Fatigue Crack Growth Life Prediction of 6061 Al-Alloy under Load Ratio Effect by Using ANFIS

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***Abstract*—*Fatigue crack growth under constant amplitude loading for a particular material strongly depends on load ratio (R). The prediction of fatigue crack growth life under such situation through deterministic approach is a tedious task. Application of artificial intelligence methods is more encouraging in those complex situations. In the present work a novel soft-computing approach i.e. adaptive neuro-fuzzy technique (ANFIS) has been applied to predict fatigue life of 6061 (AA 6061) aluminum alloy under the influence of load ratio. It has been observed that the ANFIS model predict the fatigue life of the alloy reasonably well with percentage deviation of –0.024 and prediction ratio of 1.025.*

Keywords*—*Adaptive neuro-fuzzy inference system (ANFIS); fatigue crack growth rate (FCGR); root mean squre error (RMSE); prediction ratio.

I. INTRODUCTION

Fatigue failure is an important mode of failure which occurs in almost all engineering structures/components. There are several approaches such as fail-safe, safe-life and damage tolerant approaches in fatigue literature to deal with the fatigue phenomena. Out of those, the damage tolerant approach is one of the modern approaches based on fracture mechanics principle which mainly correlate fatigue crack growth with life (i.e. No. of cycle to failure) of the specimen. In this approach the crack growth rate (da/dN) is correlated with different material parameters and above all the crack driving forces to determine fatigue life of the components. It can be represented by the functional form as:

$$\frac{da}{dN} = f\left(\Delta K, K_{\max}, R, E......\right) \qquad (1)$$

Based on this, several deterministic models [1-4] have been proposed till date to predict fatigue crack growth life to schedule inspection intervals for repairing/replacement of the components to avoid untimely catastrophic failures. However, the fatigue life prediction from those models suffers from several drawbacks. One of the major drawbacks is that the calculation of fatigue life from any prediction model involves complicated numerical integration schemes. Further, to formulate a fatigue model, several coupon tests are required which are not only costly but time consuming. In order to avoid those shortcomings, recently the researchers are taking the help of different computational techniques to predict fatigue crack growth life.

Fatigue crack growth under constant amplitude loading for a particular material strongly depends on load ratio (R) which is the ratio of minimum load ($P_{\min}$) to maximum load ($P_{\max}$). It has tremendous effect on fatigue crack growth. Some fatigue experts [5-8] have investigated its effect on fatigue crack growth and also proposed different empirical and semi-empirical models to evaluate fatigue life. However, problems associated with fatigue are difficult to solve using conventional mathematical models because of non-linearity, noise, cost, time constraint and above all the associated micro-mechanisms. Hence, soft-computing is a good alternative for handling those complex problems as it is tolerant of imprecision, uncertainty and partial truth. As such, different soft-computing methods such as, artificial neural network (ANN), genetic algorithm (GA), fuzzy logic and adaptive neuro-fuzzy inference system (ANFIS) are being used in various fields including fatigue [9-12]. However, the prediction of fatigue life considering load ratio effect using ANFIS is rare in fatigue literature. Therefore, in the present work an attempt has been made to evaluate the constant amplitude fatigue life of 6061 aluminum alloy under load ratio effect by using ANFIS technique. It has been observed that the proposed soft-computing technique predicts the fatigue life reasonable well with percentage deviation of –0.024 and prediction ratio of 1.025.

II. EXPERIMENTATION AND DATA PREPARATION

Fatigue crack growth experiment

The material under investigation was 6061 aluminum alloy received in T6 heat treated condition from rolled palte of 15 mm thickness. It was supplied by HINDALCO Industries

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Ltd., Hirakud, Distt. Sambalpur (Odisha), India. The chemical composition of the alloy as certified by the supplier is given in Tables 1.

Table.1: Chemical Composition of 6061 T6 Al-alloy

Elem-ents	Cu	Mg	Mn	Fe	Si	Cr	Al
Wt. %	0.15 – 0.4	0.8– 1.1	0.14 max	<0.02	0.3-0.7	0.04 - 0.35	Bal

The compact tension (CT) specimens for fatigue crack growth rate (FCGR) determination were machined in the longitudinal direction with notch perpendicular to rolling direction as per ASTM E-647-99 standard [13] as shown in Fig. 1. Both the sides of the specimen were mirror polished in order to facilitate the observation of crack growth. The FCGR (d*a*/d*N*) tests were conducted on as-received condition of AA 6061 T6 alloy as per ASTM E647 standard on a servo-hydraulic test machine (*Instron*-8502) having a load capacity of 250 kN in air at room temperature.

