www.ijecs.in
International Journal Of Engineering And Computer Science ISSN: 2319-7242
Volume 6 Issue 1 Jan. 2017, Page No. 19932-19935
Index Copernicus Value (2015): 58.10, DOI: 10.18535/ijecs/v6i1.13

Constant amplitude fatigue crack growth life prediction of 8090 Al-alloy by ANFIS

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Abstract: ***The aim of the current work is to predict fatigue crack growth life of 8090 T651 Al-alloy under the influence of load ratio by applying adaptive neuro-fuzzy inference system (ANFIS) technique. The model has been trained by minimization of root mean square error (RMSE) principle. It has been observed that the proposed model predicts well the fatigue crack growth life of the alloy with 0.801% deviation in comparison to experimental results.***

Keywords: Fatigue crack growth life; Load ratio; Adaptive neuro-fuzzy inference system (ANFIS); Root mean square error (RMSE).

1. Introduction

In reality, almost all engineering structures/components are subjected to cyclic or fatigue loading as more than 80% of failures takes place due to fatigue. So the study of fatigue is certainly important both for mechanical as well as metallurgical point of view. Earlier fatigue phenomena were studied by using 'safe life' approach. In this approach a component/structure is rejected once a crack/defect is detected during its service period even if it has some residual life. However, after the advent of fracture mechanics, the new design philosophies have come up which are called 'fail-safe' and 'damage tolerant' approaches. In these approaches, fatigue crack growth life is estimated by using fracture mechanics principle in order to establish timely inspection intervals to avoid catastrophic failures.

Most of the fatigue crack growth models proposed till date to predict fatigue life correlate the instantaneous fatigue crack growth rate (d*a*/d*N*) with corresponding stress intensity factor range (ΔK). However, apparent effectiveness of ΔK is known to be affected by the load ratio (minimum load / maximum load), crack closure, overload, crack size, environment, geometry, temperature etc [1]. The primary loading parameter affecting the fatigue crack growth is the load ratio *R*, which quantifies the influence of mean load. It is well known that the growth rate either increases or decreases by increasing the value of load ratio under different-loading conditions [2-4]. Therefore, the ability – to correlate and predict the fatigue crack growth rate for different load ratios is of significant importance. Different prediction models [5, 6] have been proposed to account for the *R*-ratio effect on fatigue crack growth. All such models require experimental data from fatigue crack growth tests which are costly and time consuming. To avoid this soft-computing methods have been recently applied in the fatigue literature to predict fatigue life. In the present work an attempt has been made to predict fatigue life of 8090 aluminum alloy under the influence of load ratio by applying adaptive neuro-fuzzy inference system (ANFIS). After proper training of ANFIS model, it has been observed that the prediction result is quite reasonable though it slightly overestimates the fatigue life.

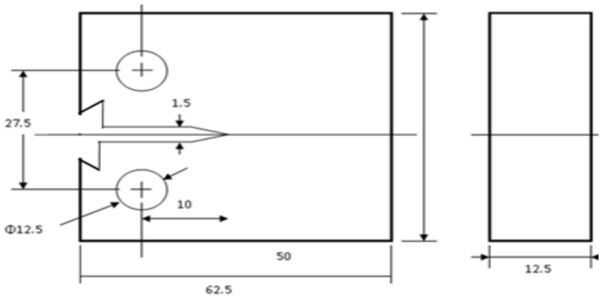

Fig. 1. Compact Tension (CT) specimen

2. Experimentation and data preparation

2.1 Fatigue crack growth experiment

In the present study, the material used for fatigue crack growth rate (FCGR) study is 8090 Al-alloy with T651 heat treated condition. The compact tension (CT) specimens with a V-starter notch have been prepared from 12.5 mm thick plates in the longitudinal transverse (LT) direction as shown in Fig. 1. The chemical composition and the mechanical properties of the alloy have been given in Table 1 and 2 respectively.

