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Neural Networks NARX for Durability Bonded Joint Prediction

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Abstract—**From the experimental data of the asymetric cleavage test at the bonded joint we studied the crack length propagation as a function of the fracture energy thanks an artificial neural networks. We used the Nonlinear Autoregressive Exogenous (NARX) neural network. The model predicts the crack length with a good agreement with the experimental findings. However, training of the stabilization crack on too long time can cause over-training.**

Keywords: Artificial Neural Network, Autoregressive Exogenous NARX, crack length,prediction.

I. Introduction

Recent developments in structural adhesives with increased performance, allow today's bonding to compete with conventional assembly techniques (brazing, riveting, bolting ...). From an industrial point of view, while structural bonding is interesting in terms of costs and lightening of structures, there is still uncertainty as to the reliability, in time and in use, of bonded joints. Similarly, when assemblies are subjected to aggressive environments (high humidity, high temperature, corrosive products, etc.). One of the main themes of adhesion is to predict the behavior of the bonded joint in mechanical stress, high temperatures and humidity environment.

Numerous predictive approaches make it possible to evaluate the degradation over time of the bonded joint. The experimental approach, based on mechanical tests, makes it possible to predict the behavior of glued joints from accelerated laboratory tests and empirical or semi-empirical laws. The output data are either reductions in mechanical strength or changes in breaking energies. Cognard [1], using the cleavage test, interprets the drop in fracture energy of bonded joints, with stainless steel substrate, cleaved during the test as a decrease in the strength of bonded joints, during the residence time in an aggressive atmosphere. The advance of the crack, during the cleavage test, shows a decrease in fracture energy as a function of time. Plausinis and Spelt [2], introducing the time parameter, have developed a method for estimating the maximum load that an adhesive joint can withstand without creep crack growth.

Mathematics is widely used also for predicting the behavior of the bonded joint. In particular, numerical analysis makes it possible to simulate stress and strain behavior in the adhesive joint [3] and provide solutions to complex problems. The University of Surrey Engineering School [4] proposes a coupled stress-diffusion analysis to study the durability of hot / wet aged bonded joints. Court et al [5] predict the breaking stress for single shear-lap joints in a wet environment from the properties of the mass adhesive before and after aging at $40C$, $95\%RH$. Statistical and probabilistic tools are also used. Reliability approaches are introduced with the partial factor method, which takes into account the stochastic nature of the effects of stress and resistance. Van Straalen [6] applied this method to bonded joints.

The purpose of this article is to propose a tool able to predict the evolution of the crack length according to the energy of rupture. The data come from experimental measurements of fracture energy and crack length as function of time. There are several approaches to material physics to time series predictions such as statistical methods and more recent methods such as artificial networks (RNA). The problem of real Time prediction amounts to estimating, at each time t, the future value of the time series, from it past value. The measurements of the energy and the crack length are performed with a time step of 10 min interval.

A. *Time series prediction*

Given the observations of breaking energy and crack length, time series prediction is used to develop models for describing the relationships between these two observations. We want to approximate the true underlying function describing the data as accurately as possible.

There are different methods for predicting and analyzing time series. Statistical, probabilistic and mathematical analysis in time series data consists in determining the trend parameters as well as the stability of the values (and their variation) over time. The mathematical methods generally used to analyze and predict time series data are regression analysis, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), Bayesian analysis, Kalman filtering, and the spectral analysis with the discrete Fourier transform and the discrete wavelet transform. However other less traditional approaches are also used such as those borrowed from AI.

Time series prediction is implemented in many areas such as meteorology, stock forecasting ... In the study of the behavior of materials and in particular in the lifetime of composites, the models of automatic learning like the networks of artificial neural networks have a lot of success [7].

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More and more scientists are applying neural networks to their forecast models. To predict the time required for the crack to grow until the critical length is reached, at which point fracture occurs [8]. In [9] they predicted fatigue crack propagation life of aluminum alloys under the influence of load ratio by using artificial neural network (ANN). Other researchers have evaluated the lifetime of a composite material through neural networks with non-linear auto-regressive exogenous structure NARX [10]. In the present paper, NARX structure is developed.

