An expert system for life prediction of woven roving glass fiber reinforced polyester under cyclic bending loading

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As the study of fatigue failure of composite materials needs a large number of experiments as well as long time, so there is a need for new computational technique to expand the spectrum of the results and to save time. The present work represents a new technique to predict the fatigue life of Woven Roving Glass Fiber Reinforced Polyester subjected to variable bending stress. Two fiber orientations, $[0^o,90^o]_{2s}$ and $[\pm 45]_{2s}$ are considered. Two neural network structures, feed-forward and generalized regression, are applied, trained and tested. The groups of data considered, are the maximum stress and the stress ratio or the SWT (Smith-Watson-Topper) parameter with the fiber orientation. On the other hand, more accurate prediction method is obtained by using a useful expert system which is designed to aid the designer to decide whether his suggested data for the composite structure is suitable or not. In this expert system a neural network is designed to consider the design data as input and to get yes or no as output.The results show improvement when using the one input SWT instead of the maximum stress and the stress ratio. Also the generalized regression neural network shows better results than that given by the feed-forward network. The designed expert system helped the designer with a100% correct conclusions about his decision of the combination of the proposed data.

نظرا لان دراسة عمر المواد المركبة والمعرضة لاحمال التعب تحتاج لعدد كبير من التجارب بالاضافة لوقت طويل، لذلك فان المصمم يحتاج لانظمة جديدة تساعده فى الحصول على النتائج مع توفير الوقت. وهذا البحث يمثل تقنية جديدة للتنبؤ بعمر التعب لمادة البولستر المدعم بالالياف بالاياف الزجاجية والمعرض لعزم انحناء متغير والمدعم بالياف فى اتجاهات مختلفة. وقد تم تصميم وتدريب واختبار نوعين من الشبكات العصبية؛ الاولى شبكات عصبية ذات تقدم امامى والثانية شبكة عصبية من نوع التحلل العام (generalized regression). وقد استخدمت مجموعتين من البيانات الخاصة بالمواد المركبة؛ الاولى تشمل اقصى اجهاد ونسبة الاجهاد واتجاه الالياف المدعمة اما الثانية فتشمل معامل SWT بالاضافة لاتجاه الالياف المدعمة. بالاضافة لذلك فقد تم تصميم نظام خبير يساعد المصمم على تحديد مدى ملائمة وصحة البيانات المقترحة. هذا وقد اظهرت النتائج حدوث تحسن ملحوظ عند استخدام معامل SWT بدلا من كل من الاجهاد الاقصى ونسبة الاجهاد كمدخلات للشبكة العصبية كما اظهرت كذلك ان استخدام شبكة عصبية من نوع التحلل العام يعطى نتائج افضل من حالة استخدام شبكات عصبية ذات تقدم امامى. واظهر النظام الخبير نسبة دقة ١٠٠ % فى الوصول الى قرارات تساعد المصمم.

Keywords: NN predication, Fatigue of composites, Expert systems, Neural network modeling

1. Introduction

The study of the fatigue phenomena is more complex for composite materials [1] than for the conventional ones. This is due to inhomogenity of composites, as they contain numerous internal boundaries. These boundaries separate the constituent materials that have different responses and different resistances to the long-term applications of external influences.

A wide literature review showed that the fatigue behavior of composite materials is dependent on many factors. However, it is impossible to include all of them in a single laboratory test.

Modeling of these factors effects involves the development of a mathematical tool derived from experimental data. Once the model is established it can significantly reduce the experimental work involved in designing new polymer composite. For this reason, Artificial Neural Networks (ANN) have recently been introduced into the field of polymer composites.

Lee et al. [2] carried out an ANN predication on the fatigue life of some carbon/glass fiber reinforced plastic

(CFRP/GFRP) laminates. Three fatigue parameters (peak stress, minimum stress and probability of failure) as well as four monotonic mechanical properties(tensile strength, compression strength, tensile failure strain and tensile modulus) were selected as the ANN inputs, which were applied to predict the fatigue life of the composite as the output. They concluded that the ANN's can be trained at least to model constant – stress fatigue behavior as well as other current life predication methods and can provide accurate representations of the stress, stress ratio and median life for carbon fiber composites from a quite small experimental dataset.

