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Creep Test Material Rupture Prediction by Neural Networks

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Abstract: This work focuses on acoustic emission analysis of mechanisms damage in fiber composite materials, subjected to heavy loads during a creep test. The goal of the present study was to develop and evaluate machine learning algorithms for the prediction of material rupture with creep test by traction method. This study aimed to predict if a tensile specimen will break in 30 seconds or not. Multilayer Perceptrons were trained retrospectively in a group of 80 samples moments and tested prospectively in a group of 16 tensile specimens. During the 5-cross validations we reached a sensitivity of 88% and a specificity of 88% in the prospective group. The mean area under the ROC (Receiver Operating Curves) was equal to 0.86. Those results are very interesting because they are a first important step in the lifetime prediction of material rupture before significant damages can occur.

***Key words*: Acoustic Emission, Creep Material Rupture, Neural Networks, Non Destructive Control.**

I. INTRODUCTION

The use of composite materials is becoming of greater interest in different industrial fields, especially aviation, automobile, etc... Several studies are however needed to guaranty the proper functioning of these materials (types of damage, lifetime prediction, type of materials, etc...). Our study focuses on evaluating if a composite material will break in a lapse of time: we choose 30 seconds. For this purpose we used the creep fatigue test with traction method. Initially, noninvasive testing such as ultrasound and acoustic emission [NEC 04], [BEN 05] were of little use in creep test and particularly in terms of rupture prediction. Meanwhile, recent studies [NEC 05], [BER 10] have suggested a new approach involving noninvasive testing to study the rupture of composite materials through the phenomena of phase transitions in the creep method. In this perspective, [NEC 05] analyzed the evolution of acoustic emission (through deformation rate) throughout the primary, secondary, and tertiary phases of creep while using polyester matrix composites reinforced with fiber glass. They even have proposed a correlation between acoustic emission during primary/secondary transition time, corresponding to the minimum deformation rate, and rupture time of the material. But this method is difficult to apply to our study since the minimum deformation rate is hard to determine (Figure 2). Our contribution involved the use of artificial neural networks to predict the rupture time of composite materials. The first part of the article details the materials and test. The second part concerns the data that were collected. The third part deals with the methods that were used; the next part concerns the results and the discussion. Finally, the conclusion and the perspectives are given.

II. MATERIALS AND TEST

A. Materials

The studied materials are manufactured by molding composite cross vacuum at the Acoustic Laboratory of the University of Maine, Le Mans, France. They were laminated by stacking up 8 plies, reinforced by unidirectional glass UDG with mass flux 300 (g/m2) and epoxy resin SR 1500 / SD 2505. These components are manufactured by the company SICOMIN. The plies are laminated and impregnated at room temperature, then placed empty with a depression of 30KPa vacuum for 8 hours between the mold and the mold cons, followed by polymerization of 8 hours at 80°C in an electric oven [KHA 10]. The cuts are made using a diamond blade saw.

B. Traction and Creep Test

To determine the lifetime of the tensile specimens, a series of tensile tests has been performed. The specimen dimensions reached 2 x 20 x 300mm. Tests were conducted on an INSTRON-type machine equipped with a cell load of 100 KN and controlled by computer (Figure 1 and 3). A two channels EPA Acoustic Emission device was used. AE (acoustic emission) measurements were achieved by the means of two resonant Micro-80 sensors with a frequency band 100 kHz - 1 MHz and a peak of resonance around 300 kHz, coupled on the faces of the specimens with silicone gel.

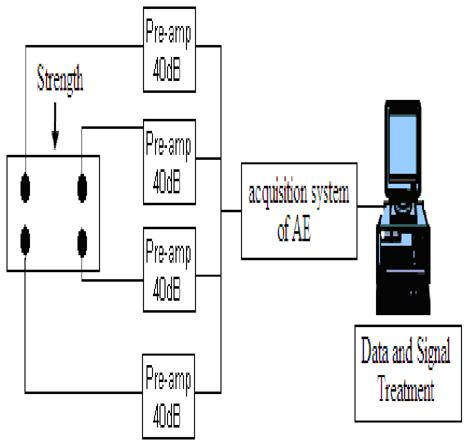

Fig 1. Diagram of the System

The calibration of each test used a pencil lead break procedure in order to generate repeatable AE signals. Several

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time-based descriptors were calculated by the acquisition system for each AE event: amplitude, energy, duration, rise time, number of times the amplitude of the event goes beyond the given amplitude threshold (called counts)... These parameters were used as input descriptors in the proposed classification method. Traction test was applied on the specimens with 30kN of strength; however creep method is based, in first time, on traction method by applying 90% of strength and then waiting until fracture (Figure 4).