This paper is organized as follows: section I presents briefly the experimental procedure. Crack length propagation modeling with NARX structure is presented in section II, followed by results and discussion in section III. The section V concludes the paper.

II. Experimental approach

It was at the Laboratory of Production Engineering (LGP) of the National School of Engineers of Tarbes that most of the experimental manipulations took place. Within this laboratory, a research activity on the durability of structural bonded joints with metallic and especially ceramic substrates has been developed in recent years. The experimental data come from the experience of the asymmetric wedge cleavage test and from J. Evieux's thesis [11]. The test AlN / adhesive / aluminum alloy studied consists of aluminum nitride, glued, using the epoxy adhesive, to a 2024 aluminum alloy blade. This blade was previously anodized to prevent breakage at the aluminum / epoxy interface. The introduction of the wedge into the test tube is carried out at a speed, generally used for this type of test, of 10 mm / min. It causes cracking of the glue joint. The initiation of this crack occurs around 8 mm penetration for the test piece with A N simply degreased. The cracking is directly interfacial, consequence of a weak adhesion. The test piece is then stored in a desiccator $(20C, 40\%RH)$, for 24 hours, the minimum time to stabilize the crack propagation. Once the crack length has been measured, the test specimen is placed in the aggressive medium (for example, immersion in brine at $70C$ or in the climatic chamber humidity medium, $70C, 90\%RH$).

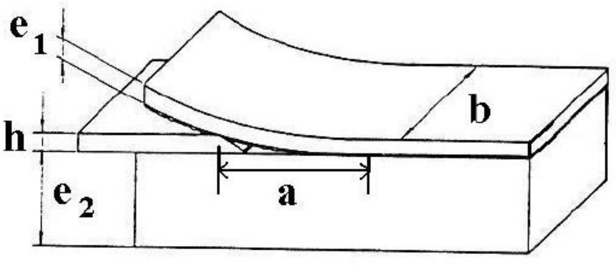

Fig. 1. Asymmetric wedge cleavage test.

The thickness of the adhesive is 0.2 mm, and the thickness of l'AlN is 4 mm. The cracks are all located at the substrate/adhesive interfaces, regardless at the surface treatment of the substrates. The crack lengths are regularly measured.

A. Experimental results

Our attention is focused on the evolution of the crack length at the AlN/adhesive, as a function of the immersion time in the aggressive liquid. We choose two cases where the AlN substrate is digressed and where AlN is treated with a laser (1 J/cm^2). The majority of the cleavage test information is at short time when the state of stress is greatest and the adhesive and interfacial bonds are the more stressed.

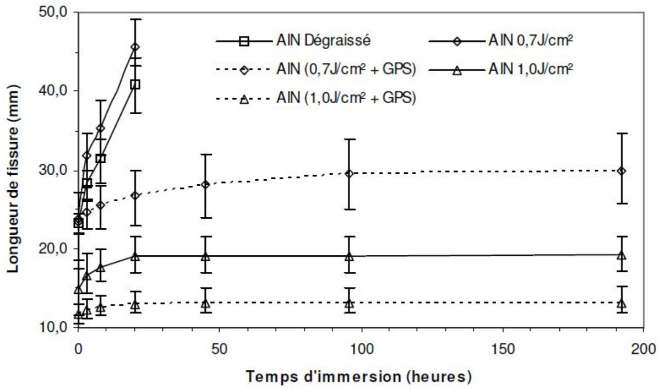

Fig. 2. Fissure.

The curve represents the average value of the crack length taken from four to five test pieces. We are interested in the crack length during the aging and on the absence or presence of the crack stabilization.