The ANN predictive results of Aymerich and Serra [3] confirmed that the properties of the basic element (lamina) and their orientation within the laminate strongly affect the fatigue performance of composite laminates. It is concluded that an ANN is a very attractive approach to predict fatigue life of laminate composites, although a larger dataset is needed when increasing the number of laminate parameters.

Al-Assaf and El-Kadi [4] applied the ANN approach to predict the fatigue life of unidirectional glass fiber/epoxy composite. Only the stress ratio (R = minimum stress/ maximum stress), the maximum stress and the fiber orientation angle were used as the ANN input, and the output was the number of cycles to fatigue failure. In order to improve the predictive accuracy, other types of ANN's were considered in a later publication [5].

El-Kadi and Al-Assaf [6] used the strain energy to be the input to the artificial neural network to predict the fatigue life of glass fiber/epoxy composites.

Choi S.W. et al. [7] studied the fatigue damage predication in notched composite laminates using an artificial network. The ANN model was developed to describe the split growth in notched AS4/3501-6 graphite/ epoxy quasi- isotropic laminates under constant amplitude fatigue. The ANN model is found to work well.

The present work is a new technique to predict the fatigue life of woven- roving glass fiber composite material subjected to variable bending stress at two fiber orientations, $[0^o,90^o]_{2s}$ and $[\pm 45^o]_{2s}$. The neural network is used in this study and compared to the experimental data [8]. Two neural network structures, feed-forward and generalized regression, are applied, trained and tested. An expert system is designed to predict whether the quality of the used composite will meet the needed requirements of stress and number of cycles to failure whatever the orientation angle is.

2. Experimental data

The dataset used in this work is adapted from reference [8]. The tests were conducted on thin tubular specimens under four-point bending configuration. The loading system produces a load in the form of sine wave with variable stress ratio R between the minimum and the maximum stresses. At each R both the maximum stress and the number of cycles to failure N were measured. Two fiber orientations; $[0^o,90^o]_{2s}$ and $[\pm 45^o]_{2s}$ are tested for each R. The test results are fitted to give the following equation.

$$\sigma_{max} = \Phi (N)^{-\beta} . \quad (1)$$

The values of Φ and β for both fiber orientations are displayed in table 1.

3. Stress representation

The local stresses are acting in the principal directions of the composites, along the fiber and perpendicular to it, are given by the following equations:

$$\sigma_1 = \sigma_x \cos^2 \alpha, \quad (2)$$

$$\sigma_2 = \sigma_x \sin^2 \alpha, \quad (3)$$

$$\sigma_6 = - \sigma_x \sin \alpha \cos \alpha, \quad (4)$$

For stress element of $[0^o,90^o]_{2s}$;

$$\sigma_1 = \sigma_x , \quad \sigma_2 = \sigma_6 = 0, \quad (5)$$

while for stress element of $[\pm 45]_{2s}$;

$$\sigma_1 = \sigma_2 = - \sigma_6 = \sigma_x / 2 , \quad (6)$$

where $\sigma_x = My/I$, and $M = M_m + A \sin \omega t$.

Table 1
Values of Φ and β for different stress ratios R

Stress ratio *(R)*	$[0^o,90^o]_{2s}$ Specimens		$[\pm 45^o]_{2s}$ Specimens	
	Φ	B	Φ	β
-1.0	202.466	0.1312	120.162	0.1185
-0.75	209.938	0.1244	130.002	0.1185
-0.50	226.980	0.1196	152.773	0.1182
-0.25	235.043	0.1140	167.002	0.1184
0.00	240.430	0.1087	181.169	0.1184