Table 1: Composition (wt. %) of 8090 Al alloy

Zn	Mg	Cu	Fe	Si	Mn	Ti	Li	Al
5.7	0.55	1.14	0.05	0.03	0.1	0.03	2.34	Bal

Table 2: Mechanical properties of 8090 Al-alloy

Young's modulus (GPa)	Yield strength (MPa)	Tensile strength (MPa)	Elongation (%)
81.2	430.0	480.0	13.0

DOI: 10.18535/ijecs/v6i1.13

Both the sides of the specimen surfaces have been mirror-polished by different grades of emery papers and subsequently by magnesium oxide (MgO) powder suspension. The specimen surfaces have been marked at 1 mm interval each and a pair of knife edges has been fixed on the face of the machined V-notch. The crack opening displacement (COD) gauge has been mounted on the knife edges to monitor the crack extension.

Initially the specimens have been fatigue pre-cracked to 1 mm in mode-I loading (crack opening mode) at constant stress intensity factor (ΔK) under given loading conditions (which include frequency: 6 Hz; load ratio: 0.1; initial and final crack lengths: 15.4 and 38.4 mm respectively). Then the constant amplitude loading (CAL) fatigue crack growth rate (FCGR) tests have been carried out at different load ratios (i.e. R = 0, 0.2, 0.4, 0.5, 0.6, 0.8) under tension-tension loading in a servo-hydraulic dynamic testing machine (*INSTRON* 8502) having a load capacity of 250 kN interfaced to a computer for machine control and data acquisition. All the FCGR tests have been conducted in constant load control (increasing ΔK) mode in accordance with ASTM E647.

2.2 Crack growth rate determination

After FCGR tests, the raw laboratory data of number of cycles (N) corresponding to the specified crack lengths (each 1 mm interval marked on the specimen) have been recorded and one of the data set for R = 0.1 has been plotted in Fig. 2 for reference. From crack length and number of cycles (a~N) plot, it has been observed that the experimental- data obtained from laboratory tests contain scatter, though it is exponentially increasing in nature.

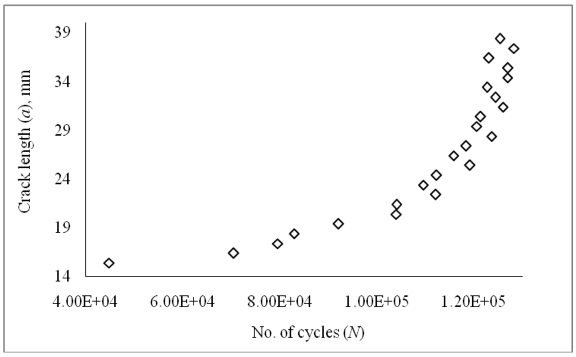

Fig. 2 – Raw experimental a~N curve for R = 0.1

Hence, the scattered experimental a~N data have been smoothened by adopting the procedure of ‘exponential model’ as per author’s earlier work [7]. The details of procedure have been mentioned in previous work for reader’s reference. After data smoothening, the modified superimposed a~N curves for all the load ratios cases have been plotted in Fig. 3.

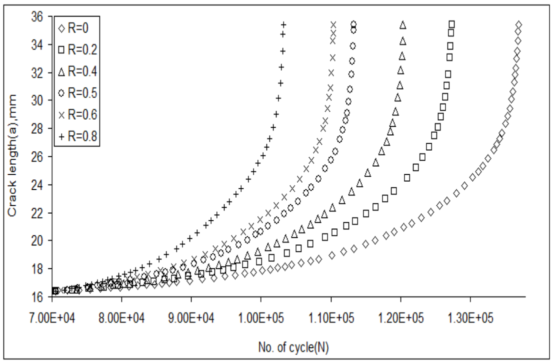

Fig. 3 – Comparison of a–N curves for different load ratios

The crack growth rates (da/dN) have been calculated directly from the smoothened a~N values as follows:

$$\frac{\mathrm{d}a}{\mathrm{d}N}=\frac{(a_j-a_i)}{(N_j-N_i)} \qquad (1)$$

Fig. 4 shows the superimposed log (da/dN) – log (ΔK) curve under different load ratios.