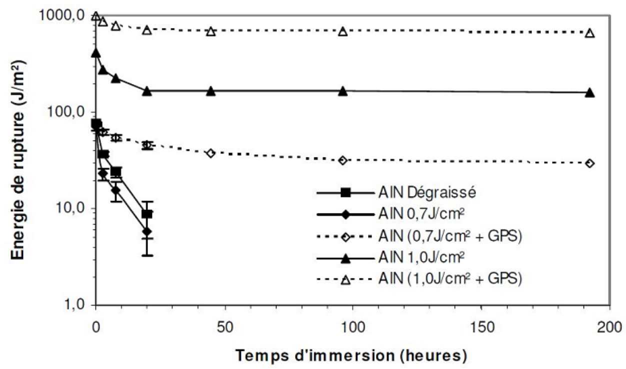

Fig. 3. Energie.

For all observations, the fracture energy decreases with the immersion time in the liquid.

From these curves we collect in a first time a sample of 120 points (for 20H duration) with a time step of $\Delta T = 10$ mn corresponding to the specimen AlN digressed and the destroyed test tube. In a second time, we collect a sample of 133 points (for 22H duration) always for a $\Delta T = 10$ mn and a specimen AlN treated with a laser at $1J/cm^2$ corresponding to the crack stabilized.

III. Prediction of joint durability with the NARX artificial neural network

Because crack length and fracture energy are time series we develop in Matlab langage an artificial neural network NARX which is a good predictor of time series.

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The non-linear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections which enclose multiple layers of the network. NARX can model a variety of nonlinear dynamic systems. The artificial neural network NARX is a two-layer network, with a sigmoid transfer function in the hidden layer and an activation function, which is linear, in the output layer. NARX model can be represented as :

$$y(t) = f(y(t-1), y(t-2), y(t-3), ...y(t-k), \\ x(t-1), x(t-2), ...x(t-k)) \quad (1)$$

where the output variable y(t) is regressed from its previous values and exogenous variables x delayed by k periods. The NARX network can be executed in two architectures :

- Series-parallel architecture named open-loop. In this execution, the real output is used instead of returning the estimated output and given by the equation:

$$\hat{y}(t+1) = f(y(t), y(t-1), y(t-3), ...y(t-k), \\ x(t+1), x(t), ...x(t-k)) \quad (2)$$

Using true values as input of the feedforward network gives precision.

- Parallel architecture or close-loop

The close-loop means that the output of the NARX network is returned to the network input by delays. Which gives the following equation

$$\hat{y}(t+1) = f(\hat{y}(t), \hat{y}(t-1), y(t-3), \\ ...\hat{y}(t-k), x(t+1), x(t), ...x(t-k)) \quad (3)$$

A. The model

We use as input the fracture energy data and for the target the crack length. The NARX network consists in three layers: input with the true values of the fracture energy, hidden and output, with weights and a bias. In practice, the structure is chosen by successive tests on weights and delay until the most satisfactory performance is obtained. We considered three types of learning while keeping the same number of hidden neurons and delay time ; we have an artificial neural network model of 9 hidden layers with a delay of 2 periods. The weights and biases vectors are randomly generated only once, in the first training phase. The Matlab software Deep Learning toolbox was used to train, validate and test the predicted NARX prediction model.

In this study, serie-parallel architecture is using for the training mode, see Figure III-A.

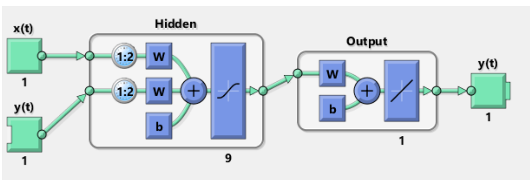

Fig. 4. Series-parallel architecture

The number of points of each curves 2, and 3 used during the training phase has a strong influence on the development of the network and the optimization of the results. But for efficient learning this number must be sufficient to allow the network and to detect the variations of the curves. For The training phase we have three kinds of target timesteps training, validation and testing: it consists on 70% for training, 15% for validation, these are used to measure network generalization, and to halt training when generalization stops improving. and 15% for the test, these have no effect on training and so provide an independent measure of network performance during and after training.. For the training we used Levenberg Marquardt's algorithm (see [12]) which is adapted to minimize nonlinear functions then it is much more efficient compared to the more general optimization algorithms.

