Experimental fatigue crack propagation simulation by ANN of a newly developed controlled rolled microalloyed steel plate

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Abstract

In this work, fatigue crack propagation life of a new microalloyed steel plate under the influence of constant load ratio was simulated by using artificial neural network (ANN). Numerous methodologies such as cycle by cycle prediction, prediction by correlation and finite element methods have been proposed for simulating fatigue life [1].

In this work, a simulation methodology has been used to estimate the crack growth rate and the Paris Law parameters (C and m) under constant amplitude fatigue loading by applying artificial neural network (ANN). The applied ANNs showed great potential for simulating the experimental fatigue crack growth complex data set. In this case especially by interpolation within the trial tested range.

Keywords: Fatigue crack growth rate; Artificial Neural Network; Constant amplitude loading

1. Introduction

In recent years neural networks have been successfully applied to a range of disciplines such as image processing and condition monitoring. Until now, there have been few studies which have addressed the application of ANNs to modeling the fatigue crack growth propagation in materials particularly in microalloyed steels [2]. ANNs are well known to be reliable to deal with large complex sets of data, which could serve as a powerful simulating computational method intended for prediction purposes too.

Most structural components generally contain defects like cracks either as a result of manufacturing, or localized damage in field operating loading conditions and in some cases by corrosion effects. The cracks may grow with time owing to fatigue principally, and will generally grow progressively faster. The residual strength of the structure, which is the failure strength as a function of crack size, decreases with increasing crack size. After a time the residual strength becomes so low that the structure may fail in service. So it is important to attempt to provide quantitative answers to the following questions: What is the residual strength as a function of crack size? What crack size can be tolerated under service loading? How long does it take for a crack to grow from a certain initial size, to the maximum permissible crack size? What is the service life of a structure when a crack-like flaw with a certain size is assumed to exist? Fatigue theories and fracture mechanics concepts can be applied to give an answer of these questions. Thus, the crack growth studies and life estimation procedures under fatigue, is essential to extend the safe service cycle of contemporary structures and components [3, 4].

Fatigue research has been one of the prime materials themes for almost 150 years and it has not lost any of its importance. Being a long well established discipline competes with some novel fields such as nanotechnology and bioscience. Unfortunately, only attracts public interest in the event of a spectacular structural failure. However, fatigue research has remained as fascinating as ever, principally, due to the increasing importance of new materials proposing novelty challenges. With today's improved experimental facilities and computational means, long-standing issues can be dealt with in a more conclusive manner than so far [5].

Large structures like bridges, ships, oil rigs, and pipelines are made of microalloyed steels plates that could contain subcritical cracks as already mentioned. To assess the safe life of the structure we need to know how long (number of stress cycles to failure) the structure can last before one of these cracks grows to a length at which it propagates catastrophically (critical size). In the laboratory experimental data on fatigue crack propagation are obtained by cyclically loading specimens containing a suitable controlled length sharp crack. A cyclic stress range is described by $\Delta\sigma = \sigma_{max} - \sigma_{min}$, and a cyclic *stress* intensity factor range (ΔK) due to the existing sharp crack can be defined by equation 1.

$$\Delta K = K_{max} - K_{min} = \Delta_{\sigma}\sqrt{\pi a} \qquad (1)$$

From this equation, the initial sharp crack is denoted by "*a*", and ΔK increases with time at constant tensile Δσ application as well as the initial crack length grows. It is known that the crack growth length per cycle (da/dN) increases with ΔK. In the steady-state the da/dN is described by the Paris law represented by equation 2.

$$\frac{da}{dN} = C\Delta K^{m} \qquad (2)$$

C and m in equation 2 are material constants. If the initial crack length is given, and the cyclic loading pattern is well defined, the critical crack length at which the crack becomes unstable and propagates catastrophically leading to failure, can be known from the experimental fatigue data [6].

The neural network used in the present study is the multilayer perceptron network using the back-propagation algorithm. This network is a popular network for supervised training and reasonably computationally efficient for a range of applications.

