Creep-rupture prediction by naive bayes classifiers

M. Darwiche[a], G. Bousaleh[b], M. Feuilloy[c], D. Schang[c] and R. El Guerjouma[a]

[a]Laboratoire d'acoustique de l'université du Maine, Bât. IAM - UFR Sciences Avenue Olivier Messiaen 72085 Le Mans Cedex 9
[b]Université Libanaise, Institut Universitaire de Technologie, 1600 Saida, Lebanon
[c]Ecole Supérieure d'Electronique de l'Ouest, 4, rue Merlet de la Boulaye, BP: 30926, 49009 Angers Cedex 01
mohamad.darwiche@eseo.fr

The purpose of this study was to predict the failure of composite materials by developing and evaluating an artificial learning algorithm that could predict their life time. This will be done by predicting whether a specimen will break within 30 seconds or not. Specimens were tested according to the creep test by the traction method. Naive Bayesian classifiers have been developed retrospectively in a group of 90 samples and tested prospectively in a group of 30 samples to evaluate and ensure the performance of this learning method. Each sample was characterized by a number of relevant parameters. By testing on the group of 30 samples, we have got the best result with a sensitivity of 90% and a specificity of 94%. The mean area under the ROC curve (Receiver Operating Curves) reached 0.92. The study can be regarded as a very important step in the term of prediction of composite material time life remaining.

1 Introduction

Manufacturers are increasingly using composite materials in various fields, especially in aviation and automotive industries. Their great advantage is their strength and stiffness associated with their lightness. However, several studies are needed to ensure proper use of these materials (types of damage over time, the prediction of their lifetime).

Creep experiments, also known as "static fatigue", is the progressive deformation of a material under constant load. With this method each sample test had a different break-time. Our study focuses on evaluating if a composite material will break in a lapse of time: we choose 30 seconds. Meanwhile recent studies [1, 2], have suggested a new approach involving non-invasive testing to study the rupture of composite materials through the phenomena of phase transitions in the creep method. In this perspective, Nechad et al. [1] analysed the evolution of acoustic emission [3, 4] throughout the primary, secondary, and tertiary phases of creep experiment while using polyester matrix composites reinforced with fiberglass. 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 was difficult to apply to our study since the minimum deformation rate was hard to determine.

We have used fibreglass material , it was the first modern composite and is still the most common. It makes up about 65 per cent of all the composites produced today and is used for boat hulls, surfboards, sporting goods, swimming pool linings, building panels and car bodies.

The first part of this paper details the materials and tests. The second part concerns the data that were collected. The third part deals with the methods that were used. The fourth part concerns the results and the discussion. Finally, the conclusion and the perspectives are given.

2 Materials and Test Results

2.1 Materials

The studied materials were manufactured by moulding 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 were laminated and impregnated at room temperature, then placed empty with a depression of 30 kPa vacuum for 8 hours between the mould and the mould cons, followed by polymerization of 8 hours at 80°C in an electric oven [5]. The cuts were made using a diamond blade saw.

2.2 Creep experiment

To determine the lifetime of the tensile specimens, a set of tensile tests were performed. The specimen dimensions reached 2 x 20 x 300 mm. Tests were conducted on an INSTRON type machine equipped with a cell load of 100 kN and controlled by computer (figure 1). 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. The calibration of each test used a pencil lead break procedure in order to generate repeatable AE signals. Several 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 30 kN of strength. However creep method was based, in first time, on traction method by applying 90% of strength and then waiting until fracture.

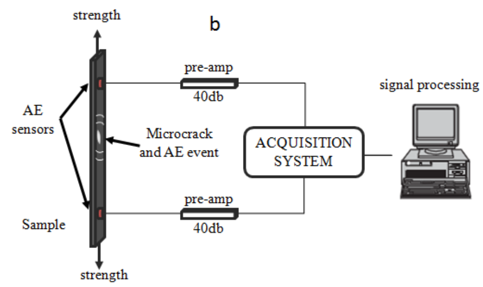

Figure 1: system schema

2.3 Acoustic Emission Activity

The acoustic emission is a phenomenon of liberation of elastic energy in the form of transient elastic waves in a material with dynamic processes of deformation. When subjected to external stresses, composite materials undergo various types of degradation resulting from local damage at the matrix, fiber and fiber-matrix interface. Generally, these mechanisms occur simultaneously, thereby reducing the mechanical properties of composite material. Degradation mechanisms are developed according to the nature of materials and mechanical stress conditions imposed. In a composite material, the stress redistribution, and consequently the rupture process resulting, depends principally on the fiber's crack characteristic, the ability of the matrix to absorb the energy released, the interface properties of fiber-matrix, the fraction volume of fiber, and the conditions of mechanical stress imposed.

