International Journal of Fatigue 33 (2011) 313–322

Contents lists available at ScienceDirect

International Journal of Fatigue

journal homepage: www.elsevier.com/locate/ijfatigue

A neural network approach to fatigue life prediction

João Carlos Figueira Pujol [a,*], João Mário Andrade Pinto [b]

[a] Cento de Desenvolvimento da Tecnologia Nuclear, Brazil
[b] Universidade FUMEC, Belo Horizonte, Brazil

ARTICLE INFO

Article history:
Received 8 January 2010
Received in revised form 31 August 2010
Accepted 6 September 2010
Available online 15 September 2010

Keywords:
Fatigue
Lognormal distribution
Step-stress
Neural networks
Evolutionary computation

ABSTRACT

In this work, a novel approach to fatigue life prediction under step-stress conditions is introduced, where the cumulative distribution function for the failure of components was implemented by means of a neural network. The model was fit to experimental data on the fatigue life of steel under step-stress conditions. For comparison, a standard approach based on the lognormal distribution function was also implemented and fit to the same experimental data. Both models were optimized by evolutionary computation, using a maximum likelihood estimator. The Kolmogorov–Smirnov test was applied to compare the results of the new approach to those obtained with the lognormal distribution function.

1. Introduction

To predict failure by mechanical fatigue, the response of materials to the several loads expected to occur during the lifetime of components must be considered. As fatigue properties cannot be deduced from static mechanical properties only, they must be directly measured by specifically designed mechanical experiments, where a constant alternate stress S is cyclically applied to the material until failure. These experiments allow the construction of the well-known S–N curves, which express the lifetime of the material as measured by the logarithm of the number of cycles N, plotted against the logarithm of S. However, in the majority of the situations, mechanical components are submitted to more than one level of stress during their lifetime. Such load variations make it inadequate to use a single S–N curve for fatigue life prediction, since these curves are built under constant stress conditions. Cumulative damage models [1], such as the cumulative exposure model [2–4], are commonly used in this situation.

To complicate matters, random factors lead to great variability in the results of fatigue tests, and a probabilistic approach is necessary to account for the uncertainties present in the lifetime of structures [1,5,6]. Usually, these probabilistic approaches are built over standard statistical distributions. However, there are many real-world situations where significant deviations from these distributions may occur. In this context, a novel approach is proposed where a statistical distribution is built by means of an artificial neural network.

Artificial neural networks, or neural networks (*NNs*) for short, are a class of computational tools inspired by the biological nervous system [7]. They consist of partially or fully interconnected simple processing units called neurons. The neuron is a nonlinear unit that receives input signals from other units or from the environment (the space of input data relevant to the problem at hand), yielding an output. The signals received by a neuron are modulated by real numbers called synaptic weights (or simply weights). By adjusting the weights through a training process, *NNs* can learn underlying relations from a given set of representative examples to solve a particular problem instead of following a predefined set of rules. In feedforward networks, the neurons are usually arranged in layers: input and output layers, which interact with the environment, and one or more layers of hidden neurons, which do not have contact with the environment. There is a definite order of evaluation of the neurons, the network receives the input signals, propagates them through all the layers, and returns signals to the environment through the output neurons (see Fig. 1). Feedforward networks with a single hidden layer and a continuous nonlinear activation function are universal approximators, in that any continuous function can be approximated to any degree of accuracy if a sufficient number of hidden neurons is provided [8]. Neural networks have been successfully applied to a number of problems in many fields of science and engineering [9].

Neural networks have also been used for fatigue life prediction. The most direct approach has been to use material properties and

* Corresponding author. Address: Rua Itapitocai 70 apt, 702-90820120 Porto Alegre-RS, Brazil. Tel.: +55 31 30693237; fax: +55 31 3069 3257.

E-mail addresses: jbhpoa@yahoo.com.br, pujol@cdtn.br (J.C. Figueira Pujol), jmap@fumec.br (J.M. Andrade Pinto).

URLs: http://www.cdtn.br (J.C. Figueira Pujol), http://www.fumec.br (J.M. Andrade Pinto).

0142-1123/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.ijfatigue.2010.09.003

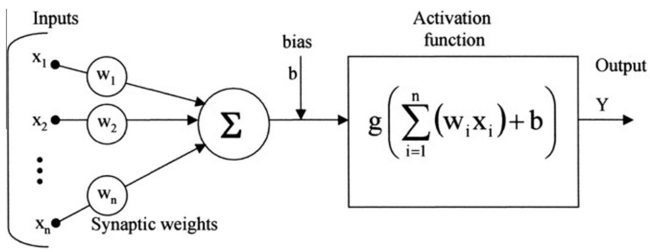

Fig. 1. The neuron is a nonlinear unit that receives input signals from neurons in the previous layer or from the environment, and transfers output signals to neurons in the next layer or back to the environment.

