OPEN ACCESS

ACTA METALLURGICA SLOVACA

2020, VOL. 26, NO. 1, 31-33

TECHNICAL PAPER

PREDICTION OF FATIGUE CRACK GROWTH DIAGRAMS BY METHODS OF MACHINE LEARNING UNDER CONSTANT AMPLITUDE LOADING

Oleh Yasniy[1)], Iryna Didych[1)], Yuri Lapusta[2)]

[1)] *Ternopil Ivan Pul'uj National Technical University, Faculty of Computer-Information Systems and Software Engineering, Ternopil, Ukraine*

[2)] *University Clermont Auvergne, CNRS, SIGMA Clermont, Institut Pascal, F-63000 Clermont-Ferrand, France*

**Corresponding author: iryna_didych@ukr.net; tel.: +380972272074, Faculty of Computer-Information Systems and Software Engineering / Ternopil Ivan Pul'uj National Technical University, 46001, Ternopil, Ukraine*

Received: 03.01.2020
Accepted: 03.02.2020

ABSTRACT

Important structural elements are often under the action of constant amplitude loading. Increasing their lifetime is an actual task and of great economic importance. To evaluate the lifetime of structural elements, it is necessary to be able to predict the fatigue crack growth rate (FCG). This task can be effectively solved by methods of machine learning, in particular by neural networks, boosted trees, support-vector machines, and *k* -nearest neighbors. The aim of the present work was to build the fatigue crack growth diagrams of steel 0.45% C subjected to constant amplitude loading at stress ratios $R = 0$, and $R = -1$ by the methods of machine learning. The obtained results are in good agreement with the experimental data.

Keywords: fatigue crack growth, stress intensity factor, stress ratio, neural network, lifetime, machine learning

INTRODUCTION

Methods of strength and durability evaluation of the responsible structural elements often need the complicated calculations. Therefore, it is important to learn how to solve the problems of fracture mechanics by methods of machine learning, in particular, neural networks (NN), support-vector machines (SVM), *k* - nearest neighbors and boosted trees, which allow to achieve high accuracy of solutions [1 – 4] .

The structural elements are often fractured by fatigue, gradually accumulating damage. It is possible to observe a small crack which grows under loading. The fatigue crack is formed mainly at the stress concentrator, that is, the place of damage, which weakens the cross-section of the material. The crack grows as long as the material is able to withstand the loading. Therefore, the basic factors that influence the strength of structural elements are the surface defects of the parts, temperature and the environment during operation, the nature of loading and loading conditions [5].

It is known that, the basic parameters characterizing the fatigue crack growth (FCG) rate da / dN are the stress intensity factor ΔK (SIF) and the stress ratio R [6 – 9]. The fatigue crack growth diagram is usually built in double logarithmic coordinates $lg\ da/dN - lg\ \Delta K$. It has the form of an S-shaped curve limited on the left by the threshold SIF range ΔK_{th}, and on the right by the critical SIF ΔK_{fc} (cyclic fracture toughness). The threshold SIF ΔK_{th} is determined experimentally. It is an important characteristic of material resistance to fatigue fracture. The diagram consists of three regions: region *I* corresponds approximately to the rate $da / dN \approx 10^{-10}...10^{-8}$ *m/cycle*, in which the rate of the FCG increases significantly with a slight change of ΔK. Region *II* has the form of a straight line. The rate in this region is in the range of $10^{-8}...10^{-6}$ *m/cycle*. In particular, it is considered that here the crack grows evenly for each loading cycle. Region *III* is characterized by accelerated FCG and corresponds the values of $da/dN > 10^{-6}$ *m/cycle* [5]. At high SIF values, the rate of crack growth is extremely high.

P. Paris and F. Erdogan found out that the FCG rate for metallic materials can be determined by the SIF [10]. In particular, the formula obtained by them describes only the second region of the fatigue fracture diagram and does not take into account the influence of the stress ratio R on the FCG rate [11].

It is known that, with increasing R the FCG rate increases [12-13]. Therefore, the Walker's equation [2, 14] is used to describe the FCG rate taking into account the stress ratio R. However, these models don't take into account the variable regions of FCG. The Forman's equation [15-16] is used to describe the FCG curve with high ΔK values. NASGRO model can describe all parts of the FCG diagram [17].