2. Experimental Procedure

This research was carried out on a new microalloyed steel plate. The chemical composition and mechanical properties are shown in Tables 1 and 2 respectively. The fatigue crack growth tests were performed using a single V-notch compact tension (CT) specimen with a 10 mm thickness Figure 1. The specimens were made in both directions to the rolling axis (L-T and T-L planes), but only the T-L direction crack growth experimental data [7] was used for the fatigue simulation. Fig. 1 illustrates the geometry and dimensions of the compact tension samples used in the experiments. A servo-hydraulic dynamic testing machine (MTS) having a load capacity of 50KN was used for the present research. An initial fatigue preckrack of 1.3 mm denoted by a_i was introduced under mode I loading condition, and subsequently subjected to constant load amplitude fatigue with a load ratio (R) of 0.6 for all tested samples. All fatigue tests were carried out at a frequency of 5 Hz with a sinusoidal wave form under room temperature conditions. Crack lengths were measured using a compliance method with a COD extensometer and were also monitored using a travel optical microscope with a 10X magnification. The stress intensity factors at every instant ahead of the crack tip were calculated by using equations 3 and 4 [8].

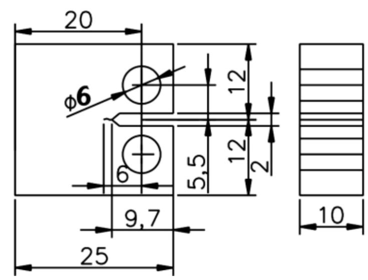

Fig. 1 presents the geometry and dimensions of compact tension samples (length units are in mm).

$$K = \frac{P_Q}{BW^{1/2}} \cdot f\left(\frac{a}{w}\right) \qquad (3)$$

$$f\left(\frac{a}{w}\right) = \frac{-13.32\left(\frac{a}{w}\right)^2 + 14.72\left(\frac{a}{w}\right)^3 - 5.6\left(\frac{a}{w}\right)^4}{\left(1-\left(\frac{a}{w}\right)\right)^{3/2}} \qquad (4)$$

Element	Composition (%)
C	0.0319
Si	0.2355
Mn	1.031
P	0.003
S	0.0026
Cr	0.4243
Mo	0.1674
Ni	1.300
Al	0.0520
Co	0.0043
Cu	0.0106

Table 1 Shows the chemical composition of microalloyed steel.

Direction	σ_y MPa	σ_{UTS} MPa	%Def	δ	E GPa
T-L	502	663	14.59	7.30	170.50
L-T	501	681	14.13	7.07	163.35

Table 2 shows the mechanical properties of microalloyed steel obtained from uniaxial tension test.

3. Design of an ANN Model for Crack Growth Rate Simulation

Different types of ANNs exist but the present research focuses exclusively the multilayer perceptron neural network using the back-propagation algorithm. This network has been chosen because it is one of the commonly network used for predictions of a numerous different phenomena's also because the back-propagation training algorithm is widely used, easily trained, relatively easy to implement and computationally efficient [2].

Figures 2 and 3 shows the schematic representation of the multilayer perceptron neural networks architecture having input, output and hidden layers used in this research to simulate the crack growth rate and the Paris parameters respectively.

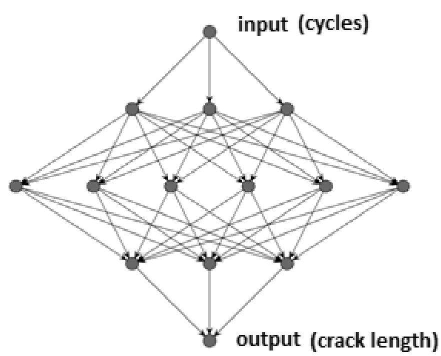

Fig. 2 represents schematic representation of the multilayer perceptron network for simulating the crack growth rate.

