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Prediction of corrosion–fatigue behavior of DP steel through artificial neural network

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Abstract

Corrosion–fatigue crack growth (da/dN) of dual phase (DP) steel was analyzed using an artificial neural network (ANN) based model. The training data consisted of corrosion–fatigue crack growth rates at varying stress intensity ranges (ΔK) for martensite contents between 32 and 76%. The ANN model exhibited excellent comparison with the experimental results. Since a large number of variables are used during training the model, it will provide a reliable and useful predictor for corrosion–fatigue crack growth (FCG) in DP steels. © 2001 Elsevier Science Ltd. All rights reserved.

Keywords: Corrosion–fatigue; Artificial neural network (ANN); Dual phase (DP) steel; Stress intensity range; Martensite

1. Introduction

Neural computing is a relatively new field of artificial intelligence (AI), which tries to mimic the structure and operation of biological neural systems, such as the human brain, by creating an Artificial Neural Network (ANN) on a computer. These ANNs are modeling techniques that are especially useful to address problems where solutions are not clearly formulated [1] or where the relationships between inputs and outputs are not sufficiently known. Artificial Neural Networks have the ability to learn by example. Patterns in a series of input and output values of example cases are recognized. This acquired 'knowledge' can then be used by the Artificial Neural Network to predict unknown output values for a given set of input values. Alternatively, Artificial Neural Networks can also be used for classification. In this case, the Artificial Neural Networks' output is a discrete category to which the item described by the input values belongs. ANN are composed of simple interconnected elements called processing elements (PEs) or artificial neurons that act as microprocessors. Each PE has an input and an output side. The connections are on the input side corresponding to the dendrites of the biological original and provide the input from other PEs. The connections on the output side correspond to the axon and transmit the output. Synapses are mimicked by providing connection weights between the various PEs and transfer functions or thresholds within the PEs. The activation of the PE results from the sum of the weighted inputs and can be negative, zero, or positive. This is due to the synaptic weights, which represent excitatory synapses when positive ($w_i>0$) or inhibitory ones when negative ($w_i<0$). The PEs output is computed by applying the transfer function to the activation, which as a result of the synaptic weights, can be negative, zero, or positive. The type of transfer function to be used depends on the type of ANN to be designed. Various literatures [1–3] are available on artificial neural network, and their applications.

This paper describes the prediction of corrosion–fatigue crack growth rate in dual-phase (DP) steels using artificial neural network. The DP steel, used in the present investigation, is primarily a low carbon steel with micro-alloying additions of vanadium and boron. These steels are the good substitutes for high strength low alloy (HSLA) class of steels, at a lower cost. The

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DP steels were being designed for use in a corrosive environment, especially in earthmoving machineries, as structural parts. Hence, the dynamic response of DP steel in a corrosive environment had to be addressed. Furthermore, this data will be useful for some of their potential application areas like gas pipelines, chemical industries and defense. There are only a few literatures [4–6] available on corrosion–fatigue behavior in DP steels. Recent experimental investigations [5,6] on the current topic yielded some very useful results. Analysis of this practically useful fatigue data through analytical tools such as 'Artificial Neural Network' will be highly beneficial both in terms of time and simplicity of complex data (for example, FCG rate prediction can be made for any combination of parameters/variables: ΔK, %martensite, da/dN, ΔK_{th}, etc.). The aim of this paper, is therefore, to apply an ANN based model for the corrosion–fatigue behavior in DP steels.

2. Proposed ANN model development methodology

Back-propagation networks are most useful for problems involving forecasting and pattern recognition. Back-propagation training is one of the most popular methods for training ANNs with back-up/historical data [2]. 'NeuroShell 2' software [3] was used in the present analysis to implement back-propagation training. In essence, back-propagation training adapts a gradient–descent approach of adjusting the ANN weights. During training, an ANN is presented with the data of thousands of times (called cycles). After each cycle, the error between the ANN outputs and the actual outputs are propagated backward to adjust the weights in a manner that is mathematically guaranteed to converge [2].

2.1. Training ANN model

The major property that deems ANNs superiority to algorithmic and other network based systems is their ability to be trained on historical information as well as real-time data. Training is the act of continuously adjusting their connection weights until they reach unique values that allow the network to produce outputs that are close enough to the desired outputs. The accuracy of the developed model, therefore, depends on these weights. Once optimum weights are reached, the weights and biased values encode the network's state of knowledge. Thereafter, using the network on new cases is merely a matter of simple mathematical manipulation of these values.

