Fatigue Crack Growth Prediction via Artificial Neural Network Technique

Konstantin N. Nechval
Applied Mathematics Department
Transport and Telecommunication Institute
Lomonosov Street 1, LV-1019, Riga, Latvia
e-mail: konstan@tsi.lv

Irina Bausova, Daina Šķiltere
Cybernetics Department
University of Latvia
Raina Blvd 19, LV-1050, Riga, Latvia
e-mail: irina.bausova@lu.lv

Nicholas A. Nechval
Mathematical Statistics Department
University of Latvia
Raina Blvd 19, LV-1050, Riga, Latvia
e-mail: nechval@junik.lv

Vladimir F. Strelchonok
Informatics Department
Baltic Russian Institute
Lomonosov Street 4, LV-1019, Riga, Latvia
e-mail: str@apollo.lv

Abstract *–The artificial neural network (ANN) technique for the data processing of on-line fatigue crack growth monitoring is proposed after analyzing the general technique for fatigue crack growth data. A model for predicting the fatigue crack growth by ANN is presented, which does not need all kinds of materials and environment parameters, and only needs to measure the relation between a (length of crack) and N (cyclic times of loading) in-service. The feasibility of this model was verified by some examples. It makes up the inadequacy of data processing for current technique and on-line monitoring. Hence it has definite realistic meaning for engineering application.*

Keywords: Artificial neural network; Fatigue crack growth; On-line monitoring.

I. INTRODUCTION

In spite of decades of investigation, fatigue response of materials is yet to be fully understood. This is partially due to the complexity of loading at which two or more loading axes fluctuate with time. Examples of structures experiencing such complex loadings are automobile, aircraft, off-shores, railways and nuclear plants. Fluctuations of stress and/or strains are difficult to avoid in many practical engineering situations and are very important in design against fatigue failure. There is a worldwide need to rehabilitate civil infrastructure. New materials and methods are being broadly investigated to alleviate current problems and provide better and more reliable future services.

Often used approaches to evaluate fatigue crack response of materials are based on fracture mechanics [1-2] and damage mechanics [3]. Generally, the Paris–Erdogan formula [1-2]:

$$\frac{\mathrm{d}a}{\mathrm{d}N} = C(\Delta K)^m \qquad (1)$$

is used to analyze fatigue crack growth process data and predict remaining life, where $\mathrm{d}a/\mathrm{d}N$ is the crack growth per cycle, a is the crack length, N is the number of loading cycles, ΔK is the stress intensity range, and C and m are material constants that are determined experimentally. However, there are many factors influencing fatigue crack growth, including loading frequency, stress ratio, loading waveform, geometric size of components and specimens, composition, concentration and temperature of environment mediums, metallurgical composition and heat treatment of materials and many other factors.

Fatigue is a mechanism of crack growth. Fatigue cracks occur by cyclic loading under lower stress condition than the maximum allowable stress. The fatigue crack growing process is classified in three regions according to the change of fatigue crack growth rate, $\mathrm{d}a/\mathrm{d}N$.

Region I is a state of crack initiation. The value of the stress intensity factor (K) is as low as the fatigue threshold (K_{th}), and the crack growth rate is very slow.

In region II, the crack growth rate increases according to the crack length. The crack growth condition in region II is the so-called stable crack growth.

In region III, the crack-growth rate quickly increases and failure of the material occurs. It is called unstable crack growth.

The boundary between regions II and III is the transition point (K_{Tr}) [4], and the stress intensity factor at failure is known as the fracture toughness (K_C).

The stress intensity factor defines the amplitude of the crack tip singularity and is a function of the applied nominal stress (σ), the crack length (a), and a geometric function (F) [5]:

$$K = F\sigma\sqrt{\pi a}. \qquad (2)$$

Numerous analytical and empirical methods have been developed to explain fatigue crack growth and predict fatigue life, and most of these methods generally require extensive fatigue test data [6]. Fatigue tests are difficult, time-consuming and costly, and in general there are no accepted criteria that can satisfy design requirements.

In recent years, an artificial neural network (ANN) has emerged as a new branch of computing, which tries to mimic the structure and operations of biological neural systems. An ANN is able to learn by example and does not have to know the theory behind a phenomenon. This quality is useful to describe problems where the relationships of inputs and outputs are not clear enough or the solutions are not easily formulated in a short time.

Pidaparti and Palakal [7] developed an ANN model to represent the fatigue crack growth behavior under spectrum loading. The inputs were information about the features in the spectrum loading and crack growth behavior, and the output was the corresponding loading cycles. A material parameter network for modified Paris Law was also developed in their study.