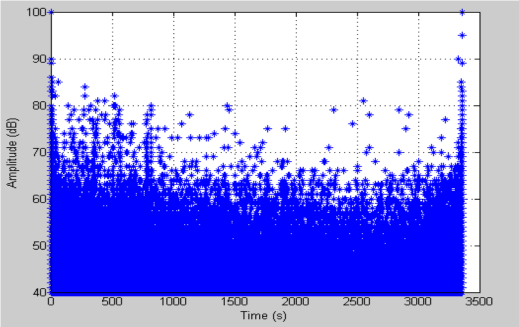

Fig 2. ***Amplitude vs. time***

Fig 3. Photo of the System

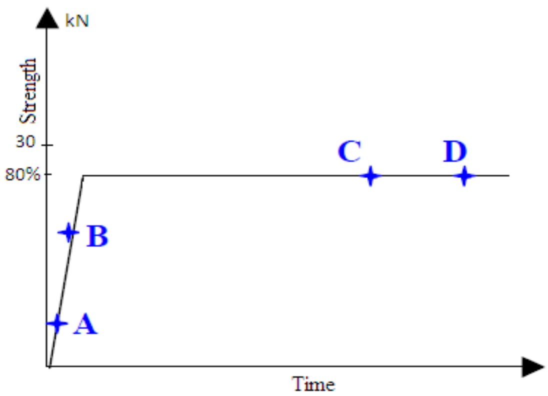

Fig 4. Creep Method (traction + fatigue)

C. Results.

The activity of acoustic emission collected during the creep test on the specimens was studied through the number of signals collected over time [GOD 09]. Figure 5 shows the cumulative number of peaks recorded with time for a creep test.

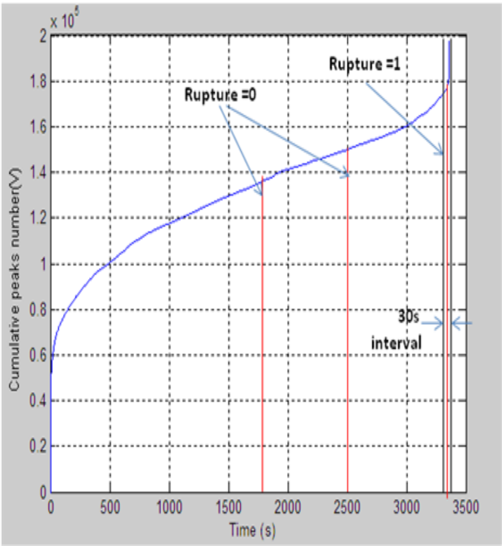

Fig 5. Cumulative Peaks Number

Figure 6 shows that the acoustic activity during a creep test has 3 phases:

Phase 1: a dramatic increase of acoustic emission since the beginning of the tests, it corresponds to an introduction and multiplication of micro-cracks within the specimen.

Phase 2: during this phase, the acoustic activity is low, it's due to the propagation of the micro-cracks, and it corresponds to a large period of specimen life-time.

Phase 3: finally in the last phase, the acoustic activity becomes very significant with high energy and high amplitude. This phase corresponds to the rapid spread of micro-cracks thereby generating a more localized cracking causing rupture of the specimen.

III. DATA

Six test tensile specimens have been tested with creep method. We got six different rupture times as results of these experiments (539.42s, 159.26s, 3362.42s, 130.36s, 1831.94s, and 845.84s). Each test conducted to obtain thousands of samples (an example of one sample is shown on Figure 7). From these thousands samples we have only used 16 samples; 8 samples were selected in the 30 seconds interval before the rupture point, and the others were randomly selected outside the last 30 seconds interval. In total we have selected 96 samples among which 50% are within a rupture period. For each signal we used three variables:

- NP: Number of Peaks.
- SD: Signal Duration.
- AT: Appearance Time.