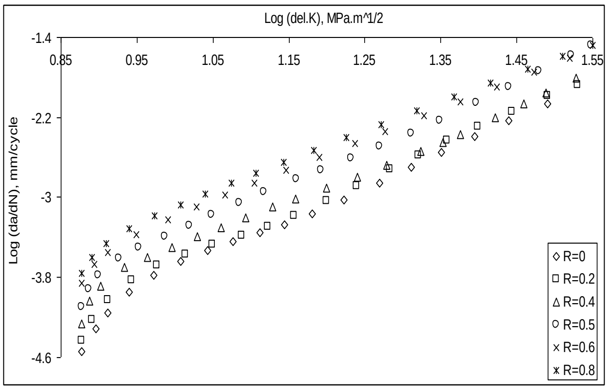

Fig. 4 – Comparison of log da/dN – log (ΔK) for different load ratios

3. Model formulation

Adaptive neuro-fuzzy inference system (ANFIS) is an integrated system of artificial neural network (ANN) and fuzzy inference system (FIS) and utilizes the advantages of both. ANFIS is a class of adaptive networks, whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm or hybrid algorithm based on a combination of back-propagation and least squares estimate (LSE). In the present investigation, type-3 ANFIS [8] topology based on first-order Takagi-Sugeno (TSK) [9] if-then rules has been used.

Earlier it has been observed that by increasing load ratio fatigue life decreases [10] and consequently intensity factor range (ΔK) also increases. Hence, during formulation of ANFIS model, the load ratio (R) and stress intensity factor range (ΔK) have been selected as linguistic input variables whereas, crack growth rate (da/dN) was taken as output variable. A set of linguistic rules have been formulated in the “If-Then” form derived from expert observation and experimentation.

The experimental data base consists of six sets of fatigue crack growth data having load ratios (R) of 0, 0.2,

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0.4, 0.5, 0.6 and 0.8. Each set for a particular load ratio consists of approximately 200 data sets with K_{max} and ΔK values along with their corresponding da/dN values. The training set (TS) has been constructed from the five experimental input/output data sets for load ratios (R) of 0, 0.2, 0.5, 0.6 and 0.8. The remaining data set (i.e. for R = 0.4) has been kept for testing which is called validation data set (VS). Before training, the pre-processing of experimental data sets has been done in order to achieve optimum modeling results. The pre-processing has been done by normalizing the input variables (i.e. R, K_{max} and ΔK) as well as output variable (i.e. da/dN) to unity. The numbers of membership functions (MF) have been chosen to be 4-4-4 corresponding to the inputs R, K_{max} and ΔK respectively. The $4\times4\times4=64$ fuzzy '*if-then*' rules have been constituted in which fuzzy variables have been connected by T-norm (fuzzy AND) operators. The premise and consequent parameters has been adjusted in batch mode based on the hybrid-learning algorithm. The model has been trained by using MATLAB with Fuzzy Logic Toolbox for 2000 epochs. The parameters of ANFIS model during training has been presented in Table 3.

Table 3 – Parameters of ANFIS model during training

Type of membership function	Generalized bell
Number of input nodes (n)	2
Number of fuzzy partitions of each variable (p)	4
Total number of membership functions	15
Number of rules $\left(p^n\right)$	64
Total number of nodes	200
Total number of parameters	300
Number of epochs	2000
Step size for parameter adaptation	0.01

The model performances during training have been verified by computing root mean square error (RMSE); coefficient of determination (R^2) and mean percent error (MPE) defined by the following equations:

$$RMSE=\left((1/p)\sum_{i=1}^{p}|t_i-o_i|\right)^{1/2} \quad (2)$$

$$R^2=1-\left(\frac{\sum_{i=1}^{p}(t_i-o_i)^2}{\sum_{i=1}^{p}(o_i)^2}\right) \quad (3)$$

$$MPE=\frac{1}{p}\sum_{i=1}^{p}\left(\frac{t_i-o_i}{t_i}\times100\right) \quad (4)$$

where't' is the target value, 'o' is the output value, and 'p' is the number of data items.

