EVALUATION OF STRUCTURAL ELEMENTS LIFETIME BY NEURAL NETWORK

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Received: 05.09.2017
Accepted: 22.11.2017

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Abstract
While in operation structural elements may have cracks, which usually grow up to critical size due to cyclic loading and the component is likely to be destroyed. Therefore, it is important to study the process of fatigue failure of structural materials. The aim of this study was to evaluate the lifetime of structural elements, taking into account the achieved level of material damage, and to predict the fatigue crack growth (FCG) rate in an aluminium D16chT alloy under regular loading by neural network (NN). The results obtained by the authors are in good agreement with the experimental data.

Keywords: fatigue crack growth, stress intensity factor, neural network, lifetime, data science

1 Introduction

Machine learning (ML) is a part of data science. ML recognises patterns effectively [1]. One of its approaches is neural network (NN) [2]. Neural network can answer a lot of open questions in mechanics. In particular, NN can predict the lifetime of structural elements.
To assess the lifetime and fatigue crack growth prediction, it is important to consider the properties of the material and the scatter of its parameters. Many existing models describe fatigue crack growth rate deterministically [3 – 8]. Also, a number of probabilistic approaches enable to estimate the probability of failure of certain structural elements or to build a distribution function of the final crack depth [9 – 12]. Fatigue crack growth rate can be presented as a function of stress intensity factor (SIF) and stress ratio R. Therefore, it is a parameter in a number of models of fatigue crack growth, namely crack closure model [13], residual compressive stress based model [14, 15], a model with two driving force parameters [16, 17]. The answers to many questions, that are interesting to mechanics, can be obtained numerically. For instance, fatigue crack growth rate and parameters of the material were estimated by NN [18, 19].
The lifetime of a structural element is the number of cycles before its failure. The length of the crack a depends on the corresponding number of loading cycles N at the moment it was measured. The fatigue crack growth rate da/dN can be presented as a function of SIF range ΔK and the stress ratio R of the loading cycle. The model, which describes the fatigue crack growth (FCG) rate, can be set by the equation:

DOI 10.12776/ams.v24i1.966 p-ISSN 1335-1532
e-ISSN 1338-1156

$$\frac{da}{dN} = f\left(\Delta K, R\right) \tag{1.}$$

where: N is the number of loading cycles; a is the length of a crack; $f\left(\Delta K, R\right)$ is a function of two variables; $\Delta K = K_{max} - K_{min}$, where: K_{min}, K_{max} are the minimum and maximum stress intensity factors of the loading cycle, respectively; $R = \sigma_{min}/\sigma_{max}$, where σ_{min} and σ_{max} are the minimum and maximum stresses of loading cycle, respectively.
In general,

$$K = \sigma\sqrt{\pi a} \cdot Y \tag{2.}$$

where: Y is the correction function, which depends on the geometry of the structure and of the crack.
Walker's equation describes the crack growth at the second part of the FCG diagram [5]:

$$\frac{da}{dN} = C\left[\left(1-R\right)^{m-1} \Delta K\right]^{n}, R \geq 0 \tag{3.}$$

where: C, m, n are the parameters of the material, determined from the experiment.
NASGRO model can describe all parts of FCG diagram [20]. This model is given by the following equation:

$$\frac{da}{dN} = C_1\left[\ \Delta K_{eff}\ \right]^{n_1} \frac{\left[1-\dfrac{\Delta K_{th}}{\Delta K_{eff}}\right]^{p}}{\left[1-\dfrac{K_{max}}{K_{Jc}}\right]^{q}} \tag{4.}$$

where: C_1, n_1, p, q are the experimentally determined constants; $\Delta K_{eff} = K_{max} - K_{op}$ is the effective range of SIF; K_{op} is crack opening SIF; ΔK_{th} is the threshold SIF; K_{Jc} is the critical SIF determined with the help of critical J_{Ic}-integral.

1.1 Neural network approach

Neural networks provide an effective recognition of images, prediction, optimisation and control of processes, fit of linear and nonlinear functions.
In practice, NN are constructed like biological neural networks of a living organism. The basis of such networks is a neuron, which is a model of nerve cells of a brain, namely a biological neuron. First, NN are able to process information using a large number of neurons simultaneously. This enables to process information much faster. Second, NN can learn and generalise [21].
Each neuron's input, which receives a certain number of signals, is the output of another neuron. Every input signal is multiplied by the appropriate weight, similar to synaptic strength, after that all results are added, and then the level of neuron activation is determined (**Fig. 1**) [22].
Generally, a NN is a system of connected simple processors (neurons), which interact with each other. The vector $\mathbf{x} = (x_1, x_2, ..., x_n)$ arrives at an artificial neuron. Each signal is multiplied by the appropriate weights w_1, w_2, ..., w_n, and fed to the adder labelled Σ. Every weight corresponds to

the power of one biological synaptic connection. The adder, which belongs to the body of the biological element, adds weighted inputs, creating an output, called NET. Each neuron of the network deals only with the signals, which it receives periodically and with the signals, which it sends periodically to other neurons. After that activation function *F* transforms the signal NET and allows the neurons to receive the output neural signal OUT.