Haque and Sudhakar [8] described an ANN model to analyze corrosion fatigue crack growth rate in dual phase steel. The inputs were the stress intensity factor range, ΔK, and volume percent of martensite content and outputs were crack growth rate. Six groups of da/dN versus ΔK relationship corresponding to different martensite contents were trained, and the neural network (NN) analysis provided a good match with the experimental data.

Aymerich and Serra [9] used a neural network to predict fatigue strength of a graphite-peek composite with 63% of fiber content. The input parameters were the number of cycles at failure and the stacking sequence of the laminate. The neural network used showed the capability of predicting fatigue life for laminated composites.

Lee et al. [10] investigated the feasibility of using ANN to predict fatigue lives of five carbon and one glass fiber-reinforced laminates. A three-parameter Weibull distribution was used to estimate the number of cycles for various levels of failure probability from experimental data. The peak stress, minimum stress and the failure probability level were the most appropriate inputs from the root-mean-square trials. They applied ANN to train fatigue data for four CFRP systems to predict the response of HTA/982. The results showed the log-life was well within the normal experimental spread of data for composite materials.

Artymiak et al. [11] applied ANN to estimate finite life fatigue strength and fatigue limit. The notch factor, tensile strength, yield strength and nominal stress were employed as input parameters. The output parameter was the endurable number of load cycles. The results showed that NN was capable of describing the expected S–N curve.

Pleune and Chopra [12] studied the effect of light water reactor coolant environments on fatigue resistance of plain carbon steel and low alloy steel using ANN. The authors showed that ANN had a great potential of predicting environmentally influenced fatigue. The ANN output of the effects of sulfur content, strain rate and temperature on the fatigue lives in air showed good agreement with the statistical model.

Venkatesh and Rack [13] developed an ANN for predicting the elevated temperature creep fatigue behavior of Ni-based alloy INCONEL 690. Five extrinsic parameters (strain range, tensile strain rate, compressive strain rate, tensile hold time, and compressive hold time) and one intrinsic parameter (grain size) were training inputs. Fatigue life defined by complete fracture of the specimen was the predicted output. Close agreement between experimental and predicted life for the test points was observed with the NN approach.

Fujii et al. [14] used a Bayesian NN for analysis of fatigue crack growth rate of nickel-based super-alloys. The database consisted of 1894 combinations of fatigue crack growth and 51 inputs. The output was the logarithm of fatigue crack growth rate. A group of seven of the best models showed minimum test error and provided a close agreement with experimental data. This NN method demonstrated the ability of revealing new phenomena in cases where experiments cannot be designed to study each variable in isolation.

Biddlecome et al. [15] developed an optimization based NN method to predict fatigue crack growth and fatigue life for multiple site damage panels. In the NN optimization each neuron represented a hole and contained pertinent information relevant to existing crack conditions. As the crack extended, the neuron gained energy. A set of energy functions was developed to define how the neurons gain energy as the system begins to converge to an optimal solution. The proposed NN was able to detect a panel failure and provide the path of crack propagation.

Kang and Song [16] determined the crack opening load the input of 100 data points of the differential displacement signal on the loading stage. The accuracy and precision of the prediction of crack opening point by the NN were estimated for 42 different cases, and the results were in good agreement with experiments.

Al-Addaf and El Kadi [17] used ANN to predict fatigue life of unidirectional glass fiber/epoxy composite laminates with a range of fiber orientation angles under various loading conditions. The best set of inputs was the fiber orientation angle, stress ratio and maximum stress. The data points for different fiber orientation angles and load ratios were tested. Although a small number of experimental data points were used for training, the results were comparable to other current methods for fatigue life prediction.

Han et al. [18] discussed an ANN method aided by a special learning set to calculate the fatigue life of flawed structures. The input data included dimensions of the fracture section, defect information and stress value. The learning results from calculated fatigue life of the back propagation (BP) network alone and from BP network with a special learning set were compared with the experimental fatigue life. The results showed the feasibility of a NN in treating fatigue life calculation problems of flawed structures both for the special learning set and normal learning set.

Choi et al. [19] presented models to predict the fatigue damage growth in notched composite laminates using an ANN, which was found to work better than the Power Law model as a predictive tool for split growth. ANN models showed the ability to capture more of the nonlinear characteristics. The linear cumulative damage rule worked well when combined with ANN models.

Smith et al. [20] explored the use of the ANN to predict the plate end debonding in FRP-plated RC beams. The ANN trained with existing data showed relatively accurate predictions, and indicated capability to be applied in parametric study and structural design to provide new insights and predictions.