4. Neural network to study the effect of stress ratio

An ANN is designed to predict the fatigue life of glass fiber reinforced polyester with the maximum stress and stress ratio R, as the input and the number of cycles to failure N is the output. The NN configuration in this case was $\{100\ [10\ 2]_2\ 1\}$, with tansigmoid for first layer and purelinear for the rest. Fig. 1 represents the plot of the measured values (experimental data), the values predicted by the NN as well as test values not included in the experimental dataset, for $[0^o,90^o]_{2s}$ fiber orientation. Another ANN configuration was used for the same data shown in fig. 1. This was $\{180\ [5\ \ 2]_2\ 1\}$ with tansigmoid for first layer and purelinear for the rest. The results for this NN are plotted in fig. 2. The results for this second configuration show an increase in the mean square error MSE, N_z, and CPU time in seconds. This suggests that increasing the number of neurons does not necessarily increase the accuracy and strength of NN.

A feed-forward NN with the structure $\{100\ [5\ \ 2]_2\ 1\}$ is applied for training the data of $[\pm 45^o]_{2s}$ fiber orientation at different stress ratios. Fig. 3 represents the measured values, the predicted values by the *NN* and test values which are not included in the experimental results. The results of this case show much satisfactory predication quality for this fiber orientation.

5. Effect of using one input (SWT) instead of two inputs (σ_{max} , R)

The careful choice of the inputs to the NN shares in the responsibility of the accuracy and strength of *NN*. To test this statement, another input called "Smith-Watson-Topper mean stress parameter ($SWT = \sqrt{\sigma_{max}\sigma_a}$), [9], is used as an input to the network instead of the two inputs used previously, σ_{max} and R. A feed-forward *NN*, $\{30\ [20\ 2]_2\ 1\}$ configuration, with tansigmoid for the first layer and purelinear for the rest, was used.

Fig. 4 shows the plot for the measured values, values predicted by the NN and the test values which are not included in experimental results, for $[0^o,90^o]_{2s}$ fiber orientations. Comparing this figure with fig. 1, the results show much improvement, much smaller Nz, but the CPU time increased. Fig. 5 shows the case for $[\pm 45^o]_{2s}$ fiber orientation with SWT as input instead of two inputs, σ_{max} and R. Comparing this figure with the corresponding one, fig. 3, shows a slight increase in the MSE, but much less CPU time.

Two orientation angles $[\pm 45^o]_{2s}$ & $[0^o,90^o]_{2s}$ were fed as an extra input to the neural network together with σ_{max} and R. The results for this extra input are shown in fig. 6. In fig. 7 the results for using SWT instead of σ_{max} and R are presented. Many trials have been done seeking the optimal NN configuration which was found to be $\{300\ [2]_1\ 1\}$ with all neurons in the three layers of the purelinear type.

A comparison between the two figures shows the same trend noted before, using SWT as one input instead of two inputs σ_{max} and R, tends to decrease the mean squared error as well as the mean absolute relative error.

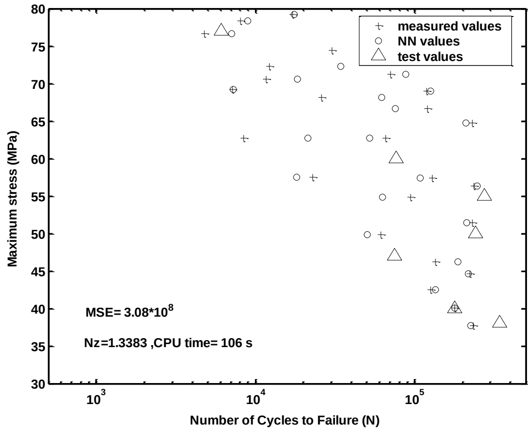

Fig. 1. ANN predication model of fatigue life using maximum stress and stress ratio for [0°,90°]$_{2S}$ fiber orientation angle with NN configuration {100 [10 2]$_2$ 1}.

