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Application of artificial neural network for predicting fatigue crack propagation life of aluminum alloys

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ABSTRACT

Purpose: In this work, fatigue crack propagation life of 7020 T7 and 2024 T3 aluminum alloys under the influence of load ratio was predicted by using artificial neural network (ANN).

Design/methodology/approach: Numerous phenomenological models have been proposed for predicting fatigue life of the components under the influence of load ratio to take into account the mean load effect.

Findings: In current research, an automatic prediction methodology has been adopted to estimate the constant amplitude loading fatigue life under the above condition by applying artificial neural network (ANN).

Practical implications: ANNs show great potential for predicting fatigue crack growth rate especially by interpolation within the tested range. However, its benefit is lost when the model is needed to extrapolate the available experimental data.

Originality/value: The predicted results are found to be in good agreement with the experimental findings when tested on two aluminum alloys 7020 T7 and 2024 T3 respectively.

Keywords: Fatigue crack growth rate; Artificial Neural Network; Constant amplitude loading

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ENGINEERING MATERIALS

1. Introduction

Most load bearing structural components generally contain defects / imperfections either as a result of manufacturing, fabrications or localized damage in service. Under different loading conditions, these defects coalesce and develop into large cracks, which propagate to critical size resulting catastrophic failure. The mere presence of a crack does not make a component or structure to be unreliable. Whatever may be the loading condition, whether cyclic or sustained loading, it is necessary to know how long a crack would take to grow to a critical size at which the component or structure would become unsafe and fail. Therefore, the crack growth studies and life prediction procedure under fatigue loading is essential in order to extend the life of in-service sophisticated components so as to provide huge savings.

It is known that load ratio (R) has a marked effect on fatigue crack growth rate. During last four decades, many prediction models have been proposed to incorporate the effect of R-ratio including crack closure model [8], models based on residual compressive stress [13,15,] two-parameter driving force models [6,14] etc. However, automatic life prediction based on soft-computing methods such as artificial neural network (ANN), genetic algorithm (GA) etc is lacking. In the current investigation, an attempt has been made to predict fatigue life under the influence of *R*-ratio by using ANN. It is observed that the predicted results are in good agreement with the experimental findings.

2. Experimental procedure

This research was carried out on 7020 T7 and 2024 T3 aluminum alloys. A summary of chemical compositions and mechanical properties of both the alloys have been presented in Tables 1 and 2 respectively. The fatigue crack growth tests were performed using single edge notch tension (SENT) specimen with a thickness of 6.48 mm. The specimens were made in the LT plane, with the loading aligned in the longitudinal direction. Fig. 1 illustrates the major dimensions of the SENT samples used in the tests. A servo-hydraulic dynamic testing machine (*Instron*-8502) having a load capacity of 250 KN was used for the present investigation. Fatigue pre-cracking was introduced under mode I loading condition to an *a*/*w* ratio of 0.3 and were subjected to constant load amplitude test maintaining six load ratios (*R*) of 0, 0.2, 0.4, 0.6 and 0.8 respectively for both the materials. All fatigue tests were run at a frequency of 6 Hz with a sinusoidal wave form under ambient laboratory condition. Crack lengths were measured using a compliance method with a COD gauge and were also controlled using an optical method with a 20X magnification. The stress intensity factors at every instant ahead of the crack tip were calculated by using the following equations [4]:

$$K = \mathrm{f}(g).\frac{F\sqrt{\pi a}}{wB} \tag{1}$$

where,

$$\mathrm{f}(g) = 1.12-0.231(a/w)+10.55(a/w)^2-21.72(a/w)^3+30.39(a/w)^4 \tag{2}$$

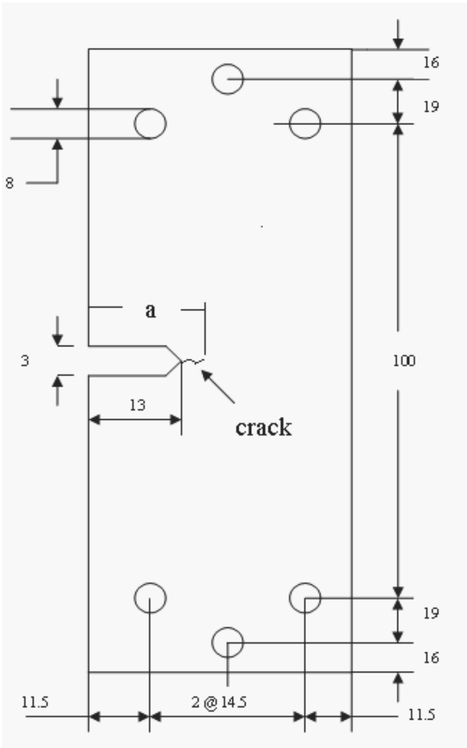

Fig. 1. Geometry of the SENT specimen (dimensions in mm)