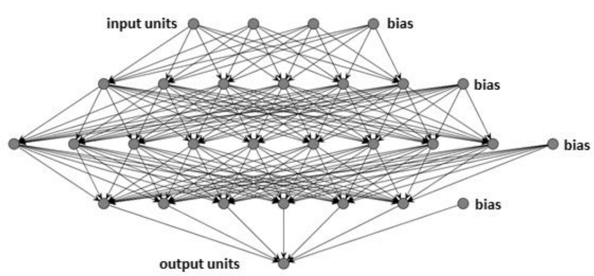

Fig. 3 represents schematic representation of the multilayer perceptron network for simulating Paris Law parameters C and m.

The networks have k inputs, m hidden units and n output units. The neurons or units of the network are connected by weights w. For instance, the bias neurons for modelling purposes are generally represented as a weight from input which is permanently set to 1. The output of a hidden unit is determined by forming a weighted linear combination of all the input values and adding the appropriate bias. The activation of a hidden neuron is obtained by transforming the linear sum of units which send output to hidden unit using a nonlinear activation function which in the present work is the sigmoid function [8].

The neural network was developed using freeware graphic interface software in java programming language and all tests were performed on a personal computer.

The experimental data used to train the network was obtained from the experimental procedure described above for crack propagation under constant amplitude fatigue loading of experimental microalloyed steel. The network is configured for an input vector within the range 0-1 so that all crack propagation experimental values were normalized within the vector range.

To determine the number of hidden layers and hidden units were selected empirically and taken in order to give the neural network a diamond shape.

During training the network output $\boldsymbol{V_{calculated}}$ may differ from the desired output $\boldsymbol{V_{real}}$ as specified in the training pattern presented to the network. A measure of the efficiency of the network is instantaneous sum-squared difference (error) between $\boldsymbol{V_{real}}$ and $\boldsymbol{V_{calculated}}$ for the set of presented training patterns, (equation 5) [3]:

$$Err = \frac{1}{2}\sum(V_{real} - V_{calculated})^2 \quad (5)$$

The two crack growth parameters selected for predicting the crack growth rate were $\boldsymbol{N}$ as input and $\boldsymbol{a}$ as output values. In the case which predicts the Paris law parameters $\Delta\boldsymbol{K}$**,** $\boldsymbol{R}$**,** and $\boldsymbol{K_{max}}$ as inputs and ***da/dN*** as output values

4. Experimental and Simulated Results

The experimental values of crack length versus number of cycles in the T-L direction to the rolling axis for a load ratio R of 0.6 is presented in figure 4.

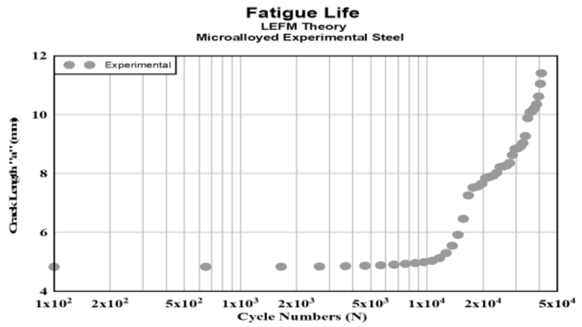

Fig. 4 presents experimental values of the crack growth in T-L direction to the rolling axis.

The simulated results of crack length versus number of cycles and comparison with the experimental data are presented in the next figures.

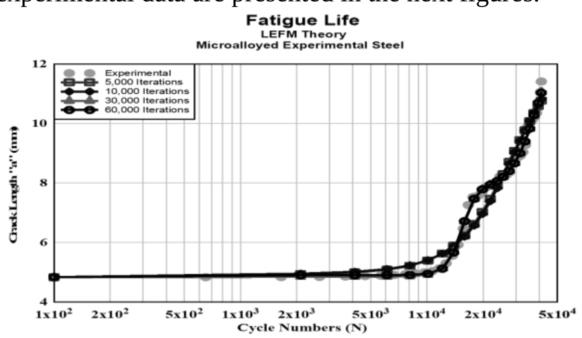

Fig. 5 presents experimental values compared with simulated values at 5,000, 10,000, 30,000 and 60,000 iterations.

