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Modeling of fatigue crack growth by neural networks

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Abstract **–** Fatigue cracks often occur in means of transport such as aircraft, vehicles and ships, as well as in power generation machinery, gas turbines. The crack growth process is complicated for many reasons, including component geometry, manufacturing defects, and applied load. In this paper, a fatigue crack growth model is developed based on the artificial neural networks (ANN) for the V-notch Charpy specimen. The ANN model mainly depends on the cyclic loading conditions and the properties of the materials on input and output the length of the crack. Experimental data on fatigue crack growth of aluminum alloy 2024 T351 for different load ratios obtained from literature were used for this investigation. The predicted crack length is in good agreement with the experimental data.

Keywords – Crack Growth, Artificial Neural Networks, Fatigue, Multi Layer Perceptron, Aluminum Alloy 2024 T351.

I. INTRODUCTION

Mechanical structures have been an important factor in the evolution of humanity since the birth of industry. In order to avoid system degradation, malfunctions and catastrophic failures, proper assessment of fatigue crack propagation and prediction of remaining service life of structures play an important role in ensuring safety, protection of environmental and economic considerations

After the first industrial revolution, researchers tried to model this fatigue phenomenon. Several traditional fatigue crack propagation models showing some limitations and ease of use. The law of Paris and Erdogan has been considered as the most fundamental model relating the crack growth rate "da/dN" to the stress intensity factor [1]. Nevertheless, a number of the factors including load ratio, frequency and environment have a significant impact on the crack driving force [2-4]. In addition, some empirical models have been proposed to take into account the load ratio and the crack closure effect and studied in many research projects [5-7] De Iorio et al. [8] and Grasso et al. [9] proposed similar new phenomenological models for fatigue crack growth. These models present alternatives to the analysis technique proposed by the ASTM E647 standard. These models are robust and have shown the ability to fit a wide range of experimental data produced with different sample geometries, materials and loading conditions. Generally, in service, the prediction of damaged components under cyclic loading can be estimated by integrating equations from classical fatigue models. So direct integration becomes complicated and robust when the stress intensity factor depends on the geometric correction factor f(a/w) and the crack length. Numerical integration requires different values of f(a/w) which must be constant over a small crack length increment [10]. Analytical methods could not handle the case well. To overcome the limitations, researchers began to think of other ways and more multidisciplinary methods. Among many others, the numerical approach and machine learning based methods have proven to be the most effective and shown the best results and are considered to be the most interesting and performing while restoring the case due to the admirable tolerance and estimation of nonlinear and multivariate complications.

Among these algorithms, support vector machine, genetic algorithms, artificial neural network (ANN), fuzzy logic, neural-fuzzy system and particle swarm optimization (PSO) are prominent. Mohanty et al. [11] introduced a modern procedure to predict the service life by adopting an "artificial neural network model" for the "SENT" specimens of aluminum alloys 7020 T7 and 2024 T3. Venkatesh et al. [12] used a backpropagation neural network to accurately predict the life of materials subjected to creep fatigue behavior at elevated temperature. Artymiak et al. [13], Kang et al. [14], Haque et al. [15] and Cheng et al. [16] used machine learning algorithms for different fatigue problems. In this paper, an artificial neural network is used to model the fatigue crack growth of aluminum alloy 2024 T351.

II. EXPERIMENTAL DATA

Experimental data obtained from fatigue tests with the load ratio R vary from 0.1 to 0.3 [17]. Experimental fatigue tests were carried out on Charpy V-notch specimens in four-point bending tests (fig 1)of Al 2024 T351 alloy extracted from a plate in T-S orientation according to ASTM E647.

Specimen dimensions are given in Table 1 , where notch depths are specified with a notch radius of 0.20 mm

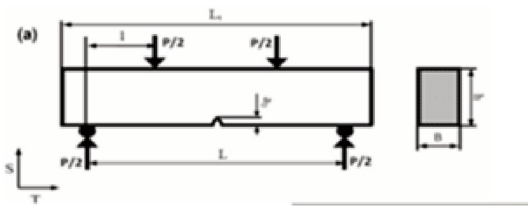

Fig.1 Schematic assembly and dimensions

Table 1. Dimension of fatigue specimens

L_t	L	l	h	B	a_0
64	50	14.5	10	10	2

The results used for the present modelling are given in fig 2. Different fatigue crack growth loading conditions characterized by the variation of the load ratio and the equivalent stress intensity factor for the initial and final crack lengths are shown in Table 2.

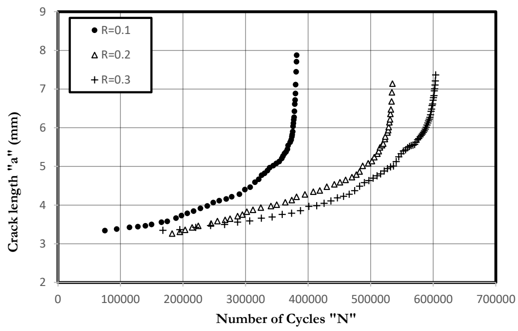

Fig 2. Experimental fatigue life of V-notch in four-point bending specimens' tests of 2024 T351Al-alloy

Table2. Experimental loading conditions and equivalents 'initial and final crack lengths for different stress ratios.