Table 1.
Chemical Composition of 7020 T7 and 2024 T3 aluminum alloys

Materials	Al	Cu	Mg	Mn	Fe	Si	Zn	Cr	Others
7020 T7	Main constituent	0.05	1.2	0.43	0.37	0.22	4.6	-	-
2024 T3	90.7– 94.7	3.8 – 4.9	1.2–1.8	0.3 – 0.9	0.5	0.5	0.25	0.1	0.15

Table 2.
Mechanical Properties of 7020 T7 and 2024 T3 aluminum alloys

Materials	Tensile strength (σ_{ut}) MPa	Yield strength (σ_{ys}) MPa	Young's modulus (E) MPa	Poisson's ratio (v)	Plane Strain Fracture toughness (K_{IC}) $MPa\sqrt{m}$	Elongation
7020 T7	352.14	314.70	70,000	0.33	50.12	21.54 % in 40 mm
2024 T3	469.00	324.00	73,100	0.33	37.00	19 % in 12.7 mm

3. Artificial neural network approach

Artificial neural network (ANN) is a new class of computational intelligence system, useful to handle various complex problems with a capacity to learn by examples. It has proved to be a powerful and versatile soft-computing method which is quite efficient in modeling complex linear and non-linear relationships on the basis of experimental data in a number of engineering fields [1,3,11,16,18]. In recent years, ANN finds its application in the field of fatigue for various purposes [2,5,9,12,19,20,22]. It can be categories as feed forward or recurrent depending on the processing of data through the network. According to the learning rules, it can be further classified as supervised, unsupervised or reinforcement ANN. Among the various classifications, multi-layer perceptron (MLP) is the most popular ANN architecture as far as engineering application is concerned. MLPs are generally used with feed forward neural networks trained with error-back propagation algorithm (error minimization technique). Various non-linear activation functions such as sigmoidal, tanh or radial (Gaussian) are used to model the neuron activity.

4. Design of an ANN model for crack growth rate prediction

In the present investigation, a nine-layer perceptron ANN with back-propagation neural controller [10] has been developed. It has got one input layer, one output layer and seven hidden layers. The input layer has got three neurons, whereas one neuron has been associated with output layer. The neurons associated in the seven hidden layers are twelve, twenty four, hundred, thirty five and eight respectively. The neurons have been chosen empirically and taken in order so as to give the neural network a diamond shapes (Fig. 2).

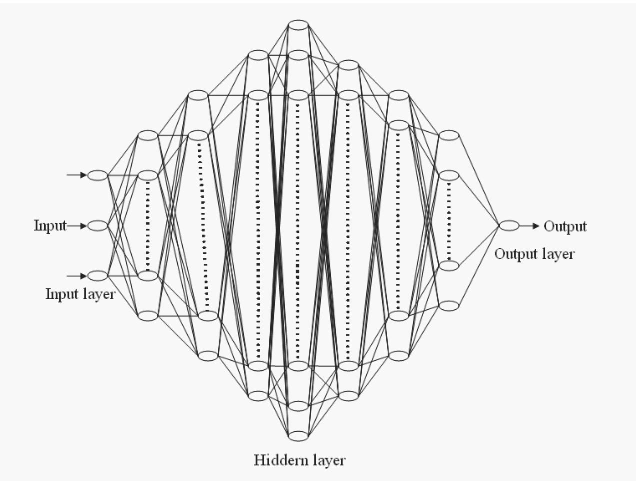

Fig. 2. ANN architecture

The input parameters to the neural network controller are as follows:
Stress intensity factor range = “sifr”; Maximum stress intensity factor = “msif”; Load ratio = “lr”.