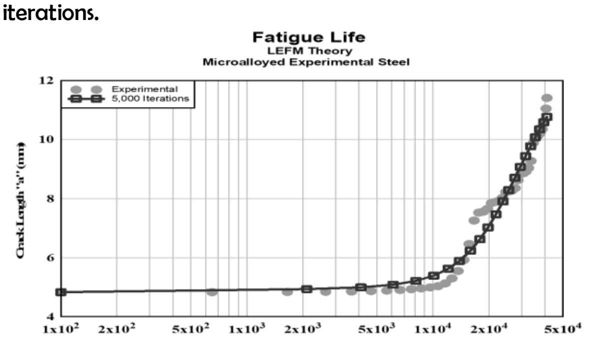

Fig. 6presents experimental values compared with simulated values at 5,000 iterations.

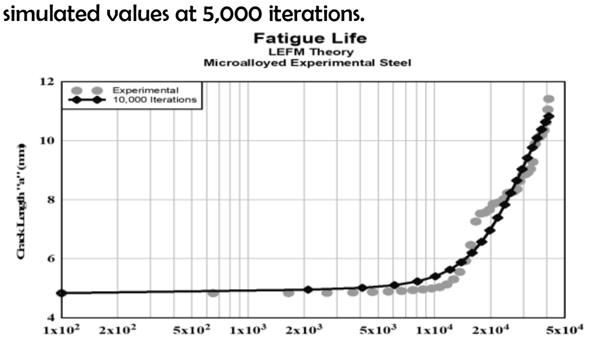

Fig. 7presents experimental values compared with simulated values at 10,000 iterations.

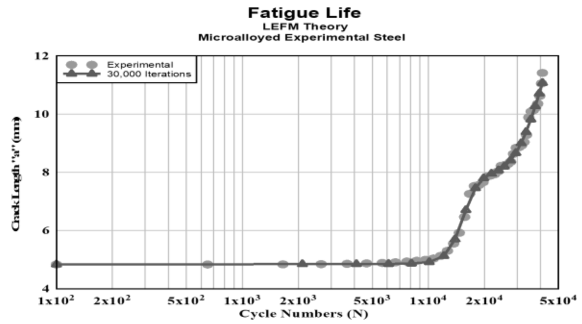

Fig. 8presents experimental values compared with simulated values at 30,000 iterations.

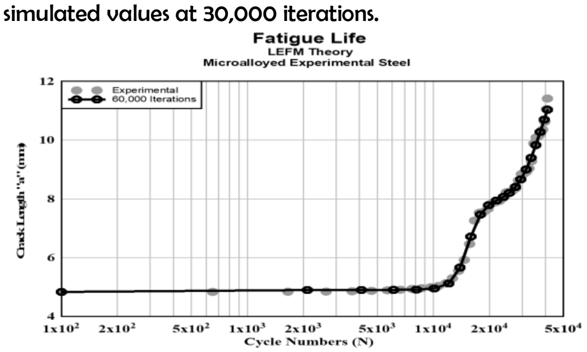

Fig. 9presents experimental values compared with simulated values at 60,000 iterations.

The experimental values of crack growth rate versus ΔK values are in the T-L direction to the rolling axis for a load ratio R of 0.6 is presented in figure 10.

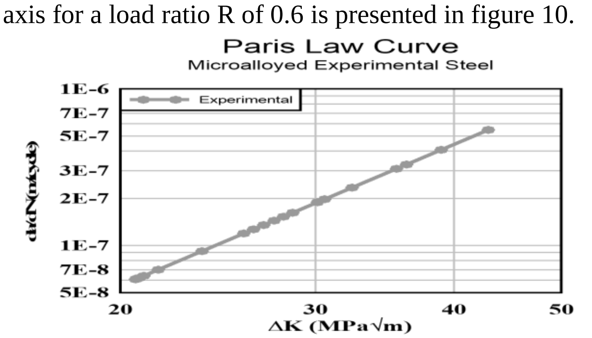

Fig. 10presents experimental values of Paris Law Curve in T-L direction.