Initially, the specimens were fatigue pre-cracked under mode-I loading with a sinusoidal waveform up to a crack length to width (*a/w*) ratio of 0.3 under given loading conditions (frequency: 6Hz; load ratio: 0.1). Then the specimens were subjected to FCGR tests under constant amplitude technique (i.e. ΔK increasing) maintaining different load ratios (*R*) of 0, 0.2, 0.4, 0.5, 0.6, 0.8 respectively separately and the test data were recorded. The crack growth was monitored with the help of a COD gauge mounted on the face of the machined notch.

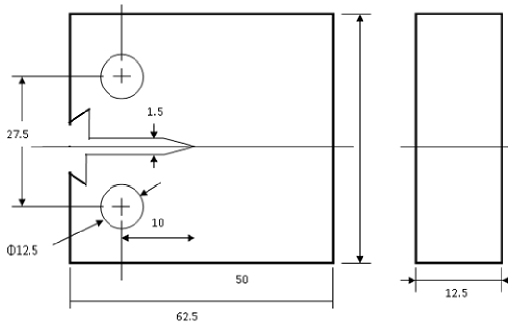

Fig. 1: Compact tension (CT) specimen geometry

Crack growth rate determination

After the fatigue crack growth rate tests, raw *a* – *N* laboratory data were obtained under each load ratio which usually contained much scatter. In order to smoothen the test data and to determine the fatigue crack growth rate, the following procedures were adopted by applying the concept of authors' previously proposed exponential [14]. The experimental *a* – *N* data were fitted with the following exponential equation as per the previous model.

$$a_j = a_i e^{m_{ij}(N_j - N_i)} \quad (2)$$

$$m_{ij} = \frac{\ln\left(\frac{a_j}{a_i}\right)}{(N_j - N_i)} \quad (3)$$

where, a_i and a_j = crack length in i^{th} step and j^{th} step in 'mm' respectively,

N_i and N_j = No. of cycles in i^{th} step and j^{th} step respectively,

m_{ij}= specific growth rate in the interval *i-j*,

i = No. of experimental steps, and $j = i+1$

The values of specific growth rate 'm_{ij}' were calculated according to the equation (3) and subsequently refined by curve fitting with calculated *a* values (i.e. crack lengths from initial to final with an increment of 0.005mm). The smoothened values of the number of cycles were calculated in the excel sheet from the refined 'm_{ij}' values as per the following equation.

$$N_j = \frac{\ln\left(\frac{a_j}{a_i}\right)}{m_{ij}} + N_i \quad (4)$$

Then the crack growth rates (d*a*/d*N*) were determined directly from the above calculated values of '*N*' as follows:

$$\frac{da}{dN} = \frac{(a_j - a_i)}{(N_j - N_i)} \quad (5)$$

The superimposed crack length (*a*) vs. number of cycle (*N*) and the corresponding log (d*a*/d*N*) vs. log (ΔK) curves at different load ratios were plotted in Figs. 2 and 3 respectively.

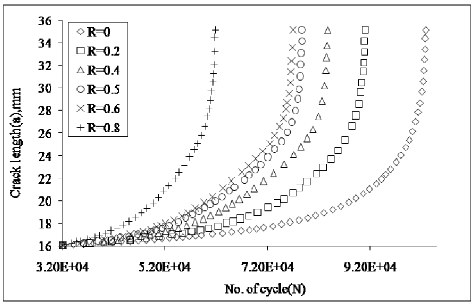

Fig. 2: Comparison of a–N curves for different load ratios

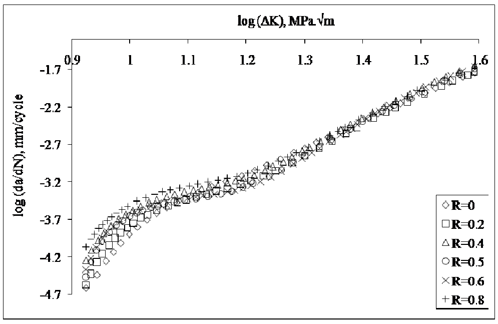

Fig. 3: Comparison of log (da/dN) – log (ΔK) for different load ratios

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III. ANFIS: METHODOLOGY

The fuzzy inference system (FIS) is generally used as a suitable tool for approximating ill-defined nonlinear functions. It can implement qualitative aspects of human knowledge and reasoning by using following four functional components as shown in Fig. 4.

