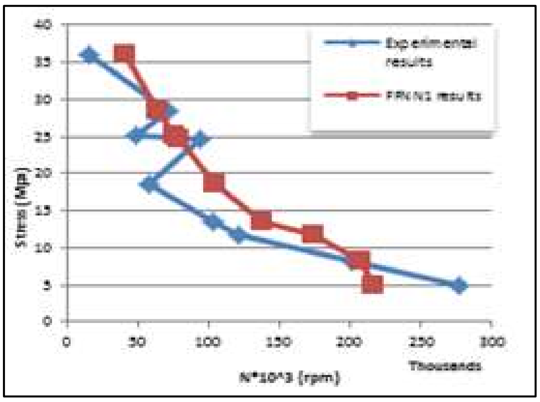

Figure15: Stress versus No of cycles to failure of both experimental results and FFNN1 (with one input parameter)

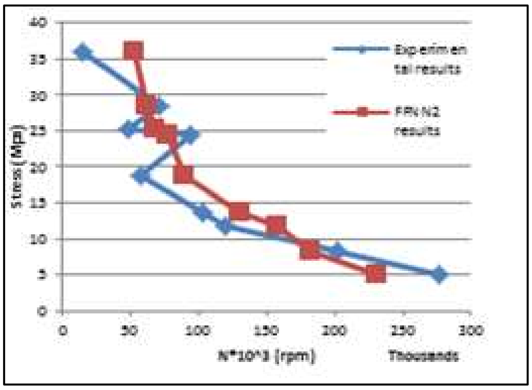

Figure16: Stress versus No of cycles to failure of both experimental results and FFNN2 (with two input parameters

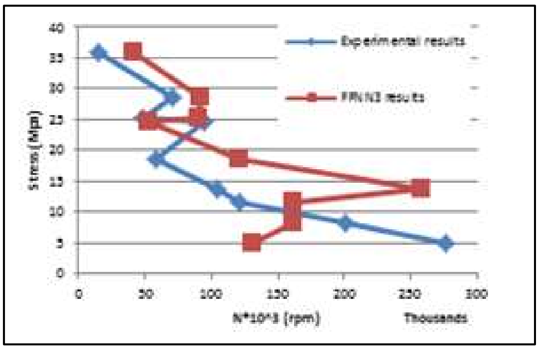

Figure 17: stress versus No of cycles to failure of both experimental results and FFNN3 (with three input parameters)

III. Prediction of fatigue life using Generalized Regression Neural Network (GRNN)

Fatigue life of (FGRC) has been predicted by using Generalized Regression Neural network (GRNN) with many models, and it works with three strategies: Firstly, one parameter, it is stress load, as an input variable to the network and one output, which is No. of cycles to failure, as an output variable of the network. Secondly, two parameters, they are stress load and angle of orientation, as the input to the network and one parameter, which No. of cycles to failure, as the output of the network. Thirdly, three parameters, they are stress load, angle of orientation and thickness of ply, as the input to the network and one parameter; it is the No. of cycles, as the output of the network. The test results of (GRNN 1, 2, 3) are listed in Tables 8, 9 and 10 respectively.

Table 8: Prediction of fatigue life using (GRNN1) with one input parameter

Stress (Mpa)	Experimental No. of cycles (rpm)	Modeling No. of cycles (rpm) by GRNN1
28.43	71590	61862.97817
24.55	94360	83133.9819
13.59	104000	118553.5964
5	277100	246369.7192
35.94	15180	38369.71967
25.17	48280	69737.169
18.64	58220	109351.7697
11.69	120720	152178.9417
8.28	201500	211361.9719

Table9: Prediction of fatigue life using (GRNN2) with two input parameters

Stress (Mpa)	Angle of orientation (θ^o)	Experimental No. of cycles (rpm)	Modeling No. of cycles (rpm) by GRNN2
28.43	75^o	71590	66152.5
24.55	75^o	94360	83614.67
13.59	75^o	104000	127682.5
5	75^o	277100	251684.2
35.94	90^o	15180	27841.96
25.17	90^o	48280	67684.2
18.64	90^o	58220	74642.82
11.69	90^o	120720	153691.3
8.28	90^o	201500	187692.2