The simulated results of crack growth rate versus ΔK values and comparison with the experimental data are presented in the next figures.

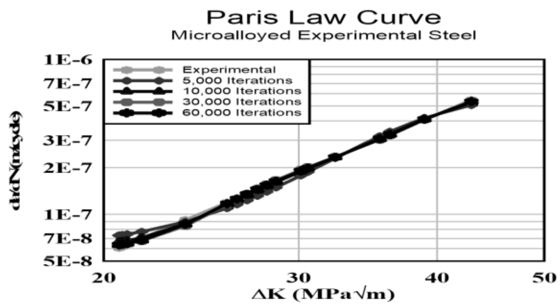

Fig. 11presents experimental values compared with simulated values at 5,000, 10,000, 30,000 and 60,000 iterations.

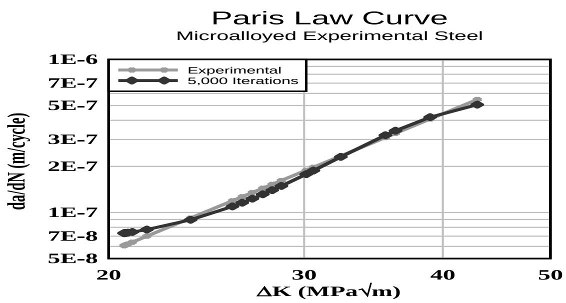

Fig. 12presents experimental values compared with simulated values at 5,000 iterations.

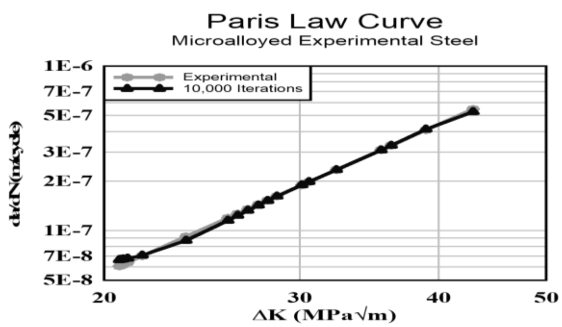

Fig. 13presents experimental values compared with simulated values at 10,000 iterations.

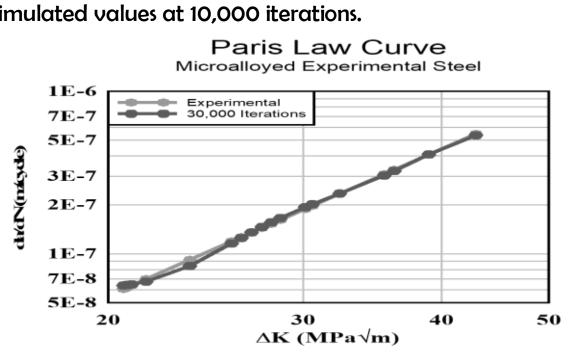

Fig. 14presents experimental values compared with simulated values at 30,000 iterations.

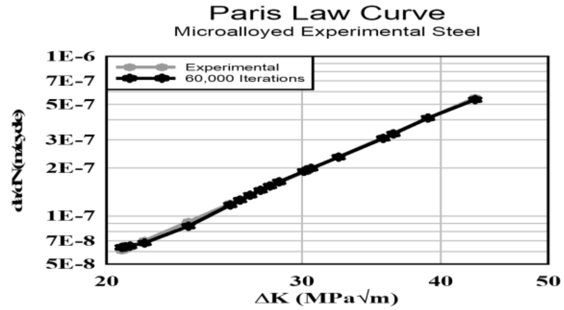

Fig. 15presents experimental values compared with simulated values at 60,000 iterations.