4. Model validation and discussion

The formulated ANFIS model has been trained by feeding the input/output data of TS which takes 327 minutes computational time. After training, the RMSE, R^2, and MPE values obtained are 0.000186, 0.99978 and 0.24867 respectively. Then, the input data for validation set i.e. for R = 0.4 has been fed to the trained ANFIS model and the output (i.e. da/dN) values have been obtained. As observed from the performance parameter of the model, the root mean squire error (RMSE) is approximately '0' and the coefficient of determination (R^2) is approximately '1'. In addition to that the mean percent error (MPE) is also very small. It means that the model has been properly trained. The trained ANFIS model has been tested for load ratio of 0.4 (i.e. VS).

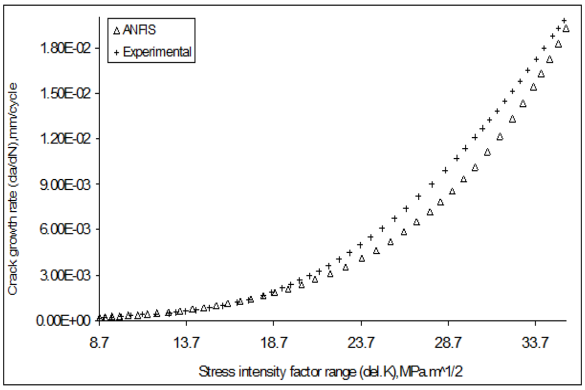

Fig. 5 – Comparison of da/dN–ΔK curves for R =0.4

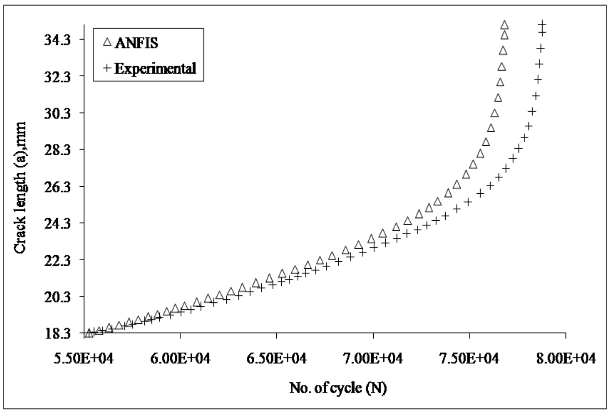

Fig. 6 – Comparison of predicted and experimental a ~ N curves for R = 0.4

The predicted crack growth rates (for R = 0.4) obtained from ANFIS model have been compared with experimental results in Fig. 5 and found to be in good agreement. The numbers of cycles (i.e. fatigue life) have been calculated as per the following equation and presented Fig. 6.

$$N_{i+1}=\frac{a_{i+1}-a_i}{da/dN}+N_i \quad (5)$$

From the result it has been observed that the fatigue life obtained from the ANFIS model is 112.391×10^3 cycles whereas it's corresponding experimental value is 110.919×10^3 cycles. Comparing the results it is found that the percentage deviation of fatigue life obtained from the proposed model is 0.801%. The prediction ratio of the model which is defined as the ration of experimental fatigue life to predicted fatigue life is 1.008 which is nearer to 1.0 and is acceptable as per the literature [11].

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5. Conclusion

The focus of this work is to develop an ANFIS model in order to predict crack growth rate and in turn the fatigue life of 8090 Al-alloy under the effect of load ratio. From the results it has been observed that the predicted fatigue life from the proposed model is 112.391×10^3 cycles with percentage deviation of 0.801% and prediction ratio of 1.008 in comparison to experimental result of 110.919×10^3 cycles. It shows that the result obtained from proposed ANFIS model is quite reasonable as far as fatigue crack growth life is concerned although it slightly overestimates the life.

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