Table 10: Prediction of fatigue life using (GRNN3) with three input parameters

Stress (Mpa)	Angle of orientation (θ^o)	Thickness of ply (mm)	Experimental No. of cycles (rpm)	Modeling No. of cycles (rpm) by GRNN3
28.43	75^o	3.3	71590	85154.67
24.55	75^o	2.9	94360	100365.9
13.59	75^o	2.9	104000	43125.65
5	75^o	3.1	277100	137265.5
35.94	90^o	3.3	15180	33326.55
25.17	90^o	3.3	48280	89235.46
18.64	90^o	2.7	58220	101319.9
11.69	90^o	2.75	120720	138263.5
8.28	90^o	2.3	201500	171326

The fatigue life of both experimental number of cycles and the output of the (RBNN1, 2, 3) are shown respectively in Figures 18, 19 and 20.

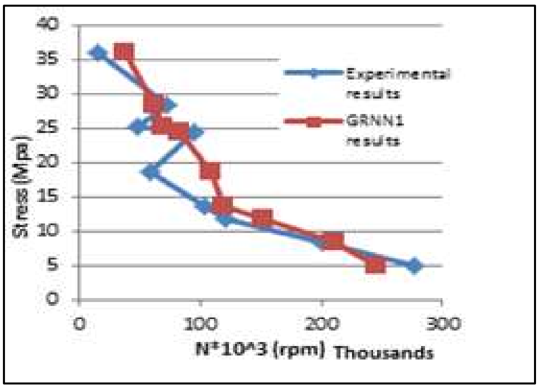

Figure 18: Stress versus No of cycles to failure of both experimental results and GRNN1 output (with one input parameter

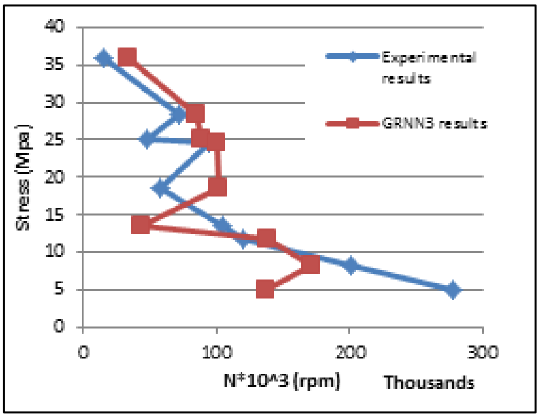

Figure19: Stress versus No of cycles to failure of both experimental results and GRNN2 output (with two input parameters)

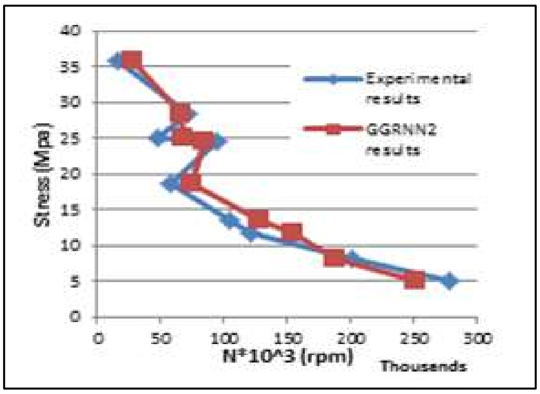

Figure 20: Stress versus No of cycles to failure of both experimental results and GRNN3 output (with three input parameter)

IV. Prediction of fatigue life using Radial Basis Neural Network (RBNN)

Fatigue life of (FGRC) has been predicted by using Radial Basis Neural Network (RBNN) with many models, and it works with three strategies: Firstly, stress load is the input variable to the network and the No. of cycles is the output of the network. Secondly, stress load and angle of orientation as the input parameters to the network and number of cycles as the output parameter of the network. Thirdly, three inputs, they are stress load, angle of orientation and thickness of ply, to the network and one output, which is the number of cycles, of the network.
The test results of (RBNN1, 2, 3) are listed in Tables 11, 12 and 13 respectively.