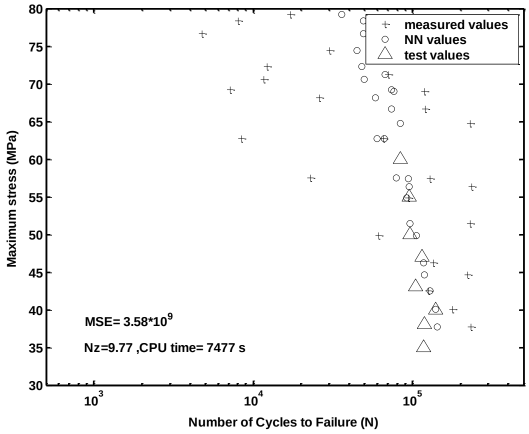

Fig. 2. ANN predication model of fatigue life using maximum stress and stress ratio for [0°,90°]$_{2S}$ fiber orientation angle with NN configuration {180 [5 2]$_2$ 1}.

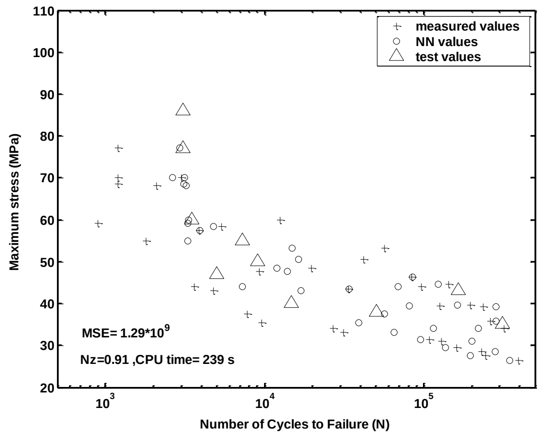

Fig. 3. ANN predication model of fatigue life using maximum stress and stress ratio for [± 45°]$_{2S}$ fiber orientation angle with NN configuration {100 [5 2]$_2$ 1}.

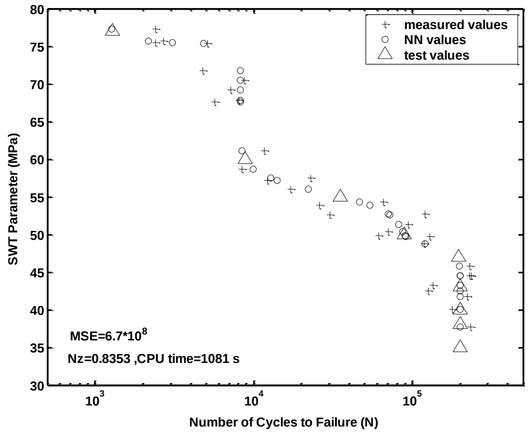

Fig. 4. ANN predication model of fatigue life using SWT parameter for [0°,90°]$_{2S}$ fiber orientation angle with NN configuration {30 [20 2]$_2$ 1}.

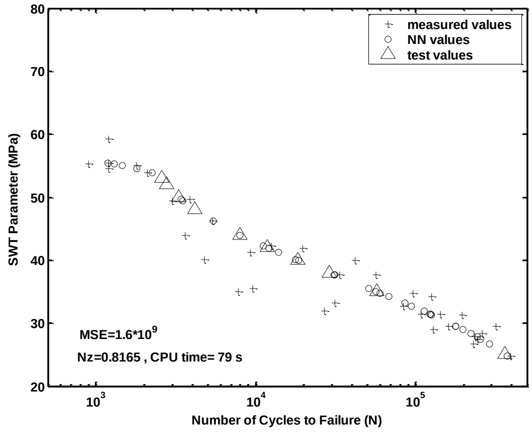

Fig. 5. ANN predication model of fatigue life using SWT parameter for [± 45°]$_{2s}$ fiber orientation angle with NN configuration {30 [20 2]$_2$ 1}.