Training data (Fig. 1) for the development of the neural network model was obtained from the recently published research work [5]. Fatigue crack growth (FCG) tests were carried out as per ASTM standard E647. The data consisted of da/dN at ΔK ranges between 5 and 16 $\mathrm{MPa}\sqrt{\mathrm{m}}$ for DP steel with martensite contents in the range of 32–76%. The input parameters—the stress intensity factor (ΔK), and volume % of martensite content (%M), and the output–fatigue crack growth rate (da/dN) were used during the network training.

2.2. Neural network architecture used

The proposed ANN model was developed using a back-propagation architecture with three layers jump connections [3], where every layer (slab) was connected or linked to every previous layer. The number of hidden neurons, for which the Gaussian activation function, $\{\exp(-x^2)\}$ was used, was determined according to the following formula [3]:

$$\#\text{ of hidden neurons}=0.5(\text{Inputs}+\text{Outputs})+\sqrt{(\#\text{ of training patterns})}$$

Given the properties of the training data used: 2 inputs, 1 output, and 49 training patterns—the number of processing elements was determined to be 9 (actual 8.5). The other network parameters were set as follows:

Learning rate: 0.10
Momentum: 0.10
Initial connection weights: 0.30
Learning stopping criteria: 20,000 epochs

2.3. System performance

The neural network used for the presented model demonstrated an excellent statistical performance [3] as shown in Table 1 for the training model and the evaluation of the trained model. In Table 1, R^2 is a statistical indicator usually applied to multiple regression analysis and it is expressed [3] as:

$$R^2=\frac{SSE}{SS_{yy}}$$

Where, $SSE=\sum(y-\hat{y})^2$, $SS_{yy}=\sum(y-\bar{y})^2$, y is the actual value, $\hat{y}$ is the predicted value of y, and $\bar{y}$ is the mean of the y values.

Fig. 2 represents the graphical comparisons between the actual experimental data and the network predicted output. It clearly demonstrates an excellent statistical performance.

2.4. Evaluation of the trained ANN model

Other experimental data [5,6] were then used to test the trained ANN model. In particular, the data were selected for the lower percent of martensite contents of 38% and higher percent of martensite contents of 61%.

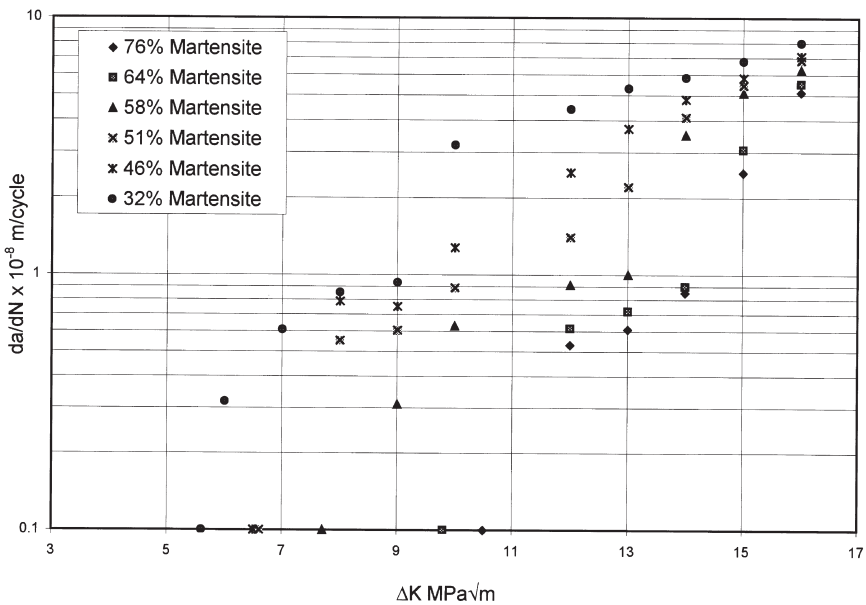

Fig. 1. Experimental data [5,6] used for network training.