Table 11: Prediction of fatigue life using (RBNN1) with one input parameter

Stress (Mpa)	Experimental No. of cycles (rpm)	Modeling No. of cycles (rpm) by RBNN1
28.43	71590	46184.85
24.55	94360	81645.27
13.59	104000	143366
5	277100	229642.2
35.94	15180	19927.57
25.17	48280	56927.78
18.64	58220	89982.19
11.69	120720	168682.5
8.28	201500	204624.9

Table12: Prediction of fatigue life using (RBNN2) with two input parameter

Stress (Mpa)	Angle of the orientation (θ^o)	Experimental No. of cycles (rpm)	Modeling No. of cycles (rpm) by RBNN2
28.43	75^o	71590	86411.68
24.55	75^o	94360	87697.19
13.59	75^o	104000	113681.5
5	75^o	277100	271681.7
35.94	90^o	15180	23671.69
25.17	90^o	48280	59861.48
18.64	90^o	58220	65846.24
11.69	90^o	120720	134612.4

8.28	90°	201500	181367.3

Table 13: Prediction of fatigue life using (RBNN3) with tree input parameters

Stress (Mpa)	Angle of orientation(θ^o)	Thickness of ply (mm)	Experimental N_f (rpm)	Modeling No. of cycles (rpm) by RBNN3
28.43	75°	3.3	71590	79294.17
24.55	75°	2.9	94360	82195.62
13.59	75°	2.9	104000	68919.86
5	75°	3.1	277100	224864.2
35.94	90°	3.3	15180	23251.97
25.17	90°	3.3	48280	89235.46
18.64	90°	2.7	58220	98134.4
11.69	90°	2.75	120720	141236
8.28	90°	2.3	201500	149615.7

The fatigue life of both experimental number of cycles and the output of the (RBNN1, 2, 3) are shown respectively in Figures 21, 22 and 23.

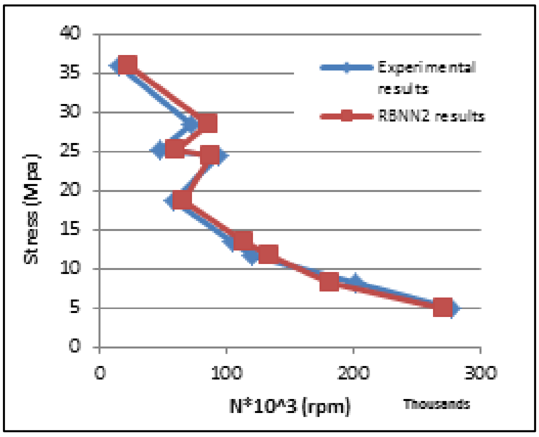

Figure 21: Stress versus No of cycles to failure of both experimental results and RBNN1 output (with one input parameter)

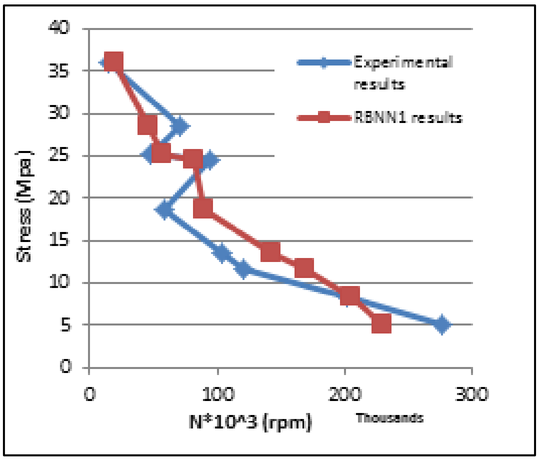

Figure 22: Stress versus No of cycles to failure of both experimental results and RBNN2 output (with two input parameters)

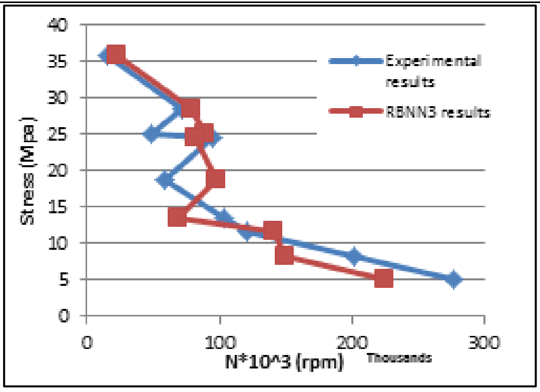

Figure 23: Stress versus No of cycles to failure of both experimental results and RBNN3 output (with three input parameters)

ANNs are used for the prediction and optimization of fatigue life of (FGRC) and found more accurate than conventional mathematical methods (as illustrated in appendix-A) because there is more than one input to the networks. The results of (RBNN3) with three input parameters give more accuracy than (FFNN3) and (GRNN3).