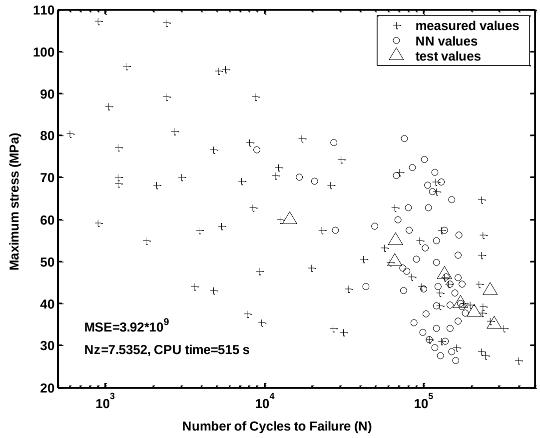

Fig. 6. ANN predication model of fatigue life using maximum stress and stress ratio for both [± 45°]$_{2s}$ & [0°,90°]$_{2s}$ fiber orientation angle with NN configuration {300 [2]$_1$ 1}.

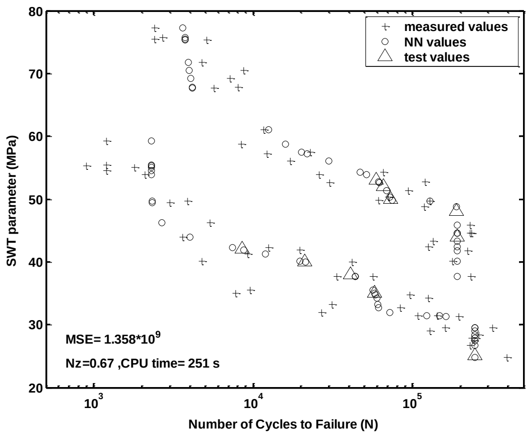

Fig. 7. ANN predication model of fatigue life using SWT parameter for both [± 45°]$_{2s}$ & [0°,90°]$_{2s}$ fiber orientation angle with NN configuration {100 [5 2]$_2$ 1}.

6. Generalized regression NN

A generalized regression NN [10] is designed based on two layers, the first, input layer, has a radial basis neurons while the second layer has purelinear ones. This network is trained by the measured values of σ_{max} and R. Figs. 8 and 9 represent the plot for the measured values, the NN values and the test values not included in the experimental results, for both fiber orientations. The results show much better predication quality for the case of [± 45°]$_{2s}$ than that for [0°,90°]$_{2s}$, which represents the same conclusions found when using feed-forward NN discussed earlier. One can see that the time needed in the present net is much smaller than the CPU time found earlier. The results using SWT as input parameter instead of σ_{max} and R are plotted in fig. 10 for [0°,90°]$_{2s}$ fiber orientation and in fig. 11 for [± 45°]$_{2s}$ fiber orientation. In the last two figures, the Nz increases, but still very low, the CPU time decreases much further. When both fiber orientations were used to train the present network no much change was found in N_z and CPU time as shown in fig. 12 for σ_{max} and R as inputs and in fig. 13 for SWT as input. The study of the prediction quality of the NN of this type, figs. 8 to13, shows at least 80% of the test values not included in the experimental results, coincide with the measured values. This, besides other factors as small CPU time and simpler architecture, favor the use of generalized regression NN.

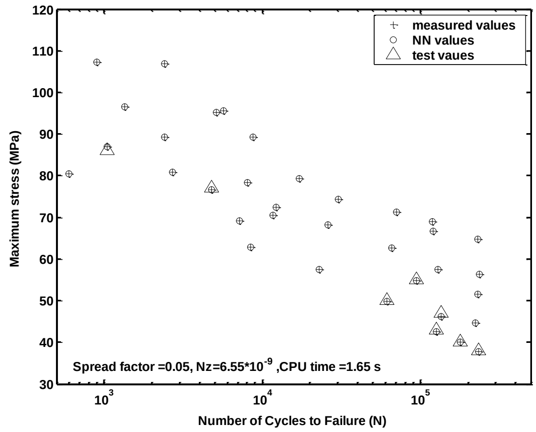

Fig. 8. Generalized regression NN predication model for fatigue life using maximum stress and stress ratio for [0°,90°]$_{2s}$ fiber orientation angle.