The output from the controller is:
Crack growth rate = “cgr”

The proposed ANN has been written in the C++ programming language and all the training tests have been performed on a personal computer. The activation function chosen in this work is the hyperbolic tangent function:

$$\mathrm{f}(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3}$$

During training, the network output θ_{actual}, may differ from the desired output θ_{desired} as specified in the training pattern presented to the network. A measure of the performance of the network is the instantaneous sum-squared difference (error) between θ_{desired} and θ_{actual} for the set of presented training patterns:

$$E_{\text{rr}} = \frac{1}{2} \sum_{\substack{all\\ training\\ patterns}} \left(\theta_{\text{desired}} - \theta_{\text{actual}}\right)^2 \tag{4}$$

where θ_{actual} represents crack growth rate (“cgr”)

The two crack driving forces: stress intensity factor range (ΔK) and maximum stress intensity factor (K_{max}) have been chosen as the two inputs as per ‘Unified Approach’ [6,7,14,21]. The third input is the load ratio (R) as the fatigue crack growth rate ($\mathrm{d}a/\mathrm{d}N$) varies with the load ratio. The crack growth rate has been chosen as the output for the present ANN model. As far as normalization of input and output parameters are concerned, classical normalization, where the range is scaled between 0 and 1, may not be applicable in every ANN model. To make the input amenable for successful learning to minimize the overall sum-squared error, the two input parameters ΔK and $K_{\max}$ have been normalized between 1 and 4, while the other one, load ratio (R) has been normalized between 1 and 3. Similarly the output $\left(\frac{\mathrm{d}a}{\mathrm{d}N}\right)$ has been normalized between 0 and 3 for network training and testing. The inputs and outputs of the training sets (TS) have been constituted from 3×65 experimental values of ΔK, $K_{\max}$ and $\left(\frac{\mathrm{d}a}{\mathrm{d}N}\right)$ data for each of the load ratios 0, 0.2, 0.4, 0.6, and 0.8 for both the alloys.

5. Results

5.1. Experimental results

The experimental values of crack length versus number of cycles for various load ratios (R) have been illustrated in Figs. 3 and 4 respectively for both the materials. The crack growth rate, $\left(\frac{\mathrm{d}a}{\mathrm{d}N}\right)$ has been calculated by incremental polynomial method as per ASTM[1]. The results have been plotted against stress intensity factor *(ΔK)* in Figs. 5 and 6.

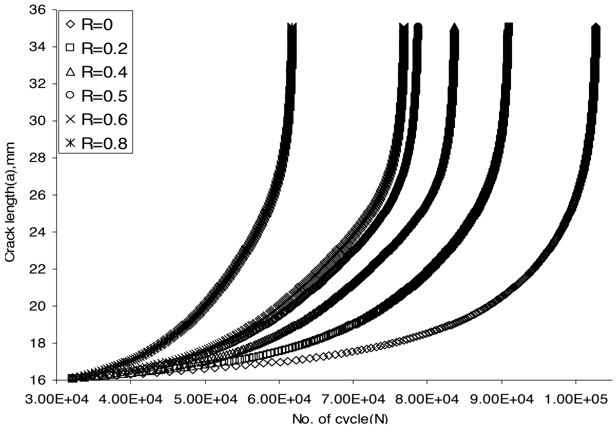

Fig. 3. Comparison of a ~ N curves for different load ratios (7020 T7 alloy)

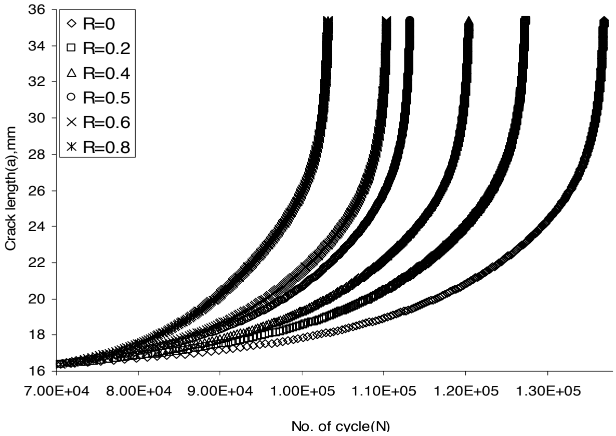

Fig. 4. Comparison of a ~ N curves for different load ratios (2024 T3 alloy)