R -ratio	a_0 (mm)	a_f (mm)	P_{min} (KN)	P_{max} (KN)	P (KN)	N (cycles)	ΔK_0 (MP$\sqrt{m}$)	ΔK_f (MP$\sqrt{m}$)
0.1	3.34	7.875	0.115	1.149	1.034	382.000	5.395	22.696
0.2	3.31	7.14	0.237	1.184	0.947	569.700	4.85	16.88
0.3	3.365	7.365	0.348	1.16	0.812	547.000	4.22	15.90

III. MODEL FORMULATION

The origin of neural networks comes from the attempt of mathematical modeling of the human brain, the first works date from 1943 and are the work of W.M. Culloch and W. Pitt [18]. An artificial neural network is structured in the form of layers. The layers consist of nodes interconnected to each other which are powered by an activation function(fig.3). The systems model is presented to the network by an input layer which communicates to one or more hidden layers for processing. The hidden layers have weighted functions that are the real driving force behind the processing. After the processing, the hidden layers involved in the process communicate with the output layers where the information is transferred out of the network. An ANN has the learning rule which continuously changes the weights of the connections based on the input presented. So, the basic components of a network look like this: Neurons; connection and weight; Spread function; learning rule.

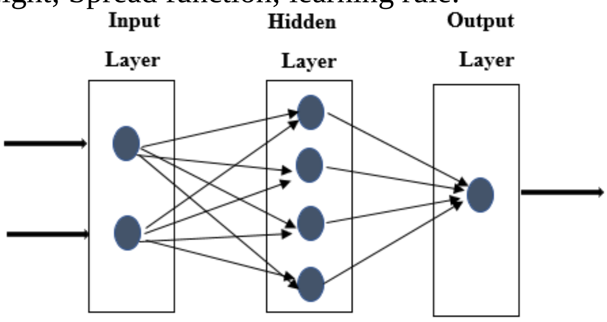

Fig.3 Structure of an artificial neural network

In our study, the developed network consists of an input layer, an output layer and several hidden layers with a well-determined number of neurons; it is a multilayer Perceptron

The process of developing an ANN always begins with the choice and preparation of the input and output data of the network, the inputs used to feed the ANN are the parameters directly linked to the fatigue phenomenon, namely: factor d stress intensity **ΔK** number of cycles **N** load ratio **R** and critical stress intensity factor KC or network output crack length **a.**

In order to develop an application based on ANN, it is necessary to divide the database into two sub-bases: one to perform the training and the other to test the elaborate network and determine its performance. In our case, the learning sub-base consists of 140 examples; this represents a rate of 70% compared to the total number of examples which is 200.

Several parameters are involved in the choice of the best ANN which gives good results such as the transfer functions, the number of neurons in the hidden layer, the learning and optimization algorithm in this contribution We used the nntool command in MATLAB Neural Network Toolbox to speed up network design

The elaborated ANN has a 4-12-1 structure (see Figure 4) consisting of a 4-element input layer, a 12-neuron hidden layer having hyperbolic tan-like transfer functions (see Equation 1), and an output layer consisting of a single neuron whose transfer function is linear (see equation 2). Error gradient backpropagation, used for ANN learning, is associated with the Levenberg-Marquardt optimization algorithm.

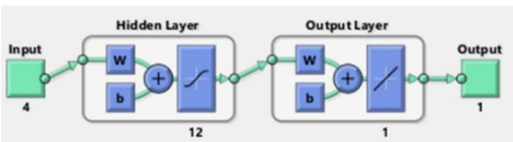

Fig.4 structure of our ANN on MATLAB

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

$$f(x) = x \tag{2}$$

By using the performance indicator (the average percentage of difference between the predicted value and the reality MAPE (eq 4) and the linear correlation coefficient R(eq 3)), we will highlight the adequate choice of the transfer function, the optimization algorithm and the number of hidden layers as well as the number of neurons they contain

$$R = \frac{\sum_{k=1}^{p}(c(k)-d).(s(k)-h)}{\sqrt{\sum_{k=1}^{p}(c(k)-d)^2 . \sqrt{\sum_{k=1}^{p}(s(k)-h)^2}}} \tag{3}$$