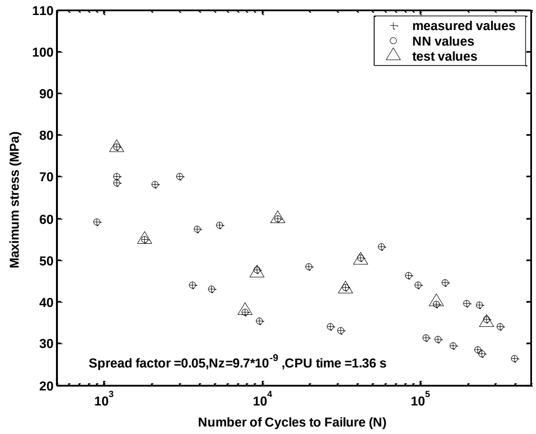

Fig. 9. Generalized Regression NN predication model for fatigue life using maximum stress and stress ratio for [± 45°]$_{2s}$ fiber orientation angle.

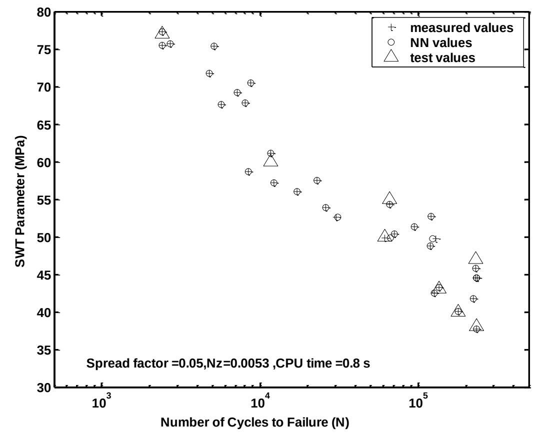

Fig. 10. Generalized Regression NN predication model for fatigue life using SWT parameter ratio for [0°,90°]$_{2s}$ fiber orientation angle .

7. Expert system design

It is very useful from the designer point of view to have an expert system aids to decide whether his suggested design for composite structure is suitable or not. A NN system is designed to consider the maximum stress, stress ratio R and the number of cycles to failure N_{needed}, as inputs and to get yes or no as output.

The expert system consists of the generalized regression NN followed by a perceptron. The input vector for the expert system is $[N_{needed} \ \ \sigma_{max} \ \ R \ \ \alpha]'$, where the last three elements of the above vector are fed in the generalized regression NN as inputs, the output of it N_{nn} which is the predicted life time of the NN, is fed together with N_{needed}, σ_{max}, R and α to the perceptron NN. The output of this last layer will be the decision, whether the design for a combination of σ_{max} R, angle of orientation and N_{needed}, is acceptable, gives a value of one, or not acceptable, gives a value of zero. Another expert system was designed to use SWT as input parameter instead of σ_{max} and R. Figs. 14 and 15 represent the block diagram of both systems. Tables 2 and 3 show the results of the trials performed using these expert systems. The results are found to be 100 % correct as compared with the expected values found by using the fitted curve eq. (1). It is worth mention here that the difference between the calculated N, using eq. (1), and the N_{nn}, the predicted life from the system, is may be due to the scatter in the experimental results used to fit eq. (1).

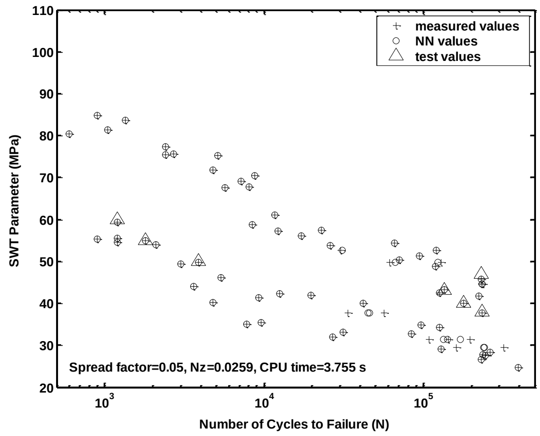

Fig. 13. Generalized Regression NN predication model for fatigue life using SWT parameter for both [± 45°]$_{2s}$ & [0°,90°]$_{2s}$ fiber orientation angles.