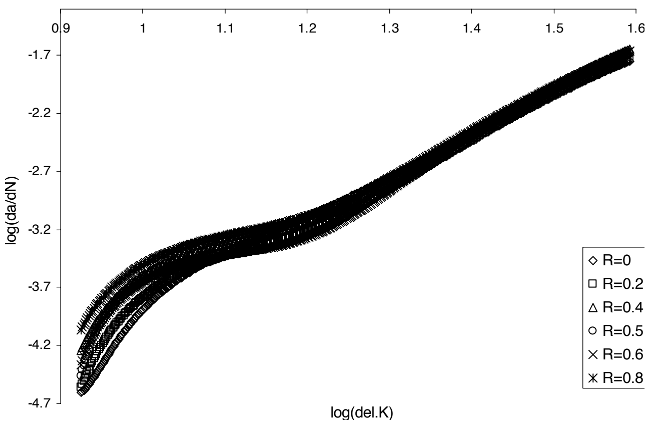

Fig. 5. Comparison of d*a*/d*N* ~ Δ*K* curves for different load ratios (7020-T7 alloy)

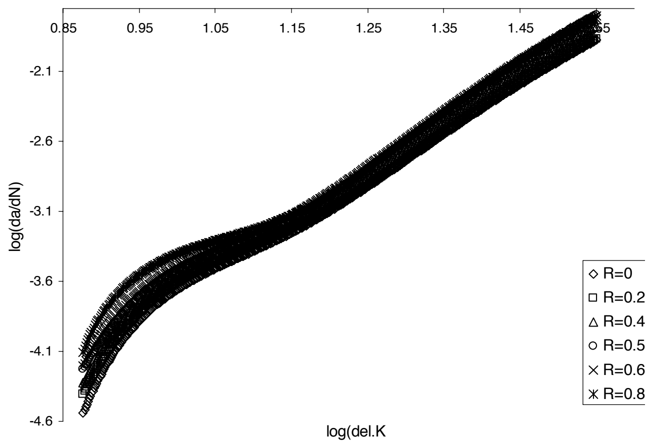

Fig. 6. Comparison of da/dN ~ ΔK curves for different load ratios (2024-T3 alloy)

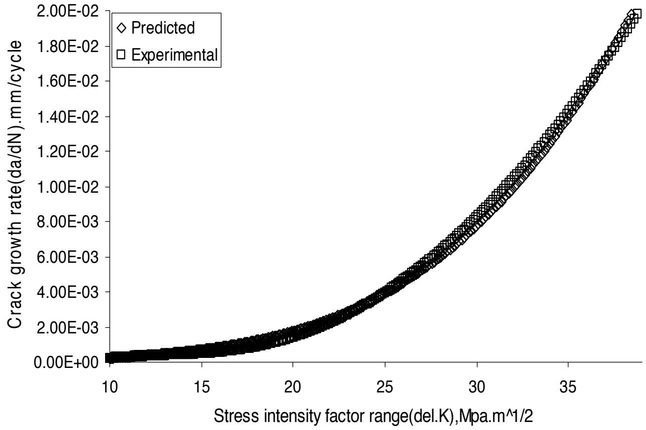

Figure 7. Comparison of predicted (ANN) and experimental crack growth rate with stress intensity range (Δ*K*) for load ratio 0.5 (7020 T7 alloy)

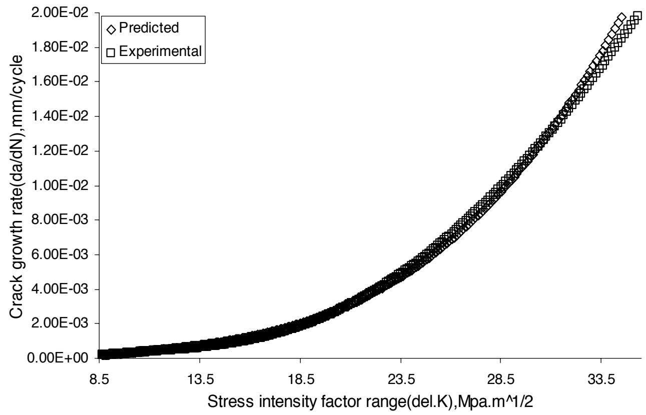

Fig. 8.Comparison of predicted (ANN) and experimental crack growth rate with stress intensity range (Δ*K*) for load ratio 0.5 (2024 T3 alloy)

Table 3.
Load scenarios and model results of the tested specimens

Test specimen	F_{max} (KN)	F_{min} (KN)	R	a_i (mm)	a_f (mm)	N_f^A Kcycle	N_f^E Kcycle	% error in N_f^A	% error in N_f^E
7020 T7	7.944	3.972	0.5	18.3	35.1	75.344	78.265	-4.365	-0.658
2024 T3	7.204	3.602	0.5	18.3	35.4	110.920	112.879	-2.099	-0.370