The activity of acoustic emission collected during the creep experiments on the specimens was studied through the number of signals collected over time. Figure 2 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.

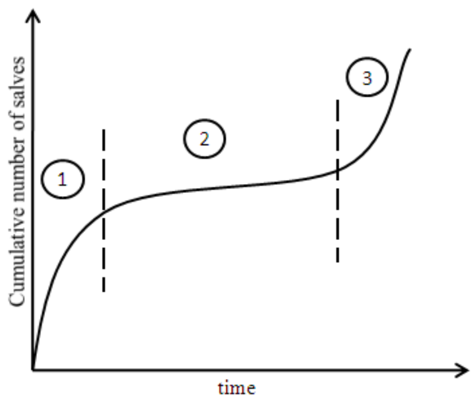

Figure 2: creep test typical form

3 Data and concept of salves selection

Six tensile specimens have been tested with creep experiment. We got six different rupture times (539.42 s, 159.26 s, 3362.42 s, 130.36 s, 1831.94 s, and 845.84 s). Each test conducted to obtain thousands of salves. An example of one burst is shown on (figure 4). From these thousands bursts we have only used 20; 10 bursts were selected in the 30 seconds interval before the rupture point, and the others were randomly selected outside the last 30 seconds interval (figure 3). In total we have selected 120 bursts among which 50% are within a rupture period. For each signal we used three parameters:

- Burst Duration : it corresponds to the time between the first and the last threshold crossing.
- Number of Peaks : it is the number of threshold crossings over the duration of the signal.
- Amplitude, its unit is the decibel (dB):

$$A = \log\left(\frac{V(t)}{1\mu V} - (preampGain)\right)$$

Preamp Gain is the value of gain of pre-amplifier's transducers EA [6] (fixed to 40 dB in our study). $V(t)$ is the voltage detected. The value of amplitude bursts retained by the purchasing system is the maximum peak amplitude obtained for the maximum voltage V_{max} detected. The distribution of the amplitudes of bursts covers the range 10-100 dB (0 dB corresponds to 1 μV at the out of the Transducer).

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.

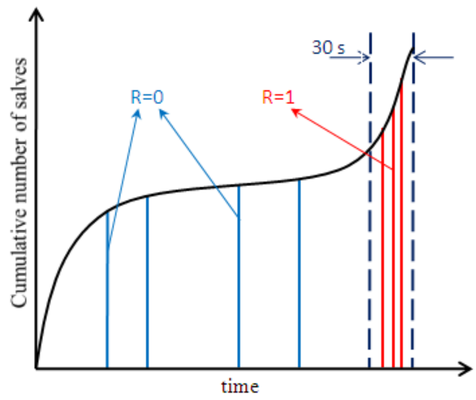

Figure 3: concept of salves selection

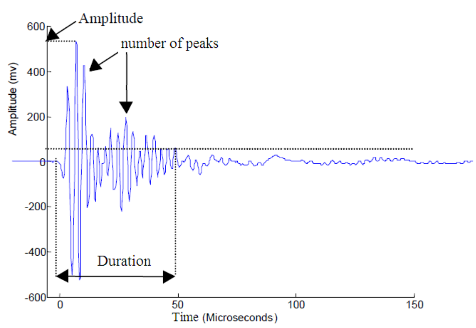

Figure 4: parameters description of salves

4 Naive bays classifiers

The method of naive Bayesian classifiers was used. This type of statistical classifiers can predict the probability that a given sample belongs to a particular class [8]. The Bayesian classifiers are based on Bayes' theorem. The naive Bayesian classifiers assume that the effect of an attribute on a given class is independent of other attributes. This assumption is called class conditional independence, it simplifies the computational complexity and, in this sense, is considered as naive.

4.1 Prediction by naive bays classifiers

The probabilistic classification method is simple, it is related to the theorem and the Bays decision rule [8]. This classifier assumes independence among variables, thus, greatly simplifies the determination of probabilities. In fact, considering there are k classes, $C_1, C_2, \ldots, C_k$. $P(X|C_j)$ the probability of each class is estimated from the univariate densities

$P(X_i|C_j)$, $i = 1, \ldots, p$. This is interesting, because it involves the estimation of individual variable p, so in one dimension, thereby avoiding the "curse of dimensionality". The probability associated with each class $P(X|C_j)$ is then estimated by

$$P\left(X|C_j\right) = \prod_{i=1}^{p} \left(P\left(X_i|C_j\right)\right)$$

Once the estimated probability, we still have to determine the *a posteriori* probability $P(C_j|X)$, for assigning an observation to classes following the Bays' theorem.