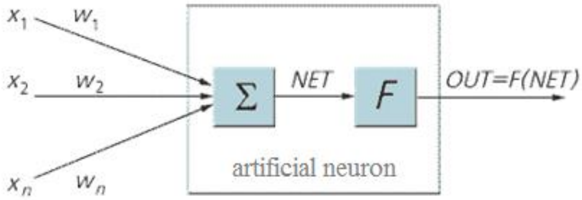

Fig. 1 Model of an artificial neuron [22]

Therefore, neurons, being connected in a large network, can answer a lot of interesting questions.

NN learn by calculating the weights between neurons. The most common method of NN learning is learning with feedback. This means that NN processes the data set and compares the actual result of its work with the expected result. Based on the difference between them, NN starts setting the weighted connections with the final layer of neurons, which continues until the difference between the results will be less than the preset number. Among different classifications, multilayer perceptron of direct distribution is the most popular architecture of NN, which learns based on back-propagation algorithm. Also, NN are able to generalize. Therefore, in the case of successful learning, the network will return the correct result based on the data that were not present in the training sample and also on the incomplete data [23]. While NN learns, the output θ_{output} is generally not equal to the target θ_{target} [23].

2 Experimental material(s) and methods

The fatigue crack growth rate was studied at STM-100 servo-hydraulic machine on the rectangular specimens. Each specimen has the following geometry: the width W was 100 mm, length L was 300 mm, and thickness B was 4 mm. Specimen contains a central through hole with a diameter *D* of 5 mm. The specimens were tested under regular loading. The wave form was sinusoidal. The test frequency *f* was 10 Hz. Stress ratios *R* were equal to 0; 0.3; 0.5; 0.7. The specimens were made of D16chT alloy plates ($\sigma_{0.2}$ = 300 MPa, σ_U = 430 MPa) according to GOST-25.506-85. The chemical composition of D16chT alloy is presented in **Table 1**.

Table 1 Chemical composition of aluminum D16chT alloy

Al	Cu	Mg	Mn	Fe	Si	Zn	Ni	Ti
90.8 – 94.7	3.8 – 4.9	1.2 – 1.8	0.3 – 0.9	0.5	0.5	0.3	0.1	0.1

One possible way of predicting the structural elements failure is to determine their lifetime using criteria of fracture mechanics.

In the present paper, the experimental FCG data in aluminum D16chT alloy were employed. These experimental data of FCG under regular loading and stress ratio *R* = 0; 0.3; 0.5; 0.7 were fitted by Walker equation and by the equation NASGRO (4.) (**Fig. 2**).

DOI 10.12776/ams.v24i1.966 p-ISSN 1335-1532
e-ISSN 1338-1156

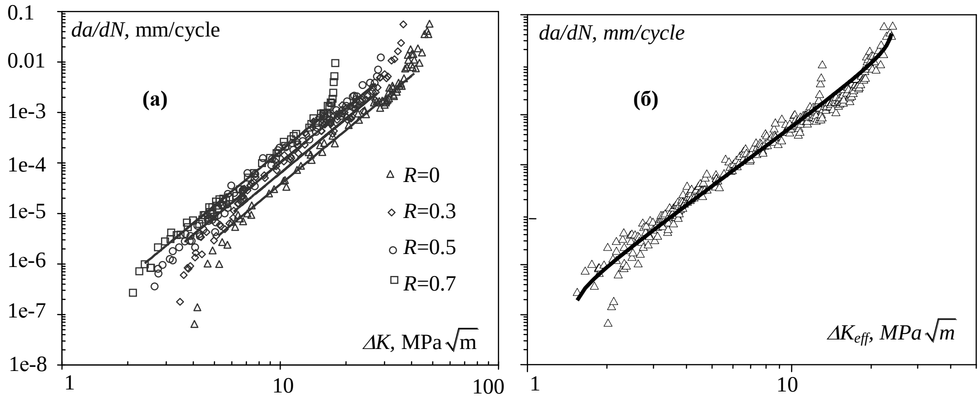

Fig. 2 The experimental data of FCG rate under regular loading and various load stress ratio in aluminum D16chT alloy and their fit by a) Walker equation, b) NASGRO equation

The parameters of the NASGRO equation are presented in **Table 2**.