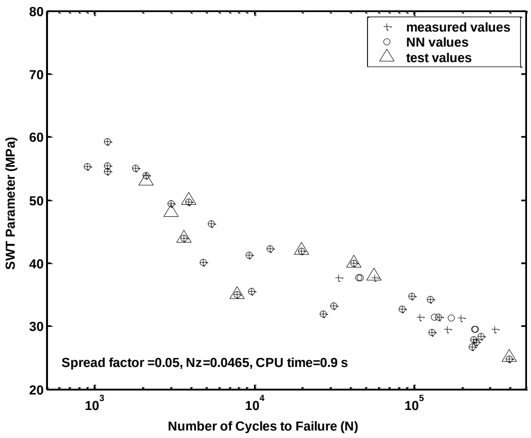

Fig. 11. Generalized Regression NN predication model for fatigue life using SWT parameter for [± 45°]$_{2s}$ fiber orientation angle.

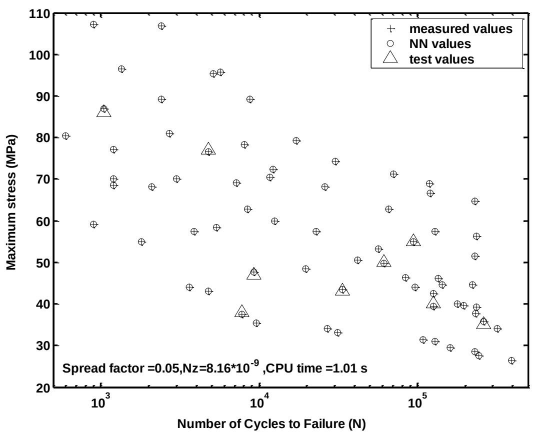

Fig. 12. Generalized Regression NN predication model for fatigue life using maximum stress and stress ratio for both [± 45°]$_{2s}$ & [0°,90°]$_{2s}$ fiber orientation angles.

8. Conclusions

The concluded points emerged in this work can be summarized as follows:

1. Using one input SWT instead of two inputs σ_{max} and R shows much improvement in the mean absolute relative error Nz, which increases the strength of the NN in predicting the life time of data not included in the experimental work.
2. Generalized regression NN shows much better results than that given by feed-forward NN. The CPU time needed for its training is

much less than that needed to train feedforward NN for the same data points.

3. The study of the prediction quality of all neural network treated in this work guarantees that 80% of the test values not included in the experimental program correctly predicted and coincide with the results obtained from eq. (1).

4. The expert system provided the designer with a 100% correct results to help him to decide whether the choice of the combination of σ_{max}, R (or SWT instead of both), fiber orientation and number of cycles to failure N, is correct or not.

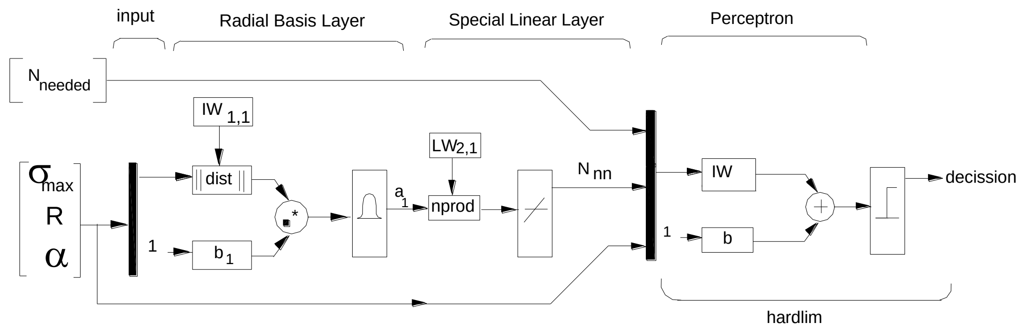

Fig. 14. Expert system with input data σ_{max}, R, N_{needed} and α.