4. Conclusions

ANNs are accurate and efficient method for prediction and optimization of the fatigue life of (FGRC). More parameters give more details about the materials, so one, two and three parameters are individual to three networks: (FFNN1, 2, 3), (GRNN1, 2, 3) and (RBNN1, 2, 3). In general, (RBNN) model gives best and more accurate results than (FFNN) and (GRNN).

5. Suggestions of Future work

Recommendations for future work are including in following:

1- Study the prediction of fatigue life of (FGRC) with unidirectional angle of fibers at (0°), (45°), (60°) and (90°) plies using Artificial Intelligence.

2- Study the prediction of fatigue life of (FGRC) with different type of layers.

3- Study of fatigue life with other parameters like; Different Stress ratio (R), different degrees of temperature and number of layers.

Using many soft computing methods for prediction and optimization, like; recurrent network, Probabilistic neural network, Neuro-genetic algorithm and Neuro-fuzzy algorithm, to compare the results for optimal prediction of fatigue life.

References

[1] V. Delft, D.R.V., de Winkel, G.D., Joosse, P.A., “Fatigue Behavior of Fiberglass Wind Turbine Blade Material under Variable Amplitude Loading,” Proc. AIAA/ASME Wind Energy Symposium, no. AIAA-97-0951, pp. 180-188, Reno, Nevada, January 1997.

[7] M. William, “Application of Artificial Neural Networks in the Quantitative Analysis of Gas Chromatograms,” University of Tennessee, Knoxville.

[8] N.K. Kasabov, “Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering,” a Bradford Book the MIT Press Cambridge, Massachusetts London, England, , p.p. 251-264, 1998.

[9] Z.G. Che, T.A. Chiang and Z.H. Che “Feed-Forward Neural Networks Training: A Comparison between Genetic Algorithm and Back-Propagation Learning Algorithm,” *International Journal of Innovative Computing, Information and Control*, Vol. 7, No. 10, 2011.

[10] Z. Reitermanova “Feedforward Neural Networks – Architecture,”

[11] Optimization and Knowledge Extraction" WDS'08 Proceedings of Contributed Papers, Part 1, p.p.159–164, 2008.

[12] H. Demuth, Mark Beale, “Neural Network Toolbox,” The Math Works, Inc., 2002.

[12] E. Kannan and M. Saravanan, “Generalized Regression Neural Network Based Expert System for Hepatitis B Diagnosis,” *Journal of Computer Science* 10, 4, pp. 563-569, 2014.

[13] D.F. Specht, “A General Regression Neural Network,” IEEE Transections of Neural Networks, Vol. 2, No. 6, November 1991.

[2] P. Brøndsted, H Lilholt, A. Lystrup, “Composite Materials for Wind Power Turbine Blades,” Annu. Rev. Mater. Res., Vol. 35 pp. 505-538, 2005.

[3] R. Talreja, “Fatigue of Composite Materials: Damage Mechanisms and Fatigue Life Diagrams,” Proceedings of the Royal Society, London, Series A, Vol. 378, pp.461-475, 1991.

[4] ASM Handbook, “Space Simulation; Aerospace and Aircraft; Composite Materials,” solid, Vol. 15, http://mihd.net/yn9up8 2000.

[5] Ch. Smith, “The History of Artificial Intelligence,” University of Washington, page 4, 2006.

[6] S. A. Oke, “A Literature Review on Artificial Intelligence,” *International Journal of Information and Management Sciences*, Vol. 19, No. 4, pp. 535-570, 2008.

[14] Z.M. Yaseen, A. El-Shafie, H.A. Afan, M. Hameed, W.H.M. Wan Mohtar, Aini Hussain, “RBFNN versus FFNN for daily river flow forecasting at Johor River, Malaysia,” Neural Computing & Application, DOI 10.1007/s00521-015-1952-6, 2015.

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Appendix

Table A.1: Comparison between of analytical and (FFNN1) results with one input parameter.