Table 2 Equation NASGRO coefficients

C_1	n_1	q	p
7.18E–12	3.76	0.25	0.25

In the present study, the two models of NN were built. The experimental data of FCG diagram of aluminium D16chT alloy at stress ratio R = 0, namely, *da/dN* vs ΔK, were the NN input and output. A number of nonlinear activation functions model the neural activity. In this case, there was chosen the logistic function.

The input and output parameters were normalized. This can significantly increase the rate of NN learning algorithm convergence. Without the normalization, the error will increase.

The dataset contains 78 experimental values of ΔK and da/dN and 25 experimental values of N and a, respectively, of D16chT alloy at R = 0. These data were preliminary transformed using $\log_{10}$ function. The main parameters of NN are the topology of NN, learning algorithm and activation function of neurons. The sum of squares error function (SOS) was chosen [24]. The training method was Broyden–Fletcher–Goldfarb–Shanno (BFGS) [25]. The volume of training sample was equal to 70%, while the volume of test sample was equal to 30%. The stop parameter of learning network was number of epochs, which in this study was equal to 1000.

3 Results and discussion

The dependency of predicted FCG rate upon the stress intensity factor ΔK at R = 0 is shown in the **Fig. 3**. The prediction was performed using NN approach.

In the first case, a multilayer perceptron (MLP), consisting of one input, six hidden and one output layer (MLP 1-6-1), was obtained. Summary of neural network is presented in **Table 3.** As a result of the study, an average relative error of NN was obtained, which is 1.6%.

Fig. 4 shows the dependence of crack length a on the number of loading cycles N. In this case, MLP, consisting of one input, eight hidden and one output layer (MLP 1-8-1), was obtained. The

DOI 10.12776/ams.v24i1.966 p-ISSN 1335-1532
e-ISSN 1338-1156

prediction according to NN method is very close to the experimental data. As a result of the study, an average relative error of NN was obtained, which is 0.8%.
Summary of neural network is presented in **Table 4.**

Table 3 Summary of neural network

Network topology	**Training performance**	**Test performance**	**Training error**
MLP 1-6-1	0.995	0.997	0.008
Test error	**Error function**	**Hidden activation**	**Output activation**
0.007	SOS	Logistic	Logistic

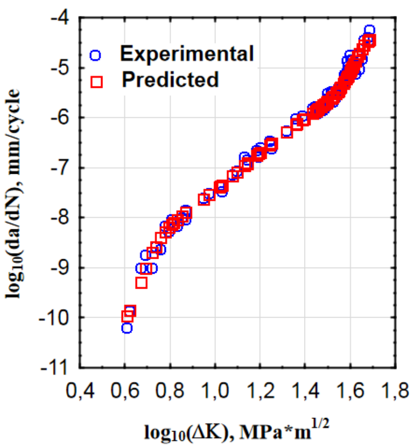

Fig. 3 The predicted FCG rate dependency on stress intensity factor ΔK at R = 0

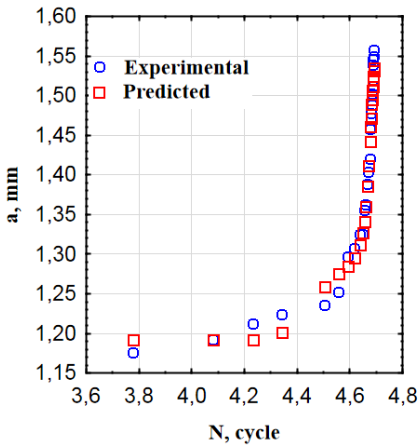

Fig. 4 Comparison of experimental crack length *a* on the number of loading cycles *N* and predicted by NN in D16chT alloy at R = 0, a_0 = 15 mm

Table 4 Summary of active network

Network topology	**Training performance**	**Test performance**	**Training error**
MLP 1-8-1	0.992	0.997	0.0001
Test error	**Error function**	**Hidden activation**	**Output activation**
0.00002	SOS	Logistic	Logistic

4 Conclusion

The FCG rate vs. ΔK and the crack length *a* vs. loading cycles number *N* in the aluminium D16chT alloy under the R = 0 were predicted by NN. The modelling results are in a perfect agreement with the experimental data. The test error was 0.007 and 0.00002, respectively.

DOI 10.12776/ams.v24i1.966
p-ISSN 1335-1532
e-ISSN 1338-1156

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DOI 10.12776/ams.v24i1.966 p-ISSN 1335-1532
e-ISSN 1338-1156