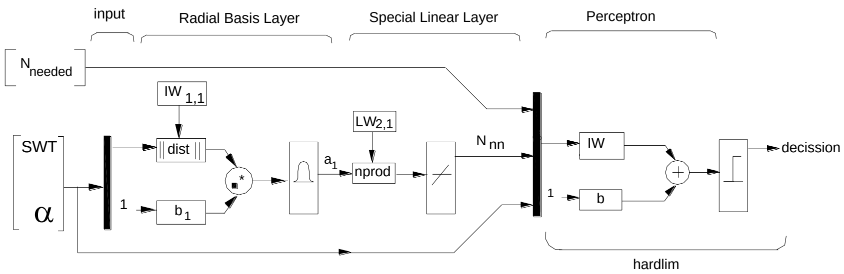

Fig. 15. Expert system with input data SWT, N_{needed} and α.

Table 2
Prediction of the expert system based on the maximum stress, stress ratio and fiber orientation angle

N_{needed}	N_{nn}	σ_{max} MPa	R	α_o	Calculated N	Reply
1620	180000	40	-1.00	0-90	233388	1.00
162900	31400	33	-0.75	±45	105871	0
35640	230000	29	-0.50	±45	1274436	1.00
63000	11700	70	-0.25	0-90	41159	0
190080	3600	44	-1.00	±45	4808	0
24300	180000	40	-0.75	0-90	613805	1.00
1800	31400	33	-0.50	±45	417881	1.00
473040	230000	29	-0.25	±45	2640296	0
1800	11700	70	-0.50	0-90	18691	1.00
3360	97200	44	-0.50	±45	37456	1.00

Table 3
Prediction of the expert system based on the SWT parameter and fiber orientation angle

N_{needed}	N_{nn}	SWT MPa	α_o	Calculated N	Reply
1620	180000	40	0-90	233388	1.00
162900	31400	31	±45	105871	0
35640	230000	25	±45	1274436	1.00
63000	11700	55	0-90	41159	0
190080	3600	44	±45	4808	0
24300	180000	37	0-90	613805	1.00
1800	31400	29	±45	417881	1.00
473040	230000	23	±45	2640296	0
1800	11700	61	0-90	18691	1.00
3360	97200	38	±45	37456	1.00

Nomenclature

A is the amplitude of applied bending moment,
a_1 is the output of the radial basis,
b, b_1 is the bias vectors of the NN,
$\|dist\|$ is the a box produces a vector whose elements indicate how close the input vector is to the vector of training set,
I is the second moment of area,
IW, $IW_{1,1}$, $LW_{2,1}$ are the weight matrices of the NN,
M is the applied bending moment,
M_m is the mean bending moment,
MSE is the mean squared error = $\frac{\sum (N_{nn} - N_{measured})^2}{n}$,
N is the number of cycles to failure,
$N_{measured}$ is the umber of cycles to failure measured from experimental work,
Nz is the mean absolute relative error= $\frac{\sum_1^n ABS(N_{nn} - N_{measured})}{n\,N_{measured}}$,
N_{nn} is the predicted number of cycles to failure,
N_{nedeed} is the required number of cycles to failure,
n is the number of experimentally measured data values,
nprod is the box produces the dot product of $LW_{2,1}$ and a_1,
R is the stress ratio = $\sigma_{min} / \sigma_{max}$, and
SWT is the Smith-Watson-Topper parameter = $\sqrt{\sigma_{max}\sigma_a}$

Greek symbols

σ_1 is the local normal stress in fiber longitudinal direction,
σ_2 is the local normal stress in fiber transverse direction,
σ_6 is the local shear stress,
σ_x is the global normal stress in fiber longitudinal direction,
σ_a is the variable stress,
σ_{max} is the maximum stress,
σ_{min} is the minimum stress,
α is the fiber orientation angle,
ωt is the angular displacement,
Φ is the constant, and
β is the constant

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