4.2 Performance measure

The 120 samples included in this study were divided into two groups. The first group of 90 samples is named the learning set. This set was used to build and determine the best kernel adjustment of variables for a naive bays classifier. The samples in the second group (30 samples, named test set) were only used to estimate the performance of selected subsets. Thus these test data are not employed in the feature selection phase and adjustment of naive bays learning process. The learning set and the test set were built with 50% of samples that are within a rupture period, randomly chosen.

To evaluate the performances of the prediction, sensitivity and specificity were used. Both characterize the percentage of good samples classification. To compute the percentages of sensitivity and specificity, we used:

$$\text{Sensitivity} = 100 * \left(\frac{TP}{TP+FN}\right)$$
$$\text{Specificity} = 100 * \left(\frac{TN}{TN+FP}\right)$$

N is the total number of samples, *TP* is the number of true positives, *TN* is the number of true negatives, *FN* is the number of false negatives, and *FP* is the number of false positives.

An essential condition must be followed for accurate estimation of the sensitivity and specificity values: the distribution of break and non-break items must be significantly balanced. With a manual selection, we had a prevalence of 50%, therefore the condition of balancing was satisfied. The ROC curves (Receiver Operating Characteristic) [7] 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 [10, 11].

To estimate the generalization error, we used a *K*-fold cross-validation [10, 11] ($K = 5$). This technique allows to give an estimation with a small bias and a small variance. Thus, the learning data set was randomly divided into *K* subsets (*K*-folds) of equal size. The classifier was trained on $K-1$ subsets, then the validation performances were measured by testing the subset that was not used during the learning phase. This process was repeated *K* times by using a different subset to estimate the validation. Therefore, the performance of the classifier was obtained by averaging the *K* AUCs. For each ROC curve, the best sensitivity and best specificity were computed by the minimization of the quantity :

$$\sqrt{\left(\left[1-\frac{sensitivity}{100}\right]^2 + \left[1-\frac{specificity}{100}\right]^2\right)}.$$

5 Results and discussion

This study aimed to predict whether a tensile specimen will break in 30 seconds or not. The Bayesian classifiers were trained in a retrospective group of 90 samples and tested prospectively in a group of 30 samples. The results are presented in Table I and Table II, where △ means that a variable was not selected; 1, 2, 3 represent the selection of the first parameter (number of peaks), the second parameter (signal duration), and the third parameter (amplitude). As shown in Table 1, the best performance in the training set has reached an average K-AUC of 0.86. In the prospective test we achieved a sensitivity of 90% and a specificity of 94%.

Table 1: *K*-cross validation results in the learning set

Selected variables	Sensitivity (%)	Specificity (%)	AUC
1, 2, 3	78 ± 2.19	82 ± 3.36	0.86 ± 0.086
1, 2, △	74 ± 3.25	77 ± 2.18	0.79 ± 0.054
1, △, 3	76 ± 1.35	81 ± 3.51	0.84 ± 0.092
△, 2, 3	75 ± 1.86	79 ± 3.33	0.81 ± 0.076

Table 2: *K*-cross validation results in the learning set

Selected variables	Sensitivity (%)	Specificity (%)	AUC
1, 2, 3	90	94	0.92
1, 2, △	88	92	0.89
1, △, 3	89	93	0.90
△, 2, 3	86	90	0.88

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 5 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 90 samples while the cross-validations could only take 72 samples for each of the *K* learning processes, therefore the naive bays classifier 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.

6 Conclusion

This study has taken a step in the direction of prediction creep material rupture. Thus, the three indexes (Number of Peaks, Signal Duration and amplitude) introduced in a naive bays classifier could reliably predict material rupture with 88% of sensitivity and 92% of specificity in a prospective group of 30 samples. Further research in this area could include the addition of several parameters as inputs to the Bayesian classifier, and predict which phase a burst belongs.

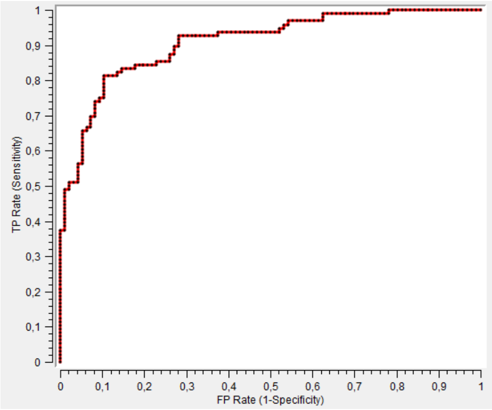

Figure 5: final ROC curve on the test set

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