1) The performance of the model: To more accurately assess the quality of forecasts, we use the mean squared error (MSE) for the three cases. Indeed, this indicator makes it possible to compare the real and forecast data. Low values of these indicators mean accurate forecasts. The mean squared error is defined by

$$MSE = \frac{\sum_1^N |y - \hat{y}|^2}{N} \quad (4)$$

where N denotes the numbers of patterns pairs.

B. The case of the destroyed test-tube

1) The training phase: We used 60 points (10 H) of each learning curve and test, in the second time 80 points and in the third time 100 points.

TABLE I
ESTIMATION RESULTS FOR THE DIFFERENT MODELS.

models			
number of points	60	80	100
MSE	0.000122	0.000743	0.000929

According to the calculation result of the average error, a better learning is obtained for 60 points.

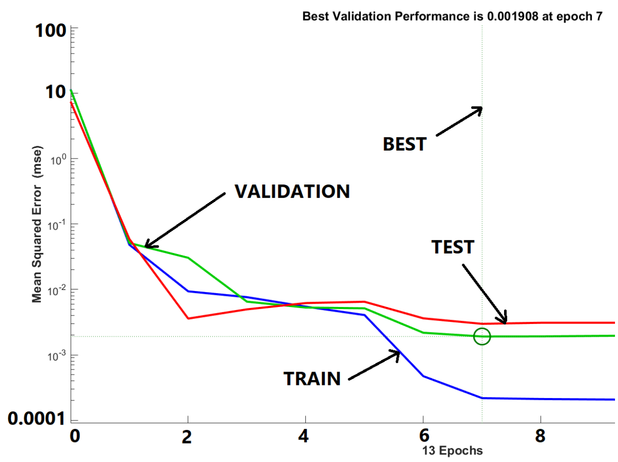

Fig. 5. Performance of the static neural networks NARX for 60 points

Fig III-B1 represents the error evolution MSE during the validation.

Regression R Values measure the correlation between outputs and targets. The outputs are correlated with

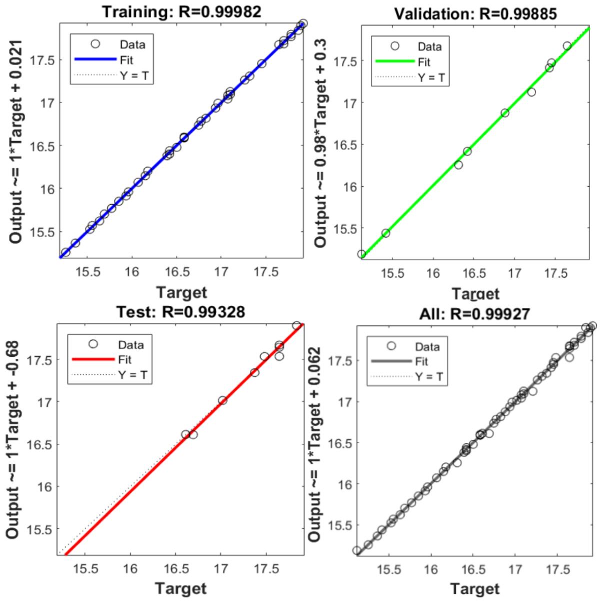

Fig. 6. Correlation between the outputs and the target values.

the corresponding target values for training and testing, and the R value is 0.99927 for the total response. There is a relatively linear relationship between outputs and targets. These results show a good fit in learning and testing.

