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Fatigue Life Prediction of 6082 T651 Al-alloy under Low Temperature Spike Overload by ANFIS

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ABSTRACT: In the present work, the fatigue crack growth tests of 8090 T651 Al-alloy under interspersed single spike overload at various low temperatures such as 0°C, -30°C, -45°C, -60°C, and -75°C have been studied. From the experimental findings it has been observed that the fatigue crack growth rate decreases after the application of overload as the overload temperature decreases. The experimental data have been subsequently used to estimate the fatigue crack growth rate and subsequently the fatigue life of the alloy. From the modelling results, it has been found that the proposed ANFIS model slightly under estimates the fatigue life of 6082 T651 Al-alloy with -1.67% deviation from experimental findings.

KEYWORDS: Fatigue crack growth life; Low temperature overload; Adaptive neuro-fuzzy inference system (ANFIS); Root mean square error (RMSE).

I. INTRODUCTION

Aircrafts are frequently confronted with low temperatures during flight at high altitudes. Aluminium and lithium alloys are generally use to make aircraft structures though in some cases it is being replaced by composite materials. During flight, in addition to different types of fatigue loadings, the aircrafts may come across gust spectrum loading. Hence, fatigue crack growth under interspersed low temperature spike overload is quite essential in those cases. Till now, some works have been done [1-5] to characterize the damage tolerance properties of several Al-alloys under adverse environmental conditions. However, very few works have been undertaken to study fatigue properties at low temperature. It has been reported that fatigue resistance improves as the temperature decreases in Al-Li alloys [6] and some steels [7]. Gasqueres et al. [8] have investigated the fatigue crack growth behavior of a naturally aged Al-alloy and observed that crack growth rate in a colder environment is slower than in ambient air.

As far as fatigue crack growth under interspersed low temperature single spike overload is concerned, almost no works have been done till date. So, the present investigation aims at studying the fatigue crack growth rate of 6082 T651 Alalloy under single spike overload at different low temperature such as 0° C, -30° C, -45° C, -60° C, and -75° C. From the experimental results it has been observed that the fatigue crack growth rate decreases as the overload temperature lowers. The experimental data have been subsequently used to estimate the fatigue crack growth life of the above alloy by applying adaptive neuro-fuzzy inference system (ANFIS) technique. It has been found that the proposed ANFIS model slightly under estimates the fatigue life of 6082 T651 Al-alloy with -1.67% deviation from experimental findings.

II. MATERIALS AND METHODS

Fatigue crack growth experiment

Sometimes In the present study, the fatigue growth tests have been performed on 6082 T651 aluminum alloy using single-edge notched tension specimens having a thickness of 6.5 mm. The chemical composition and the mechanical properties of the alloys are listed in Table 1 and 2 respectively.



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Table 1. Chemical composition of 6082 T651 Al-alloy (wt. %)

Zn Mg	Cu Cr	Fe S	i Mn	Ti Ni
0.06 0.85	0.05 0.0	02 0.30 0	0.94 0.46	0.03 <0.01
Table 2. Mechanical properties of 6082 T651 Al-alloy				
Yield	Ultimate	Elongation	Reductio	n Hardness,
stress (0.2%	tensile	(%)	In area, 9	6 HV
proof)	strength			
(N/mm^2)	(N/mm^2)			
322.0	339.0	13.4	46.7	100

The single edge notch tension specimens (Fig. 1) have been made in the longitudinal transverse (LT) direction from the plate. The LT orientation means loading is in longitudinal (L) direction and crack growth is in transverse (T) direction with respect to axis of the plate.



Fig. 1. Single Edge Notched (SEN) Specimen geometry

The pre-cracking of the specimens has been carried out as per the requirements of ASTM E647 [9] on servo-hydraulic *Instron*-8502 machine under cyclic load control condition in air at room temperature. The loading frequency and the load ratio (*R*) have been kept as 5 Hz 0.1 respectively. The ratio of crack length (*a*) to width (*w*) is nearly 0.3 after pre-cracking. After pre-cracking, the test specimens have been subjected to constant load test (i.e. progressive increase in ΔK with crack extension) up to *a/w* ratio of 0.4 and subsequently subjected to single spike overload cycle at a loading rate of 7 KN/min.