In this paper, the authors attempt to forecast what will happen to the structure according to the current work condition, and to predict the fatigue life of structures during the continuous learning process by ANN technique.

II. Artificial Neural Networks

An ANN can be considered as a black box that has the capacity to predict an output pattern when it recognizes a given input pattern [21].

The neural network must first be "trained" by processing a large number of input patterns and evaluating the output that resulted from each input pattern. Once trained, the neural network is able to recognize similarities when presented with a new input pattern, and is able to predict an output pattern. The ANN models are composed of various nonlinear computational elements interrelated through a network of connections.

ANN can be categorized by learning, topology or data types. Some ANNs are classified as feedforward while others are recurrent depending on how data is processed through the network. By their learning rules, they can be supervised training ANNs or unsupervised or self-organizing ANNs.

Among the various classifications, multi-layer perceptron (MLP) is the most popular and widespread ANN architecture for engineering problems. MLPs are generally used with feedforward neural networks trained with the standard backpropagation algorithm. MLPs are supervised networks that require training to produce a desired response. They learn nonlinear function mappings and are capable of learning a rich variety of nonlinear decision surfaces. Nonlinear functions can be represented by multi-layer perceptrons with units that use nonlinear activation functions.

III. Development of an ANN Model

The purpose of the ANN is to provide a mathematical structure that can be trained to map a set of inputs to a set of outputs. Fig. 1 illustrates an ANN identical to the one used in this study.

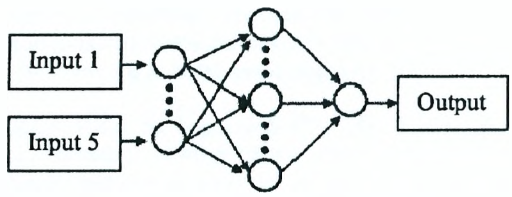

Fig. 1. Artificial neural network.

This ANN consists of the input layer, one hidden layer, and the output layer. Each layer consists of nodes or neurons. Each node has a sigmoid activation function associated with it. Each interconnection between the nodes has a weight associated with it. The nodes in the hidden and output layers sum the weighted inputs from the sending nodes and apply this net input to the activation function. The output of the network is determined by applying the inputs and computing the output from the various nodes activations and interconnection weights. The hidden layer in the ANN shown in Fig. 1 has 14 neurons. In this study, as a training algorithm of the ANN for the stress intensity factor, an error back propagation (BP) with a momentum updating algorithm was used to train the ANN [22-23]. Although a simple BP algorithm has been used widely, it has some important drawbacks. Firstly, the learning rate should be chosen to be small enough to provide minimization of the total error function. However, for a small learning rate, the learning process becomes very slow. On the other hand, large values of the learning rate correspond to rapid learning, but lead to parasitic oscillations, which prevent the algorithm from converging to the desired solution. Moreover, if the error function contains many local minima, the network might get trapped in some local minimum, or get stuck on very flat plateaus [23].

The error back propagation with momentum updating algorithm has some advantages compared with simple error back propagation and consists of initializing the network with random activation levels and weights. Training is accomplished by adjusting the weights to minimize the error between the predicted ANN outputs and the observed values (the stress intensity factor). The activations and weights are adjusted by using a backward momentum term, which may improve the convergence rate and the steady state performance of the algorithm. The ANN shown in Fig. 1 was constructed using MATLAB software [24].

In this study, the fatigue crack growth data were divided into two groups, a training set and a test set. The training set of the fatigue crack growth data was used to train the network and the trained ANN was evaluated with the test set, exclusively. The performance of the trained ANN was tested by evaluating the coefficient of determination (R^2), standard error of calibration (SEC), standard error of prediction (SEP), and bias [25].

The coefficient of determination, R^2, is used to measure the closeness of fit and can be defined as:

$$R^2 = 1 - \frac{\sum (y - y_p)^2}{\sum (y - y_m)^2}, \tag{3}$$

where y is the actual measured value, y_p is the predicted value by the trained ANN and y_m is the mean of the y values. Clearly, the coefficient of determination is a reasonable measure of the closeness of fit of the trained ANN, since it equals the proportion of the total variation in the dependent variable, in this study the number of cycles that is explained by the trained ANN. The coefficient of determination cannot be greater than 1. A perfect fit would result in R^2=1, a very good fit near 1, and a poor fit would be near 0.