MATERIAL AND METHODS

Machine learning: Background and Modeling

Progress of modern technology, in particular, high demands for accuracy and efficiency, have led to the creation of methods that solve a number of important tasks. Therefore, neural networks, support-vector machines, *k* - nearest neighbors, boosted trees are powerful algorithms of supervised learning, which can be used to predict FCG.

NN consist of a very large, though the finite, number of items that form the input layer, one or more hidden layers of computational neurons, and one output layer. The input signal is transmitted over the network in the direction from layer to layer [18]. Such networks are usually called multilayer perceptrons, which quite accurately solve different tasks. NN determines the relationship coefficients between neurons, whereas the computational power of a multilayer perceptron is in its ability to learn on its own experience and the backpropagation algorithm. The idea of this algorithm is based on an error correction. The basic parameters of NN are its topology, algorithm of training and the functions of the neurons activation. In the current study, the sum of squares error function (SOS) was chosen and the training method was Broyden–Fletcher–Goldfarb–Shanno (BFGS) [19-22]. The stop parameter of learning network was number of epochs, which in this study was equal to 1000.

The boosted trees algorithm reflects the natural thinking of human processes while making a decision [23]. The data obtained by building and using boosted trees are logical and easy for visualizing and interpreting. The algorithm of building the boosted trees structure consists of the creating and cancellation stages of trees. In creating trees, one chooses the criteria of splitting and termination of learning, whereas in the course of trees cancellation, some branches are removed. The boosted trees method is used when the results of one decision influence the next, in particular, for making consistent decisions.

The ideas of the methods of support-vector machines and *k*-nearest neighbors are the simplest [24]. In the first method, the data are presented as points in the space. The training data are split into two categories. The training algorithm creates a model attributing new data to a certain category. Geometrically, it looks as if we are trying to draw a straight line centrally between two sets. The nearest to this straight line points are the support vectors. The support-vector machines method, as any method of machine learning, has many parameters. In this case, the basis objects are the regularization parameter, the loss function, which treats as errors only predicted values deviating from the actual values by a distance greater than ε, and the kernel parameter γ. As the kernel function, the radial basis

function (RBF) is used. The method of *k*-nearest neighbor assigns a new object to the class that is the most common over *k*-nearest neighbors of the training sample. The distance between *k*-nearest neighbors is usually chosen as Euclidean. The aim of the learning process is to minimize the loss function, which should decrease. In the current study, the loss function was chosen as the mean squared error (MSE) [4]:

$$E = \frac{1}{n}\sum_{i=1}^{n}(y_{prediction} - y_{true})^2 \quad (1.)$$

where: $y_{prediction}$ [m/cycle] - the predicted element of sample
y_{true} [m/cycle] - the true value of the sample element
n - the volume of the training sample

Therefore, to train the networks one needs a dataset that contains as many observations as possible. In particular, it is advisable to experiment with different networks topologies to avoid getting the erroneous result in the case, if the learning process has found the local minimum of the target loss function. Therefore, if in the next experiment one observes underfitting, that is, the network issues a dissatisfactory result, we should try adding a new hidden layer. On the other hand, if the error started to grow, that is, overfitting occurs, one should try to remove one or more hidden layers.
The prediction error was Mean Absolute Percent Error (MAPE):

$$MAPE = 100\% \cdot \frac{1}{n}\sum_{i=1}^{n}\frac{|y_{true} - y_{prediction}|}{|y_{true}|} \quad (2.)$$

Experimental material(s) and methods

During the operation, a railway axle undergoes static and cyclic loading, including random loading, bending, as well as corrosive action of environment and climate temperatures.
The FCG rate in axle steel was predicted by methods of machine learning according to the experimental data of FCG obtained for 0.45% *C* steel and stress ratios R = 0, –1 [25]. The sample consisted of 200 elements, 70% of which were chosen randomly for the training sample and 30% were left for estimating the quality of predictions. The input parameters were the SIF range ΔK and the stress ratio R. The FCG rate da/dN under regular loading for the stress ratios R = 0, –1 was chosen as the output parameter. The input and output parameters were normalized using the decimal *log* function to decrease the prediction error.

RESULTS AND DISCUSSION

The dependences of the experimental FCG rates da/dN_{exp} on the predicted FCG values da/dN_{pred} for R = 0, –1 are shown in Fig. 1.