With d and h are respectively the mean values of the targets (experimental values) and the outputs of the ANN (calculated values)

$$MAPE = \frac{|c-s|}{c}(\%) \tag{4}$$

With

C : the experimental value

S: the predictive Value

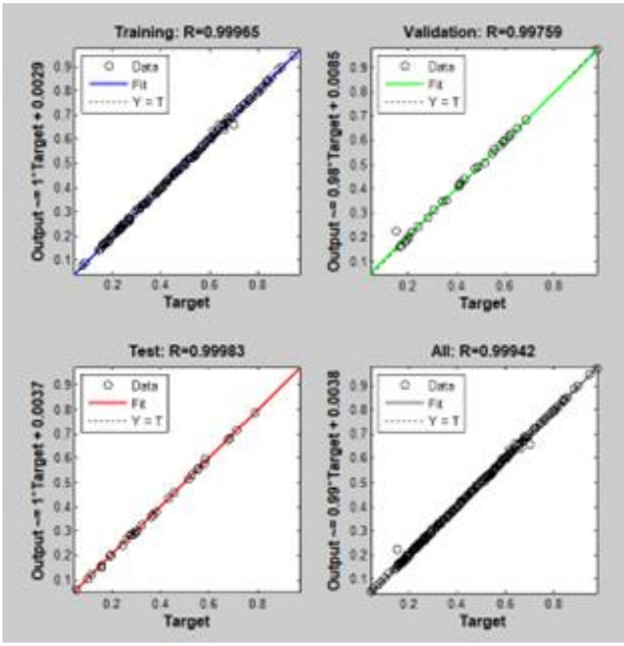

Fig 5. The performance indicator of a 4-12-1 structure

The results obtained show that the Best ANN configuration based on a transfer function of hyperbolic tangent type in the hidden layer and linear in the output layer

The results show that the value of the coefficient R (fig 5) stabilizes towards a value close to 1 beyond 12 neurons of the hidden layer. This phenomenon occurs when the network has memorized the examples of the learning base

IV. Result and Discussion

The numerical model was examined by comparing the cracking curves (a-N) of the studied material obtained from ANN with the experimental results.

Figures 6 to 8 show the evolution of the crack length “a” as a function of the number of cycle for different stress ratios R from 0.1 to 0.3. Note that the difference between the two results is very small for the stress ratios 0.1 and 0.3. Regarding the shift illustrated in the charge ratio 0.2 is related to the dispersions of the experimental results.

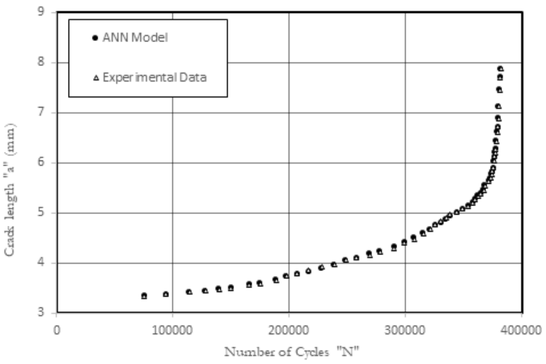

Fig.6 Comparison of predicted and experimental fatigue life for 2024-T351 at R=0.1

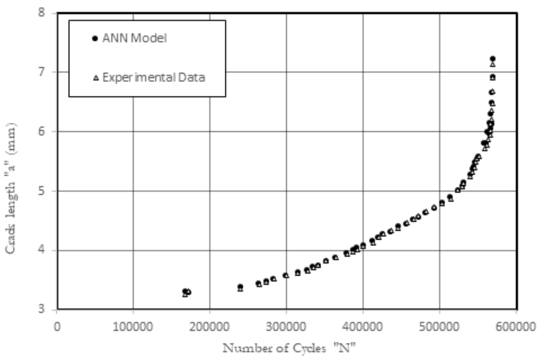

Fig.7 Comparison of predicted and experimental fatigue life for 2024-T351 at R=0.2

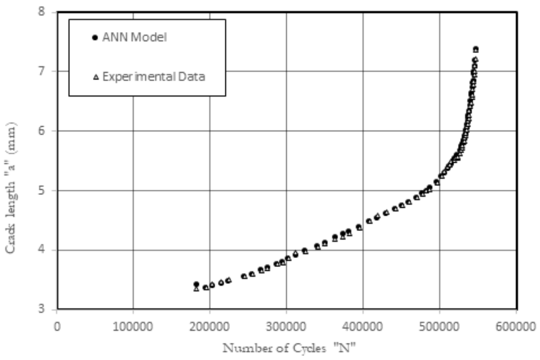

Fig.8 Comparison of predicted and experimental fatigue life for 2024-T351 at R=0.3

V. CONCLUSION

In this article It has been explained that the process of fatigue crack growth is a very complex, highly nonlinear dynamic process, due to many factors, such as component structure, material properties and loading environment. It was also pointed out that due to the powerful universal arbitrary approximation capability of complex nonlinearity and dynamics, the ANN technique is a potential new method for fatigue crack propagation estimation. the neural network, it was possible to reveal the effect of each factor influenced on the growth of cracks This demonstrates the ability of this method to reveal new phenomena in cases where experiments cannot be designed to study each variable in isolation.

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