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by FFNN1
71590	70080	50980	52760	64663.43
94360	94590	61850	66760	79143.28
104000	162720	133130	149260	138581.7
277100	204400	321210	231360	216653.8
15180	27490	30020	36890	41306.87
48280	77300	51440	52250	76669.09

58220	90760	61940	65900	104272
120720	139640	163990	149460	174576.4
201500	155410	276210	187790	207916.3

Table A.2: Comparison between of analytical and (FFNN2) results with two input parameter.

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by FFNN2
71590	70080	50980	52760	61842.66
94360	94590	61850	66760	78127.79
104000	162720	133130	149260	130368
277100	204400	321210	231360	231411.6
15180	27490	30020	36890	52915.57
48280	77300	51440	52250	68808.33
58220	90760	61940	65900	89495.61
120720	139640	163990	149460	157397.1
201500	155410	276210	187790	182553.2

Table A.3: Comparison between of analytical and (FFNN3) results with three input parameters

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by FFNN3
71590	70080	50980	52760	92409.05
94360	94590	61850	66760	53106.45
104000	162720	133130	149260	257841.5
277100	204400	321210	231360	131283.3
15180	27490	30020	36890	41526.69
48280	77300	51440	52250	91129.76
58220	90760	61940	65900	121669.5
120720	139640	163990	149460	161797.6
201500	155410	276210	187790	161779.9

Table A.4: Comparison between of analytical and (GRNN1) results with one input parameter

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by GRNN1
71590	70080	50980	52760	61862.98
94360	94590	61850	66760	83133.98
104000	162720	133130	149260	118553.6
277100	204400	321210	231360	246369.7
15180	27490	30020	36890	38369.72
48280	77300	51440	52250	69737.17
58220	90760	61940	65900	109351.8
120720	139640	163990	149460	152178.9
201500	155410	276210	187790	211362

Table A.5: Comparison between of analytical and (GRNN2) results with two input parameters.

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by GRNN
71590	70080	50980	52760	66152.5
94360	94590	61850	66760	83614.67
104000	162720	133130	149260	127682.5
277100	204400	321210	231360	251684.2
15180	27490	30020	36890	27841.96
48280	77300	51440	52250	67684.2
58220	90760	61940	65900	74642.82
120720	139640	163990	149460	153691.3
201500	155410	276210	187790	187692.2

Table A.6: Comparison between of analytical and (GRNN3) results with three input parameters.

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by GRNN3
71590	70080	50980	52760	85154.67

94360	94590	61850	66760	100365.9
104000	162720	133130	149260	43125.65
277100	204400	321210	231360	137265.5
15180	27490	30020	36890	33326.55
48280	77300	51440	52250	89235.46
58220	90760	61940	65900	101319.9
120720	139640	163990	149460	138263.5
201500	155410	276210	187790	171326

Table A.7: Comparison between of analytical and (RBNN1) results with one input parameter.

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by RBNN1
71590	70080	50980	52760	46184.85
94360	94590	61850	66760	81645.27
104000	162720	133130	149260	143366
277100	204400	321210	231360	229642.2
15180	27490	30020	36890	19927.57
48280	77300	51440	52250	56927.78
58220	90760	61940	65900	89982.19
120720	139640	163990	149460	168682.5
201500	155410	276210	187790	204624.9

Table A.8: Comparison between of analytical and (RBNN2) results with two input parameters

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by RBNN2
71590	70080	50980	52760	86411.68
94360	94590	61850	66760	87697.19
104000	162720	133130	149260	113681.5
277100	204400	321210	231360	271681.7
15180	27490	30020	36890	23671.69
48280	77300	51440	52250	59861.48
58220	90760	61940	65900	65846.24
120720	139640	163990	149460	134612.4
201500	155410	276210	187790	181367.3

Table A.9: Comparison between of analytical and (RBNN3) results with three input parameters.

Experimental N_f (rpm)	Linear reg. eq. N_f (rpm)	Power law reg. eq. N_f (rpm)	Poly. Reg. eq. N_f (rpm)	Modeling N_f by RBNN3
71590	70080	50980	52760	79294.17
94360	94590	61850	66760	82195.62
104000	162720	133130	149260	68919.86
277100	204400	321210	231360	224864.2
15180	27490	30020	36890	23251.97
48280	77300	51440	52250	89235.46
58220	90760	61940	65900	98134.4
120720	139640	163990	149460	141236
201500	155410	276210	187790	149615.7