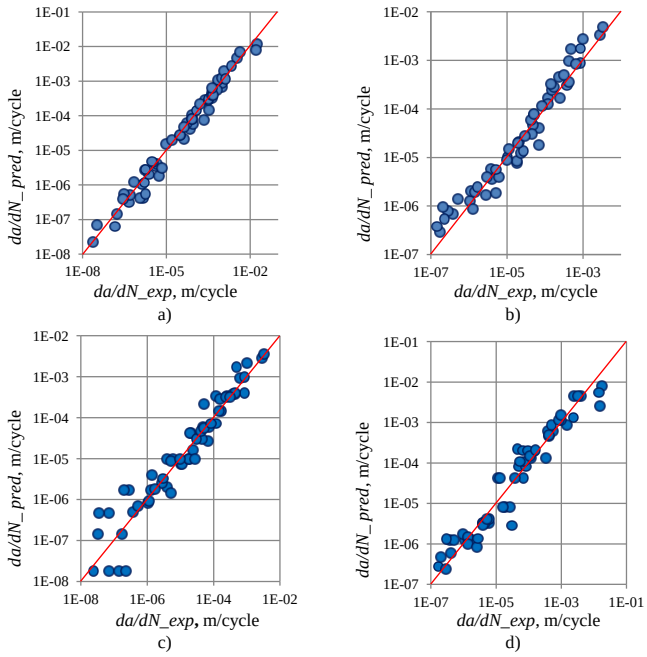

Fig. 1 The experimental (da/dN_{true}) and predicted (da/dN_{pred}) FCG rates for R = 0, –1 by methods of neural networks (*a*), support-vector machines (*b*), *k*-nearest neighbors (*c*), boosted trees (*d*)

There were built the experimental and predicted dependences of the FCG rate da/dN on the SIF range ΔK for R = 0, –1 using the methods of machine learning (Fig. 2).

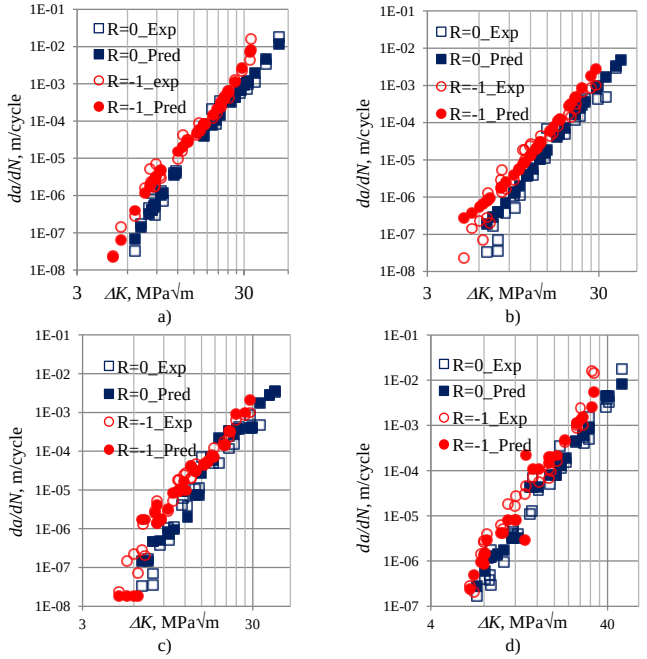

Fig. 2 The experimental da/dN_{true} and predicted da/dN_{pred} dependences of FCG rate on the KIN ΔK for R = 0, –1 by the methods of neural networks (a), support-vector machines (b), *k* - nearest neighbors (c), boosted trees (d)

The parameters of the constructed neural networks, support-vector machines, *k* - nearest neighbors and boosted trees are summarized in Tables 1−3.

Table 1 Parameters of Neural Network and Boosted trees

Stress ratio	Name of network	Function of hidden activation	Function of output activation	Number of repetitions (for boosted trees)
R = 0, –1	MLP 2-6-1	Logarithmic	Exponential	200

Table 2 Parameters of Support-Vector Machines

Stress ratio	Regularization parameter	Insensitive loss function ε	Kernel Parameter γ	Number of support vectors
R = 0; –1	10	0,1	0,5	30 (bounded by 19)

Table 3 Parameters of *k* -Nearest Neighbors

Stress ratio	Number of nearest neighbors	Distance
R = 0; –1	1	Euclidean

The error of the NN method for the test sample is 4.5%, the support-vector machines is 5.5%, the *k* - nearest neighbors is 5.5% and the boosted trees is 6.7%.