The output data (rupture or not) consisted of a binary variable representing whether each selected signal is within the 30 seconds interval before the rupture time or not.

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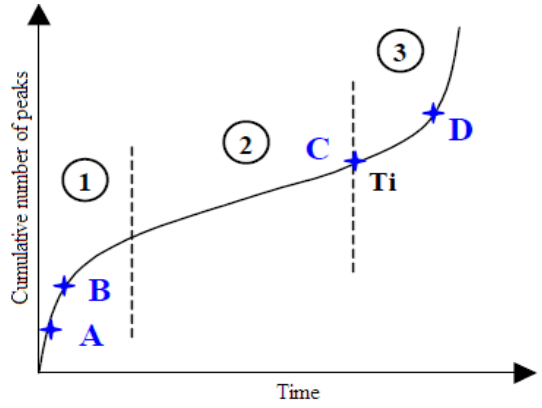

Fig 6. Cumulative Number of Peaks with Creep Test

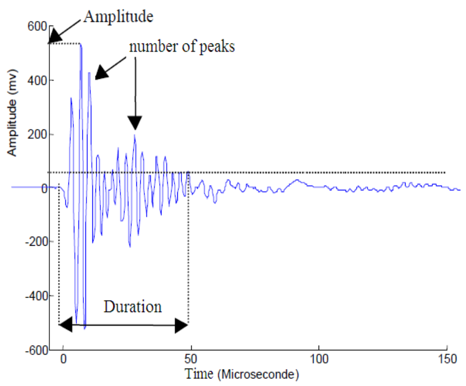

Fig 7. Signal Description

IV. METHODS

A. Prediction by Neural Networks

Neural networks learning machines [BIS 95], [BIS 06] and [HAY 99] were used to predict the time of rupture. One-hidden-layer has been chosen for the type of architecture, with sigmoid type as activation function. The number of neurons in the hidden layer belongs to the interval [3, 18]. During the learning phase, neural networks are trained by the "Levenberg-Marquardt" algorithm. More explications of our method will be given later in the paper.

B. Performance measure:

Sensitivity and specificity parameters were used to evaluate the quality of the prediction. Both characterize the percentage of break and non-break classification. To compute the percentages of sensitivity and specificity, we used:

- Sensitivity= 100*(TP/TP+FN)
- Specificity = 100*(TN/TN+FP)
- N: total number of samples
- TP: number of true positives
- TN: number of true negatives
- FN: number of false negatives
- FP: number of false positives

An essential condition must be followed to have accurate estimations of sensitivity and specificity values: the distribution of break and non-break must be significantly balanced. With a manual selection, we had a prevalence of 50%, therefore the condition of balancing was satisfied. The ROC curves were used to find the best architecture by plotting sensitivity and 1-specificity. The area under the ROC curve (AUC: Area under the Curve) can be interpreted as the test accuracy: the higher the area, the higher the accuracy. The 96 samples we had in our study were divided into two groups. 80 samples in the first group were used for the learning set; this phase was used to determine the best architecture. The 16 samples in the second group (test set) were used to estimate the performance of the selected architecture. K-fold cross validation (K=5) method was used to estimate the generalization error by giving an estimation with a small bias and a small variance; K-1 subsets were used to train the classifier; the remaining subset was used to estimate the performances. Therefore, the mean value of the K AUCs was the performance of the classifier.