- A rule base containing a number of fuzzy if-then rules.
- A decision-making unit as the inference engine.
- A fuzzification interface which transforms crisp inputs to linguistic variables.
- A defuzzification interface converting fuzzy outputs to crisp outputs.

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 [15] topology based on first-order Takagi-Sugeno (TSK) [16] if-then rules has been used.

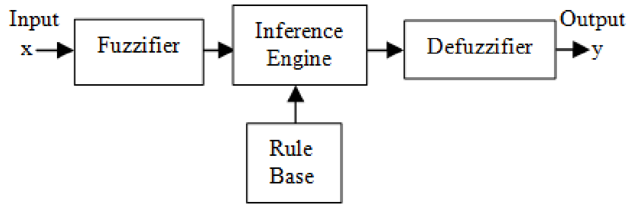

Fig. 4: Fuzzy Inference System

The structure of proposed ANFIS model consists of a number of interconnected fixed and adjustable nodes corresponding to first-order TSK fuzzy model as shown in Fig. 5. It is composed of five layers having three inputs and one output. Bell-shaped membership function has been chosen for the present investigation because it is the best membership function type [17]. A hybrid-learning algorithm is applied to adapt the premise and consequent parameters to optimize the network. Heuristic rules are used to guarantee fast convergence.

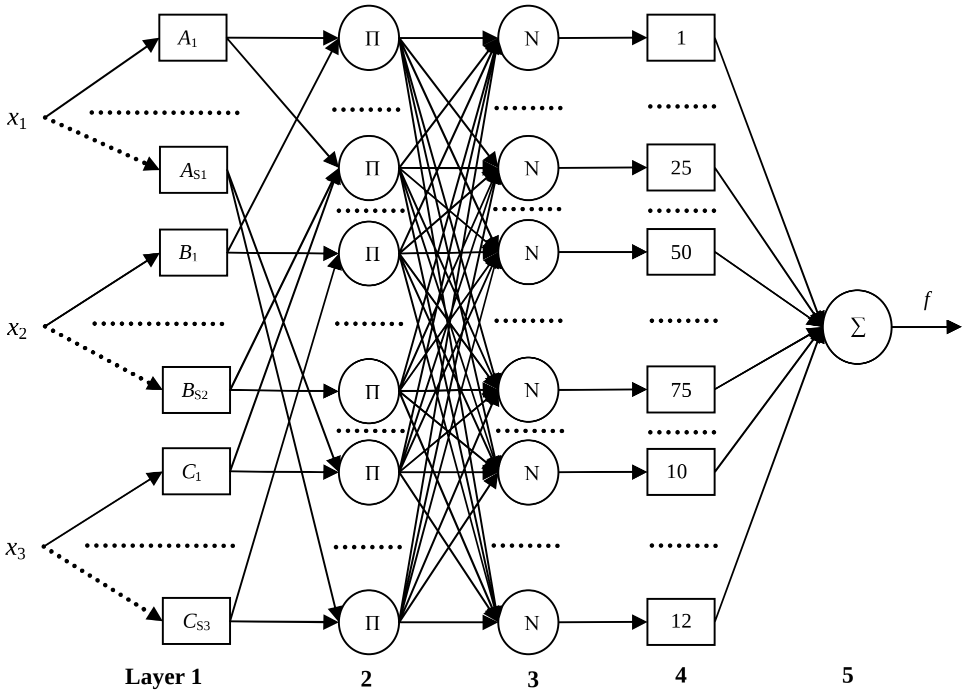

Fig. 5: Structure of the ANFIS model

IV. APPLICATION DESIGN

It is known that fatigue crack growth life decreases as load ratio increases [18]. Accordingly, the maximum stress intensity factor (K_{max}), and the stress intensity factor range (ΔK) are also affected by load ratio. Therefore, during model formulation load ratio (R), maximum stress intensity factor (K_{max}), and stress intensity factor range (ΔK) were selected as linguistic input variables whereas, crack growth rate (da/dN) was taken as output variable. A set of linguistic rules formulated in the "If-Then" form were derived from expert observation and experimentation.

