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Diagnosis of fatigue crack growth with recursive random weight networks ☆

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ABSTRACT

Recursive random weight networks (RRWNs) have been developed to diagnose fatigue crack growth in ductile alloys under variable amplitude loading. The fatigue crack growth process is considered as a recursive network system. RRWNs are constructed by taking the current loading, crack opening stress, and the previous computed crack length as inputs of the network system. The input weights of conventional single-layer feed-forward neural networks are uniformly and randomly selected. The output weights of RRWNs are globally optimized with the batch learning type of least squares. The trained RRWNs are capable of determining the dynamics of crack development. The proposed model is validated with fatigue test data for different types of variable amplitude loading in alloys. Compared with other experimental diagnosis models, RRWNs show excellent performance in predicting crack length growth.

1. Introduction

Fatigue crack growth under variable amplitude loading has previously been extensively investigated in [1–6]. Most of these existing methods were derived from the modifications of the Paris equation [7]. State-space model [1,2,4,6,8], as a different form of the Paris equation, has been widely used to deal with the prognosis of crack growth. In this model, two parameters (crack length and crack opening stress) are selected as the state variables [3]. State-space models can be recursively computed based on empirical data. However, numerous researchers prefer to use of a prepared look-up table of the crack length-dependent correction factor derived from experiments to aid in crack growth assessment because of the high nonlinearity and complexity of the crack growth process. Deriving this look-up table from a large amount of experimental data is time consuming. Furthermore, a prepared look-up table may be inappropriate for use under variable environments and conditions.

In practice, fatigue crack growth modeling remains a challenging task because of numerous uncertainties, as well as the ambiguous relationship that exists in crack growth modeling. As an alternative scheme, neural modeling can be employed to assess crack growth. The process of crack growth assessment is an input–output nonlinear model agitated by the applied remote stress. The crack growth model can be considered as a virtual nonlinear neural system with applied loads associated with the previous crack information as input. Neural network models, which have complex and ambiguous modeling process mechanisms, can be employed as an input–output structure to realize fatigue crack growth assessment [9,10]. Among the widely used neural network models, recursive feed-forward neural networks (RFNNs) [11] are dynamically driven networks

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with one feedback loop. RFNNs take the current output as the next input of the neural network. However, this model cannot account for the crack opening stress induced by the applied remote stress. Furthermore, back propagation (BP), a typical learning algorithm for RFNNs, always suffers from slow learning speed, as well as from the unsatisfactory generalizability of the parameter tuning process. A novel learning algorithm known as the random weight network was recently proposed in [12–14] to improve the learning speed of traditional training algorithms for feed-forward neural networks (FNNs) with random variables. That is, hidden weights and biases are considered as random variables that obey some distributions on some domains. The output weights of FNNs are calculated using the Moore–Penrose generalized inverse of a linear system. Compared with the conventional BP algorithm, random weight networks (RWNs) possess a more concise architecture, faster learning speed, and better generalization ability in prediction applications.

In this paper, we design RRWNs to describe fatigue crack growth. Unlike conventional random weight networks [12], RRWNs possess a recursive neural network architecture with a low-degree polynomial added to conventional single-layer FNNs to depict the relationship in consecutive cycles. Moreover, crack opening stress is added to the crack growth model as an important internally driven factor in fatigue crack development. The harmonious structure consisting of a neural network and polynomial can describe various crack growth rates and reduce the number of hidden nodes, thereby preventing the occurrence of overfitting and improving generalization ability. In the training phase, the current crack length associated with the corresponding crack opening stress calculated using the applied maximum and minimum stresses is taken as the input of the network in the next cycle. The interior weights and biases of RRWNs are randomly assigned in terms of uniform distribution in some domains, whereas the exterior weights are determined by the generalized inverse of the hidden layer matrix. The trained RRWNs are capable of learning the dynamics of crack development. The proposed model is validated by using fatigue test data for different types of variable amplitude loadings in 7075-T6 alloys and is then compared with the other widely used diagnosis models in experiments with Porter data.

The remainder of this paper is organized as follows: Section 2 describes the problem of fatigue crack growth. Section 3 proposes RRWNs to assess fatigue crack growth. Section 4 discusses the model validation and comparison using with fatigue test data under different loading cases. Section 5 concludes the study.

2. Problem formulation

In the fracture mechanics literature [5–7], the dynamics of fatigue crack growth are usually expressed as a derivative with respect to the number of cycles, which is identical to having the crack length increment in the cycle. As a widely used fatigue crack growth model, the first-order nonlinear difference equation, which is agitated by the maximum applied stress S_k^0 and the crack opening stress S_k^{max} in the kth cycle, is employed to describe the evolution of crack length. The nonlinear difference equation has the following structure [2]:

$$a_{k+1} - a_k = h(\Delta K_k^{eff}) \tag{1}$$

with

$$\Delta K_k^{eff} = \sqrt{\pi a_k} F(a_k)(S_k^{max} - S_k^0) \tag{2}$$

where a_k is the crack length at the end of the kth cycle, $h(\cdot)$ is a non-negative monotonically increasing function, and ΔK_k^{eff} is the effective stress intensity factor. The maximum applied remote stress S_k^{max} and the crack opening stress S_k^0 in the kth cycle are the excitations of the crack growth model in Eq. (1). $F(a_k) = \sqrt{sec(a_k\pi/2)}$ is a crack-length-dependent correction factor that is dependent on crack length that compensates for the finite component geometry.

In practice, crack opening stress is an important factor in crack initiation. Experimental data reveal that the corresponding crack opening stress rapidly increases to the peak value from its steady state and then decreases slowly to its steady state when a single cycle overload is applied. Although the crack opening stress is not necessarily a measurable quantity during the crack growth process, the value can be determined based on a finite history of input, including the peaks and valleys of stress agitation and crack length measurements [15]. Eqs. (1) and (2) show that if the maximum applied remote stress is taken as the external input, the crack growth largely depends on the crack opening stress. As an internal state variable, the dynamics of the crack opening stress with the cyclic stress agitation of variable amplitude loading has been extensively studied in [16]. Eq. (1) is used to compute for the crack growth recursively. The crack opening stress is often obtained by recursively solving the complex first-order difference equation using Eq. (1), in which many parameters should be determined relative to the material properties. According to the empirical formula given in [17], the following empirical equations are used to calculate the crack opening stress for a center-crack tension specimen in our work:

$$S_k^0 = \left(\frac{1}{1+\eta}\right)S_{k-1}^0 + \left(\frac{\eta}{1+\eta}\right)S_k^{oss} + \left(\frac{1}{1+\eta}\right)(S_k^{oss} - S_{k-1}^0) + \left(\frac{1}{1+\eta}\right)[S_k^{oss} - S_k^{oss\_odd}]U(S_{k-1}^{min} - S_k^{min})[1 - U(S_k^{oss} - S_{k-1}^0)] \tag{3}$$

The steady crack opening stress S_k^{oss} is a function of the minimum stress S^{min}, the maximum S^{max}, the specimen geometry, and the flow stress S^{flow}, which can be computed by Eq. (4)

$$S_k^{oss} = [A_k^0 + A_k^1 R_k + A_k^2 (R_k)^2 + A_k^3 (R_k)^3] S_k^{max} \tag{4}$$