Table 1
Network system performance

	Network training	Network evaluation
R^2	0.9898	0.9911
Minimum absolute error (mm/cycle)	0.002×10^{-5}	0.014×10^{-5}
Maximum absolute error (mm/cycle)	0.614×10^{-5}	0.540×10^{-5}

The comparative evaluation between the actual experimental data and the ANN output is shown in Fig. 3, which clearly shows a high degree of coherency.

3. Conclusions

Prediction of corrosion–fatigue behavior through artificial neural network provided an excellent matching with the experimental findings. ANN based model can be used with a high degree of accuracy and reliability,

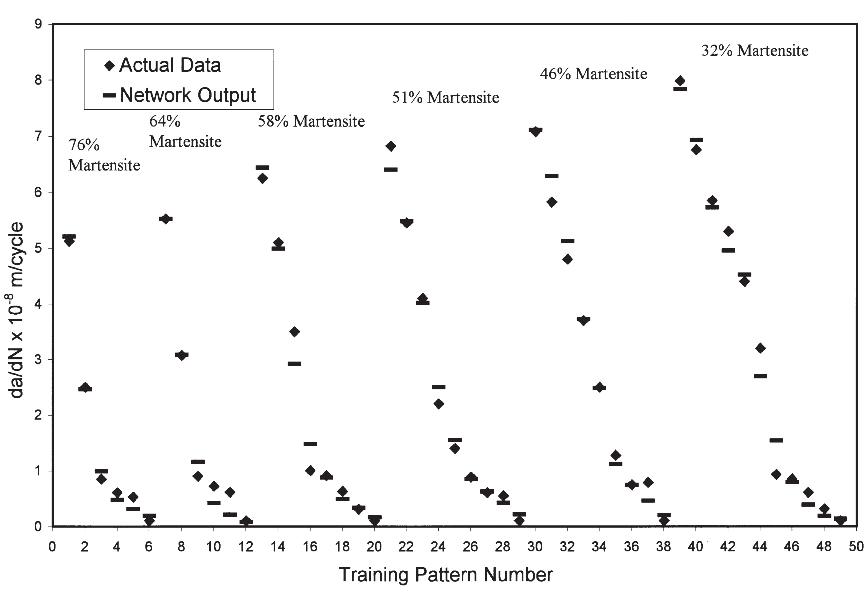

Fig. 2. Actual and network da/dN vs training data pattern numbers.

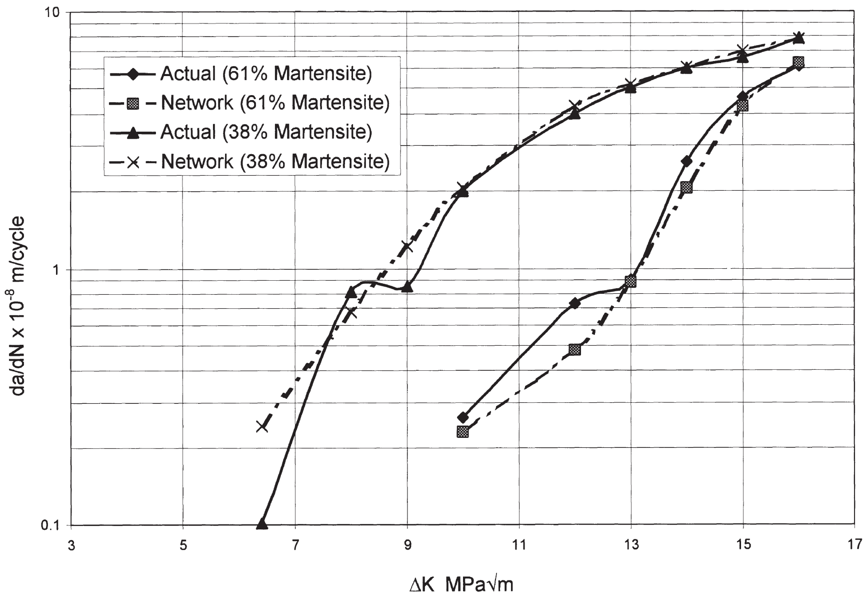

Fig. 3. da/dN vs ΔK for 38 and 61% martensite contents, for evaluation of the trained ANN model.

since a large number of variables were used during training the ANN model for predicting the corrosion–fatigue crack growth in DP steels. The practical benefits of this model can be extended to any proportion/combination of microstructures in DP steels for their potential applications in corrosion environment.

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