The experimental data base consisted of six sets of fatigue crack growth data having load ratios (R) of 0, 0.2, 0.4, 0.5, 0.6 and 0.8. Each set for a particular load ratio contained

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approximately 300 data of both K_{max} and ΔK along with their corresponding da/dN (calculated as per the procedure mentioned earlier). The model was applied to simulate the crack growth rate of an unknown input/output data set for load ratio of 0.5 as validation set (VS) by constructing a training set (TS) with five known input/output data sets for load ratios (R) of 0, 0.2, 0.4, 0.6 and 0.8.

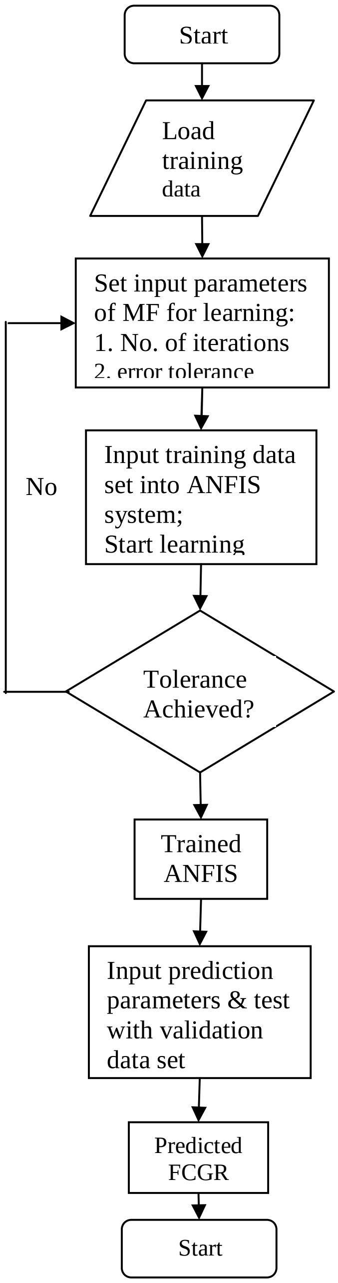

Fig. 6: Flow chart of ANFIS hybrid learning algorithm

Fig. 6 shows the flow chart of ANFIS hybrid learning algorithm. Before applying ANFIS model, the pre-processing of experimental data is essential in order to achieve optimum modeling results. The input variables i.e. load ratios (R), maximum stress intensity factor (K_{max}) and stress intensity factor range (ΔK) were normalized in such a way that their maximum values were normalized to unity. The crack growth rate (da/dN), which constituted the system output, was also normalized in similar manner. The numbers of membership functions (MF) were chosen to be 5-5-5 corresponding to the inputs R, K_{max} and ΔK respectively.

The $5\times5\times5=125$ fuzzy '*if-then*' rules constituted in which fuzzy variables were connected by T-norm (fuzzy AND) operators. The adjustment of premise and consequent parameters was made in batch mode based on the hybrid-learning algorithm. The model was trained for 4000 epochs until the given tolerance was achieved.

Table 2 summarizes all the characteristics of ANFIS network used during training. As per Fig. 5, layer 1 had 15 (5×3) nodes with 45 parameters. Layers 2, 3 and 4 had 125 (5^3) nodes each with 500 parameters associated in layer 4.

Table 2: Characteristics of the ANFIS network

Type of membership function	Generalized bell
Number of input nodes (n)	3
Number of fuzzy partitions of each variable (p)	5
Total number of membership functions	15
Number of rules (p^n)	125
Total number of nodes	394
Total number of parameters	545
Number of epochs	4000
Step size for parameter adaptation	0.01

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

$$RMSE=\left((1/p)\sum_{i=1}^{p}|t_i-o_i|\right)^{1/2} \quad (6)$$

$$R^2=1-\left(\frac{\sum_{i=1}^{p}(t_i-o_i)^2}{\sum_{i=1}^{p}(o_i)^2}\right) \quad (7)$$

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$$MPE = \frac{1}{p}\sum_{i=1}^{p}\left(\frac{t_i - o_i}{t_i}\times 100\right) \qquad (8)$$

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

The model was trained and tested by using MATLAB with Fuzzy Logic Toolbox. The performance of the model during training and testing was verified through three statistical indices (Eqs. 6 to 8) and presented in Table 3.

Table: 3 Performance of ANFIS model

During training			During testing			Computational Time (Min.)
RMSE	R^2	MPE	RMSE	R^2	MPE	
0.00127	0.9985	0.2758	0.0129	0.9986	0.7796	384

V. DISCUSSION

As observed from the performance table, the MPE and RMSE values for the training data were negligible in both the cases. MPE values for testing were found to be slightly higher than those for training. The coefficient of determination was found to be close to 1.0 during training. However, its value for testing was slightly less than unity. Based on the above statistical performances, the trained ANFIS model was tested for load ratio of 0.5. The predicted crack growth rates curve (for *R*=0.5) obtained from ANFIS model has been compared with experimental results in Fig. 7 and found to be in good agreement.