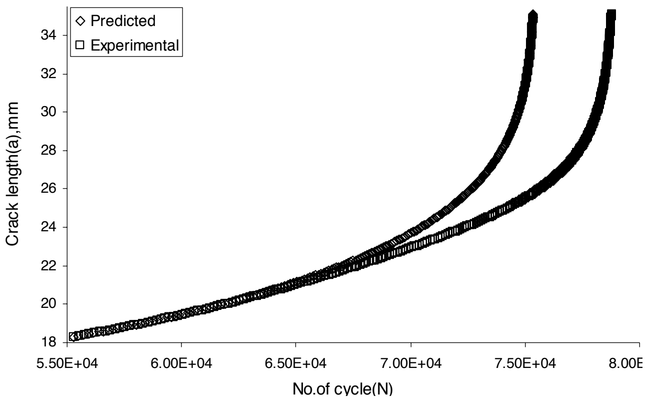

Fig. 9. Comparison predicted (ANN) and experimentally obtained crack length with number of cycle (N) for load ratio 0.5 (7020 T7 alloy)

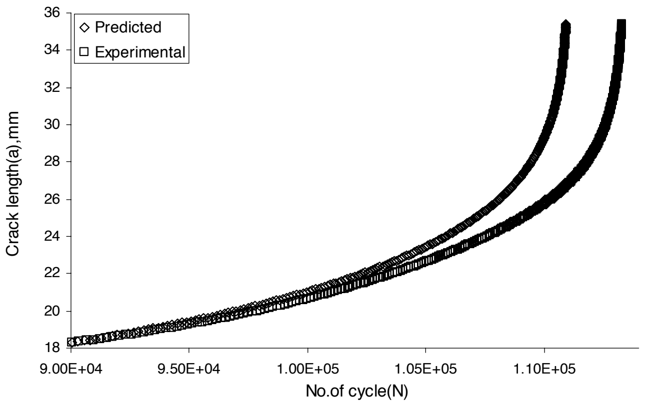

Fig. 10. Comparison of predicted (ANN) and experimentally obtained crack length with number of cycle (N) for load ratio 0.5 (2024 T3 alloy)

5.2. Prediction by ANN model

Out of six experimental sets of load ratios (R = 0, 0.2, 0.4, 0.5, 0.6, 0.7. 0.8), the data set of load ratio 0.5 was left as validation set (VS). The adopted nine-layer perceptron (MLP) neural network model was applied to simulate the crack growth rate of the validation set for both the cases. The numbers of hidden neurons, minimum error and number of iterations were chosen empirically as 7, 1×10^{-6} and 4, 48, 000. The input parameters, stress intensity factor range (ΔK), maximum stress intensity factor (K_{max}) and load ratio have been fed to the trained ANN model in order to predict the corresponding crack growth rate $\left(\frac{\mathrm{d}a}{\mathrm{d}N}\right)$ for the validation set. The predicted crack growth rate results have been presented in Figs. 7 and 8 respectively along with experimental findings for comparison. It is observed that the simulated da/dN ~ ΔK points follow the experimental ones quite well. The number of cycles has been calculated from the simulated $\left(\frac{\mathrm{d}a}{\mathrm{d}N}\right)$ values by taking the first experimental 'a' and 'N' values of 0.5 load ratio data set as the initial values and assuming an incremental crack length of 0.05mm in steps. The predicted a ~ N value of the ANN model has been compared with the experimental data in Figs. 9 and 10 respectively and a quantitative comparison of the prediction results have been presented in Table 3 for both the materials.

6. Conclusions

In this work, fatigue crack propagation life of 7020 T7 and 2024 T3 aluminum alloys under the influence of load ratio was predicted by using artificial neural network (ANN). A data base consisting of six sets (R = 0, 0.2, 0.4, 0.6, 0.7. 0.8) of experimental data for each of the above alloys were used to train the ANN model. It was subsequently applied to predict the fatigue life for the unknown data set of R = 0.5. The model results were found to be in good agreement with the experimental findings.

ANNs show great potential for predicting fatigue crack growth rate especially by interpolation within the tested range. However, its benefit is lost when the model is needed to extrapolate the available experimental data.

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