The SEC measures the scatter of the actual measured values (y) about the values calculated by the trained ANN (y_p) and can be defined as [25]:

$$\mathrm{SEC} = \left[\sum \frac{(y - y_p)^2}{n - p - 1} \right]^{1/2}, \tag{4}$$

where n is the number of data and p is the number of variables.

The trained ANN was then used to predict the number of loading cycles using the measured data that were not used in training the ANN.

The bias and SEP represent the mean and standard deviation of the differences between the actual measured values of the number of loading cycles and the predicted values of number of loading cycles, and are given by the following equations [26]:

$$\mathrm{bias} = \frac{\sum (y - y_p)^2}{n}, \tag{5}$$

$$\mathrm{SEP} = \left[\sum \frac{[(y - y_p) - \mathrm{bias}]^2}{n - 1} \right]^{1/2}. \tag{6}$$

IV. EXAMPLE

The material used for the present example was 0Cr18Ni9 austenitic stainless steel. Center crack tension specimens were machined for tests. Cyclic loading with sinusoidal waveforms at 5 Hz was used in tests. The pre-made crack length was 7.0 mm. Crack growing length was monitored by microscope.

The testing results are shown in Table 1. Initial five couples of crack length and cyclic times of loading were selected in table as primary data sets before predicting the next. But only the next N is better-estimated value, and its follows only can be for reference.

Table 1. Data of specimen

a (mm)	N (test)	N (prediction)	Absolute error
7.000	0	–	–
7.810	6080	–	–
8.570	11520	–	–
9.330	16580	–	–
10.05	20680	–	–
10.58	23680	23715	35
11.14	26540	25845	695
11.88	29480	28323	1157
12.60	32500	30910	1590
13.20	34760	33543	1217

It will be noted that N (prediction) is the value predicted by the forward five data sets.

From Table 1 we can see that the absolute error is in the normal region with the stochastic of fatigue problem. The feasibility is shown with better calculating result.

The behavior of fatigue crack growth can be divided into two stages: stable crack growth stage and accelerating crack growth stage. To avoid damage to the testing machine caused by specimens fracturing, the upper tests were all stopped in the stable crack growth stage. According to the form of a~N curve, we can judge whether the crack state is in accelerating growth stage or not by the following criterion: when continuous several estimated values are clearly bigger than measure values. This means the crack in the component may have been in accelerating stage. Its physical meaning is that the slope of the estimated curve is clearly a lot bigger than that of real curve (Fig. 2). This is an alarm for the supervisors that the component will possibly fracture, and some protective measures should be taken.

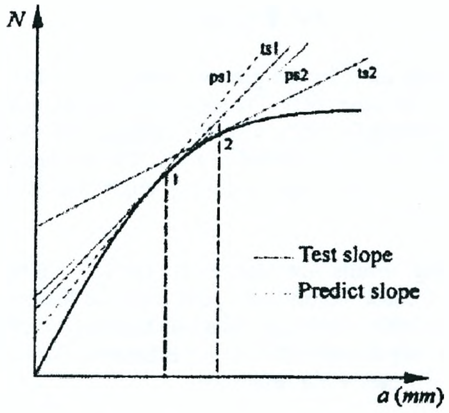

Fig. 2. Phisical meaning of the criterion.

Using on-line data processing method the risk of equipment damage before reaching its design life is cut down, and it is a good monitoring method for extending in-service equipment, too. So material behaviors are brought into full play. It makes up for the inadequacy of causing material waste by considering safety factor in design.

Applying ANN technique to predict the fatigue life of structures, complex calculation of ΔK and determination of the constant C, m are omitted, environment factor need not be thought about, and Paris formula need not be revised and integrated. All these make the predicting method simple. It especially fits for engineering application.

ANN technique for data processing uses only one characteristic parameter. It does not consider the effect of the other parameters, in fact, the effect of all parameters were included in $a \sim N$ relation. So this method focuses on certain specimens, eliminating the effect of other cases for estimating the result.

With the different effect of the changeable surroundings to the same component, the stable crack growth rate will change relevantly. So the constants C and m in Pairs formula should often change, which makes Pairs formula difficult to predict the correct remaining life. But they have the same loss-stability criterion to judge whether the crack is in accelerating growth stage or not by ANN technique. However, model of ANN can follow the change, and make the right prediction. So this technique is especially fit for on-line fatigue crack growth monitoring.

V. Conclusion

An ANN technique for data processing of on-line fatigue crack growth monitoring was developed, which has a clear criterion and makes users employ it easily without enough special knowledge. But as an engineering technique it should be further tested and verified in factories.

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