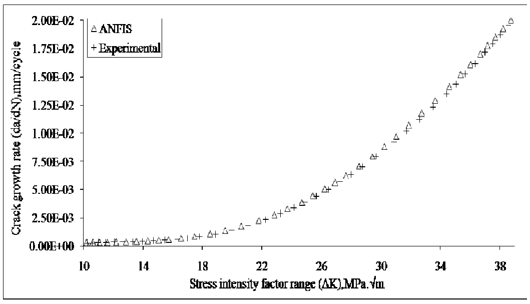

Fig. 7: Comparison of da/dN–ΔK curves for *R*=0.5

The numbers of cycles (fatigue life) have been calculated as per the following equation.

$$N_{i+1} = \frac{a_{i+1} - a_i}{da/dN} + N_i \qquad (9)$$

The predicted (ANFIS) numbers of cycles are presented along with experimental results in Table 4 for quantitative comparison. The crack length vs. number of cycle (*a~N*) curve has been plotted in Fig. 8.

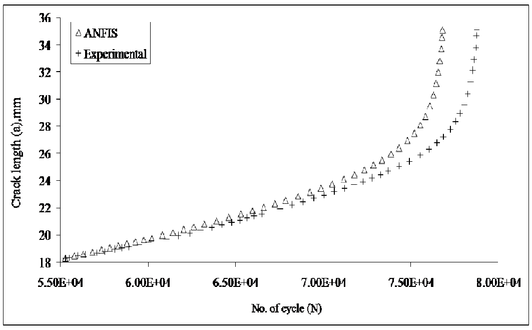

Fig.8: Comparison of predicted (ANFIS) and experimental crack length with number of cycle

The performance of the model was evaluated by comparing the prediction results with the experimental findings by the following criteria:

- Percentage deviation of predicted life from the experimental life i.e.

$$\%\,Dev = \frac{predicted - Experimental}{Experimental}\times 100$$

- Prediction ratio which is defined as the ratio of actual life (i.e. experimental) to predicted life i.e.

Prediction ratio, $P_r = \frac{actual}{predicted}$

- Error bands i.e. the scatter of the predicted life in either side of the experimental life within certain error limits.

Performance of the model result from first two criteria has been presented in Table 4.

Table.4: Prediction results of the model

Fatigue life ($\times 10^3$ cycle) ANFIS	Fatigue life ($\times 10^3$ cycle) Experimental	% Deviation ANFIS	Prediction ratio ANFIS
76.826	78.783	–0.024	1.025

It is observed that the ANFIS model prediction is reasonable in comparison to experimental findings as far as prediction of fatigue life is concerned. Further, the prediction ratio is approximately 1.0, which is adequate and also acceptable [19]. Fig. 9 illustrates the performance of the alloy evaluated graphically under the third criteria. It is observed that the scatter of the predicted life is within ± 0.025%.

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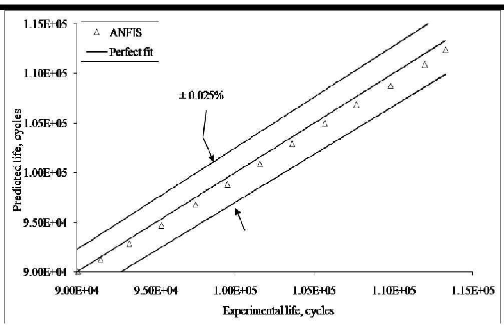

Fig. 9: Error band scatter of predicted lives for R = 0.5

VI. CONCLUSION

The focus of this work was to develop an ANFIS model in order to predict crack growth rate and in turn the fatigue life of 6061 Al alloy under the effect of load ratio. It has been observed that the predicted fatigue life from ANFIS model is 76.826×10^3 cycles whereas from experimental result it is 78.783×10^3 cycle. As far as performance of the model is concerned the percentage deviation of predicted fatigue life from the experimental result is –0.024 whereas the prediction ratio is 1.025. It can be concluded that the adaptive neuro-fuzzy technique (ANFIS) can be reasonably applied to predict the fatigue life under constant amplitude loading taking into account the load ratio effect.

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