experimental conditions as input data to a neural network, whose output is the number of cycles until failure. For example, Mathur et al. [10] demonstrated the ability of neural networks to predict fatigue life. In this case, the input to the neural net include: volume fraction, tensile modulus, tensile strength, applied load parameters, probability of failure, statistical parameters of fatigue life, etc. The output is the logarithm of the number of fatigue life cycles. Troudt and Merril [11] implemented a feedforward neural network for diagnosis and prognosis purposes. The neural network is supposed to evaluate degradation on components under mechanical stress in real time to predict when they will eventually fail. Alternatively, the neural network can be combined with other models to estimate fatigue life. For example, Artymiak et. al [12] trained four multilayered feedforward neural neural networks to build *S–N* curves. Vassilopoulos et al. [13] proposed to predict fatigue life by using a feedforward neural network to build constant life diagrams. Kang et al. [14] combined a feedforward neural network with the critical plane method to predict fatigue life. Another strategy has been to use neural networks to estimate the fatigue crack growth rate [15–17]. Neural networks have also been applied to address the stochastic aspects of the fatigue phenomenon. For example, Janezic et al. [18] implemented a feedforward neural network to estimate the parameters of the Weibull distribution. Similarly, Bučar et al. [19] designed a probability density function using a weighted sum of Weibull density functions modulated by real-valued coefficients, whose values are determined by a feedforward neural network. The list of such applications is endless (see [20–22] for additional material on the subject).

The next logical step would be to replace the standard statistical distributions with a probability distribution built from scratch. That is the proposal of the present work, to use a feedforward neural network to compute the probability that a component submitted to a specified level of stress fails until a specified number of cycles. The numerical model was tested on fatigue data collected from step-stress experiments carried out on steel specimens. The new paradigm was compared to a standard statistical approach based on the lognormal distribution.

This work is organized as follows: in Section 2 the experimental setup is described, Section 3 describes the step-stress model, in Section 4 the maximum likelihood is discussed, in Section 5 the optimization procedure is introduced, in Section 6 the approach using a standard statistical distribution function is described, in Section 7 the approach based on the neural network is presented and, in Sections 8 and 9, results comparing both methods are reported and discussed. Finally, Section 10 concludes and provides suggestions for further research.

2. Description of the fatigue experiments

Flex-rotational fatigue tests were carried out on *SAE 8620* steel specimens [23] (chemical composition and mechanical properties of the material are shown in Tables 1 and 2, respectively). The test

Table 1
Chemical composition of the *SAE 8620* steel [45].

Element	% Min.	% Max.
C	0.18	0.23
Si	0.15	0.30
Mn	0.70	0.90
Cr	0.40	0.60
Ni	0.40	0.70
Mo	0.15	0.25
P	<0.03	
S	<0.04	
Co	<0.1	
Pb	0	0.15
Cu	<0.3	
Al	<0.1	
U	<0.1	
W	0	0.1

Table 2
Mechanical properties of the *SAE 8620* steel with 95% confidence level [45].

Property	Value
Yield strength – $\sigma_{0.2}$ (MPa)	370 ± 10
Tensile strength (MPa)	602 ± 24
Elongation (%)	21 ± 2
Reduction of area (%)	39 ± 1
Breaking strength (MPa)	432 ± 19
Endurance limit (MPa)	194 ± 5

specimens were designed and manufactured according to suggestions by Cazaud [24] and the ASTM standards [25], to produce specimens whose geometry and smoothness do not interfere with the test results (see Fig. 2). Moreover, the experiments were carried out under refrigeration provided by natural water. Each specimen was submitted to three levels of stress, viz.: S_1, S_2 and S_3. S_1 was set to 258 MPa during 35,000 cycles and S_2 = 238 MPa was applied for 65,000 cycles. S_3 was set to 20 values selected at regular intervals of 10 MPa to cover a broad load range below the yield strength of the material (see Table 2). S_3 was applied until failure or until the machine reached 5×10^6 cycles, a condition that qualifies as a type I censoring mechanism [26].

The test suite was planned according to the *S–N–P* curves of the material (see Fig. 3). In preliminary experiments (not reported in the paper), five specimens were submitted to a step-stress condition with S_1 set to 258 MPa for 50,000 cycles, and S_2 set to 238 MPa for 100,000 cycles. A third level of stress was then applied to each of the five specimens by setting S_3 to 218 MPa, 198 MPa, 178 MPa, 158 MPa and 148 MPa. The specimens submitted to S_3 = 158 MPa and 158 MPa failed around 1.0×10^6 cycles. Even with the great dispersion expected in fatigue test results, such load configuration would probably not allow censoring (an undesirable simplification of the model). Therefore, the number of cycles for the application of the first and the second levels of stress were reduced to 35,000 cycles and 65,000 cycles, respectively.

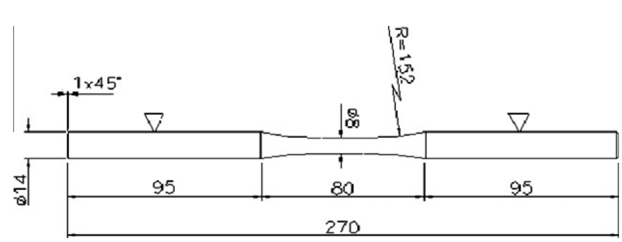

Fig. 2. Geometry of the specimens used in the fatigue tests [45].