5. Simulations by the ANN model

The network training was implemented out of 2 sets of experimental data leaving one set for the validation process. The adopted multi-layer perceptron neural network models were used to predict the crack growth rate and the Paris Law parameters for both the cases. The number of hidden units, error and number of iterations were chosen empirically and are presented in the next tables

Iterations	Hidden u.	Hidden L.	Error
5,000	12	3	0.183592
10,000	12	3	0.195318
30,000	12	3	0.017877
60,000	12	3	0.017001

Table 3 shows hidden neurons, hidden layer for the crack growth rate case and the validation by means of the instantaneous sum-squared difference.

Iterations	Hidden u.	Hidden L.	Error
5,000	24	3	0.116063
10,000	24	3	0.011053
30,000	24	3	0.009493
60,000	24	3	0.005106

Table 4 shows hidden neurons, hidden layer for the Paris Law parameters case and the validation by means of the instantaneous sum-squared difference.

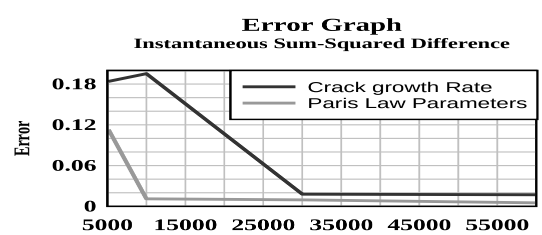

Fig. 16 shows graphical representation of the solution convergence in terms of process iterations

The simulated crack growth rate results have been presented in figures 5-9 respectively along with experimental findings for comparison. It is observed that the simulated crack a-N points follow the experimental ones quite well at 30,000 and 60,000 iterations; however the simulated crack a-N at 5,000 and 10,000 iterations reflects the typical accurate behavior of the crack growth rate phenomena as reported in literature.

In the case of Paris Law Parameters the results have been plotted in figures 11-15 respectively along with experimental results for comparison. It is observed that the simulated Paris Law behavior is well reflected by the simulation process presenting a more accurate prediction at 30,000 and 60,000 iterations.

A quantitative comparison between the experimental and simulated results for both crack growth rate and Paris Law parameters are presented in the next tables.

Iterations	Initial crack length (mm)	Final crack length (mm)
Experimental	4.831	11.411
5,000	4.831	10.768
10,000	4.831	10.824
30,000	4.831	11.068
60,000	4.831	11.032

Table 5 presents the quantitative comparison between experimental and simulated values for crack growth rate prediction.

Iterations	da/dN (m)	C	m
Exp.	$5.5x10^{-8}\Delta K^{3.965}$	$5.5x10^{-8}$	3.965
5,000	$7.0x10^{-8}\Delta K^{4.095}$	$7.0x10^{-8}$	4.095
10,000	$6.4x10^{-8}\Delta K^{4.068}$	$6.4x10^{-8}$	4.068
30,000	$6.3x10^{-8}\Delta K^{4.087}$	$6.3x10^{-8}$	4.087
60,000	$6.2x10^{-8}\Delta K^{4.091}$	$6.2x10^{-8}$	4.091

Table 6 presents the quantitative comparison between experimental and simulated values for Paris Law parameters prediction.

6. Conclusions

In this research, fatigue crack growth rate and Paris Law parameters of microalloyed experimental steel under the influence of constant load amplitude with a ratio R of 0.6 of T-L direction to the rolling axis was simulated by using artificial neural network (ANN). A data base consisting of 2 sets of experimental data for each of the above features was used to train the neural network architecture. It was later applied to simulate the crack growth rate and the Paris Law parameters for a set of experimental results.

The simulated results were found to be in good agreement with the experimental discoveries. It has been demonstrated that neural networks are an important engineering computational tool due to the ability of learning key characteristics that are implicit in some phenomena’s (in this case exponential growth); then the neural network make use of them in problem prediction, where the estimate has a variable behavior but with asimilar behavior pattern over time.

7.References

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