C. Neural Networks

Each input has been normalized to obtain a mean value of 0 and a standard deviation of 1. To get a better statistical estimation, the K-cross-validation is repeated several times. Thus, the learning has been done hundreds of times for each case. Furthermore, we used the early stopping method to avoid over fitting of the neural networks. In the learning phase: 48 samples were used for the learning phase, 16 were used to avoid the over fitting and 16 were used to evaluate the neural network. Then the mean value of the *K* AUCs was computed. The best mean value was retained to choose the best number of neurons in the hidden layer. With this optimal number of neurons, we trained a final neural network on the 80 samples of the learning set with early stopping again: 64 samples in the learning phase and 16 to avoid over fitting. Finally, this final neural network was then tested in a "blind" way on the test set composed of 16 samples. All data were analyzed off-line using software that we have developed, written in MatLab and based on the Toolbox neural networks

V. RESULTS AND DISCUSSION

The goal of the present study was to develop and evaluate machine learning algorithms for the prediction of creep test material rupture. This study aimed to predict if a tensile specimen will break in 30 seconds or not. Multilayer Perceptrons were trained retrospectively in a group of 80 samples and tested prospectively in a group of 16 samples. Results are shown in Table I and Table II, where □ means that a variable has not been selected; 1, 2, 3 represent respectively the selection of the first parameter (Number of Peaks), the second parameter (Signal Duration), and the third parameter (Appearance Time). As shown in the tables, the best performance in the training set reached a mean value of the K AUCs equal to 0.77. We kept the item 1, 2, □ because it has the lowest standard deviation of AUC. In the prospective test we reached a sensitivity of 88% and a specificity of 88%. These performances were achieved by a multi-layer Perceptrons composed of 13 neurons.

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Table 1. Prospective results in the learning test set

Selected variables	Sensitivity (%)	Specificity (%)	AUC
1, 2, 3	88 ± 5.19	77 ± 8.67	0.77 ± 0.092
1, 2, □	88 ± 6.11	76 ± 8.53	0.77 ± 0.082
1, □, 3	87 ± 5.70	76 ± 8.23	0.76 ± 0.093
□, 2, 3	88 ± 5.89	76 ± 9.86	0.76 ± 0.104

Table 2. Prospective results in the final test set

Selected variables	Sensitivity (%)	Specificity (%)	AUC
1, 2, 3	88	76	0.65
1, 2, □	88	88	0.86
1, □, 3	95	88	0.92
□, 2, 3	97	88	0.98

It could be surprising that the performances in the final test set are higher than the performances of the *K* mean sensitivities and specificities in the learning set. Therefore, we could be worried with the generalization aspects of the learning machine. Two answers can be given to this question: the final ROC curve that is shown on Figure 8 seems to be able to give good generalization possibilities because it is significantly round (of course, this curve has not been used to compute the sensitivity and the specificity in the final test set). The second point concerns the fact that, the final learning machine is trained on 64 samples while the cross-validations could only take 48 samples for each of the *K* learning processes, therefore the network could have learned better. Those results are very interesting because they are a first significant step in the lifetime prediction of material rupture before significant damages can occur.

VI. CONCLUSION AND PERSPECTIVES

This study has taken a step in the direction of prediction creep material rupture. Thus, two indexes (Number of Peaks, Signal Duration) introduced in a neural network could reliably predict material rupture with 88% of sensitivity and 88% of specificity in a prospective group of 16 samples. Further research in this field could include adding more parameters as inputs to the neural networks. Furthermore, SVM (Support Vector Machines) [VAP 00], [SUY 02], [CHA 03] and [DAR 10] and/or mixture of experts could perhaps improve the results.

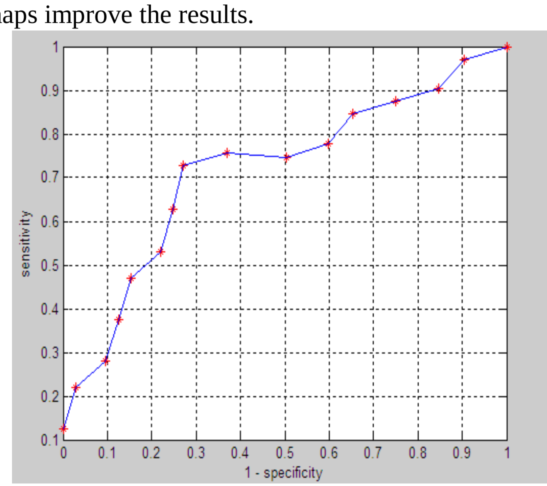

Fig 8. Final ROC curve on the test set

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