2) Prediction of the crack length: Here is how to design a neural network that predicts the target series from past values of inputs and targets. After the training phase, the NARX is converted to the parallel architecture see Figure III-B2 which is used for the multi-step-ahead prediction phase. In order to evaluate the performance

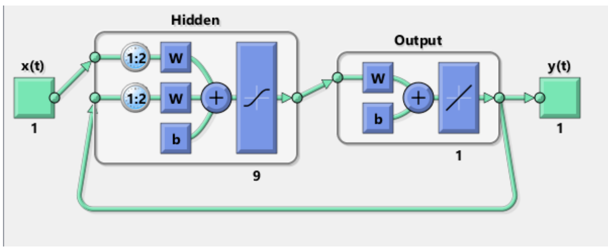

Fig. 7. Parallel architecture

of the developed NARX network, we tested it on another database. The prediction of the crack propagation is performed on the remainder of the sample belonging neither to the learning base nor that to that of the validation or the test. A comparison is then made between the predicted values and the true values. The best obtained error performance is 0.000197 for MSE, for 60 points. Then Figure III-B2 shows the crack length prediction with with neural netwoks model:

The predicted crack length is relatively close to the experimental values. The NARX model is therefore able to predict the crack length and thus its stabilization where not, despite a not very high number of points. Fig. 10 represents the measured and predicted values for this sample.

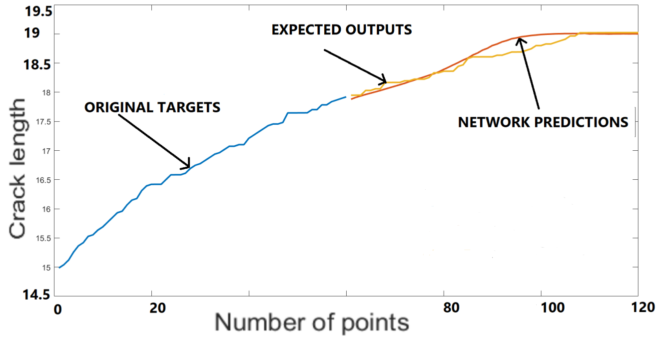

Fig. 8. Comparison of predicted (NARX) and experimental crack length for 60 points

TABLE II
PERFORMANCE RESULTS FOR THE STABILISED CRACK.

models			
number of points	73	93	113
MSE	0.000342	0.000796	0.000721

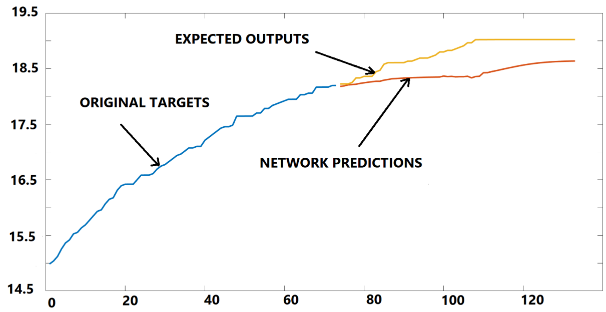

Fig. 9. Comparison of predicted (NARX) and experimental stabilized crack for 60 points

C. Case corresponding to the crack stabilized

Now we study the sample of AlN laser treated 1 J/cm^2, we have 133 points, we used 73 points of each learning curve and test, in the second time 93 points and in the third time 113 points. We obtain for 2 times delay and 9 hidden layers, the following performance:

Despite learning a few more points, according to the table II, the MSE error tells us that the network is less efficient.

We see in particular on the figure III-B2 that the prediction for 60 points in the case of the stabilized crack, is not as efficient as for the first case. But we do see, however, the tendency to stabilize the crack.

IV. DISCUSSION

The simulations of this paper are performed using samples of 120 and 133 points. The numbers of points is important in the training phase. Il is sufficient to detect and predict the stabilization of the crack.

The crack length being stabilized, if one considers stabilization times too long, there is a risk of "over-training" the part corresponding to the stabilization at the expense of the crack propagation phase. Indeed, we note the case where the training phase is performed on a large part corresponding to the stabilized crack, the NARX is less effective.

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V. Conclusion

This present paper demonstrates that developed NARX is capable in predicting crack propagation. NARX is good predictor for the real time forecasting of the stabilization or not of the crack. This article is completed by the study of D. Ghorbanzadeh on the change-point which determines the point of change of state of the breaking energy.

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