CONCLUSION

The predicted FCG rate data are in good agreement with the experimental ones. In the present study, the NN prediction accuracy is 95.5%, which is the best among the applied methods. Support-vector machines, *k* - nearest neighbors, and boosted trees also show good results in terms of accuracy. The methods of machine learning are powerful and efficient tools which allow evaluating the FCG behavior.

REFERENCES

[1] O. P. Yasnii, O. A. Pastukh, Yu. I. Pyndus, N. S. Lutsyk, I. S. Didych: Materials Science, 54(3), 2018, 43–48. https://doi.org/10.1007/s11003-018-0189-9

[2] I. Didych, O. Pastukh, Yu. Pyndus, O. Yasniy: Acta Metallurgica Slovaca, 24(1), 2018, 82-87. http://dx.doi.org/10.12776/ams.v24i1.966

[3] J. R. Mohanty, B. B. Verma, D. R. K. Parhi, D. R. Ray: Archives of Computational Materials Science and Surface Engineering, 1(3), 2009, 133–138.

[4] R. M. V. Pidaparti, M. J. Palakal: Journal of Aircraft, 32(4), 1995, 825-831. https://doi.org/10.2514/3.46797

[5] Yasnii P.V.: *Plastychno deformovani materialy: vtoma i trishchynotryvkist* [Plastically deformed materials: fatigue and fracture toughness], first ed., Lviv: Svit, 1998. [in Ukrainian]

[6] M. Klesnil, P. Lukas: Materials Science and Engineering, 9, 1972, 231-240. https://doi.org/10.1016/0025-5416(72)90038-9

[7] D. Kujawski, F. Ellyin: Engineering Fracture Mechanics, 28(4), 1987, 367-378. https://doi.org/10.1016/0013-7944(87)90182-2

[8] S. Dinda, D. Kujawski: Engineering Fracture Mechanics, 71(12), 2004, 1779-1790. https://doi.org/10.1016/j.engfracmech.2003.06.001

[9] D. Kujawski: International Journal of Fatigue, 23(8), 2001, 733-740. https://doi.org/10.1016/S0142-1123(01)00023-8

[10] P. C. Paris, F. A. Erdogan: Journal of Basic Engineering, 85(4), 1963, 528−533. https://doi.org/10.1115/1.3656900

[11] A. F. Siqueira, C.A.R.P. Baptista, O.L.C. Guimarães, C.O.F.T. Ruckert: Procedia Engineering, 2(1), 2010, 1905-1914. https://doi.org/10.1016/j.proeng.2010.03.205

[12] C. M. Hudson: NASA TN D-5390, 1969, 34.

[13] C. M. Hudson, J. T. Scardina: NASA TMX- 60125, 1967, 24.

[14] W. Zhang, H. Liu, Q. Wang, J. A. He: Materials (Basel), 10(7), 2017,689. https://doi.org/10.3390/ma10070689

[15] E. Richey III, A.W. Wilson, J.M. Pope, R.P. Gangloff: *Computer modeling the fatigue crack growth rate behavior of metals in corrosive environments*, first ed., NASA Contractor Report 194982, Virginia, 1994

[16] C. Proppe, G. Schuëller: In ICF10, Honolulu, USA, 2001

[17] [06.07.2017], www.nasgro.swri.org

[18] S. Haykin: *Neural Networks: A Comprehensive Foundation*, 2nd ed., Prentice Hall, 1999

[19] D. N. Richard: *Applied regression analysis*, third ed., John Wiley & Sons, New York, 1998

[20] I. Goodfellow, Y. Bengio, A. Courville: *Deep Learning*, The MIT Press, 2016

[21] Ph. D. Wasserman: *Neural Computing: Theory and Practice*, New York: Coriolis Group (Sd), 1989

[22] K. Gurney: *An introduction to neural networks*, first ed., Taylor & Francis Group, London, 1997

[23] T. M. Mitchell: *Machine learning*, McGraw-Hill Science/Engineering/Math, London, 1997

[24] A. Smola, S.V.N. Vishwanathan: *Introduction to Machine Learning*, Cambridge University Press, 2010

[25] O. Yasniy, Y. Lapusta, Y. Pyndus, A. Sorochak, V. Yasniy: International Journal of Fatigue, 50, 2013, 40–46. https://doi.org/10.1016/j.ijfatigue.2012.04.008