All the experiments have been conducted in ambient temperature on a servo-hydraulic dynamic testing machine (*Instron*-8502) with 250 kN load cell, interfaced to a computer for machine control and data acquisition. The test specimens have been fatigue pre-cracked under mode-I loading to a crack length to width ration (a/w) of 0.2 and have been subjected to constant load test maintaining a load ratio of 0.1. The sinusoidal loads have been applied at a frequency of 5 Hz. The fatigue crack has been allowed to grow up to an a/w ratio of 0.3 and subsequently subjected to single spike overload cycle at a loading rate of 7 KN/min.



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The specimens have been subjected to mode-I overloads at an overload ratio of 2 ($R_{ol} = K_{ol}/K_{max}^B$) maintaining different temperatures of 0°C, -45°C, -60°C, and -75°C where, is the maximum stress intensity factor range for the base line test. During overloading the specimens have been kept in liquid nitrogen chamber to maintain the required low temperature. The cooling chamber consisted of two inlet ports in lower end and two outlet ports in upper end connected by blind holes as shown in Fig 2. A gap of 4 mm has been maintained on either sides of the specimen in order to avoid direct physical contact with cooling chamber walls. Temperature has been measured with a sixteen channel RTD indicator with a temperature range of -120 °C to 400 °C. Then, the fatigue crack growth test has been continued in mode-I. The crack growth has been monitored with the help of a COD gauge mounted on the face of the machined notch. The stress intensity factor *K* has been calculated using following equation;

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

where, $f(g) = 1.12 - 0.231(a/w) + 10.55(a/w)^2 - 21.72(a/w)^3 + 30.39(a/w)^4$ (2)

Experimental results

It has been observed that the experimental data of crack lengths (a) and number of cycles (N) obtained from the crack growth tests contain much scatter. These data have been smoothened by adopting the procedure of exponential model proposed earlier by the author [10].



Fig. 3. Comparison of $a \sim N$ curves for different low temperature overloads

The superimposed curve of $a \sim N$ at different low temperature overload cases has been plotted in Fig. 3. The crack growth rates (da/dN) have been calculated directly from the smoothened $a \sim N$ values as follows:



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$$\frac{\mathrm{d}a}{\mathrm{d}N} = \frac{\left(a_{j} - a_{i}\right)}{\left(N_{i} - N_{i}\right)}$$

(3)

Fig. 4 shows the superimposed $da/dN \sim \Delta K$ curve under different low temperature overload cases.



Fig. 4. Comparison of $da/dN \sim \Delta K$ for different low temperature overloads

ANFIS architecture

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 [12] topology based on first-order Takagi-Sugeno (TSK) [13] if-then rules has been used.



Fig. 5.Structure of ANFIS model with two input parameters [11]

Assuming a TSK type FIS of first order, below rules can be incorporated to construct a fuzzy model [14]: Rule I:

IF
$$(X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } B_1)$$
 THEN $(f_1 = m_1 X_1 + n_1 X_2 + r_1)$ (4)
Rule II:

IF
$$(X_1 \text{ is } A_2 \text{ and } X_2 \text{ is } B_2)$$
 THEN $(f_2 = m_2 X_1 + n_2 X_2 + r_2)$ (5)
Rule III:

IF
$$(X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } B_2)$$
 THEN $(f_3 = m_3 X_1 + n_3 X_2 + r_3)$ (6)

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Rule IV:

IF (X₁ is A₂ and X₂ is B₁) THEN $(f_4 = m_4 X_1 + n_4 X_2 + r_4)$

In the above expressions, the fuzzy sets of corresponding input parameters are denoted by $A_{1,2}$ and $B_{1,2}$. The name of statement in IF section is antecedent and those which are in THEN sections is called consequences. Different layers of Fig. 5 are explained here briefly [11, 14]:

Layer 1 – This layer performs the task of turning raw input data to linguistic terms. From the Fig. 5, there are two nodes linked to each of input parameters X_1 and X_2 . The node function chosen is Gaussian type [11] as described below:

$$O_i^1 = \beta(X) = \exp\left(-\frac{1}{2}\frac{(X-Z)^2}{\sigma^2}\right)$$
(8)

where, the notation O is the output of layer, Z denotes the centre of Gaussian membership function and σ is the variance term. These variables are adjusted and optimized during the learning process by ANFIS model to provide better performance of model.

Layer 2 – This layer determines the level of accuracy and effectiveness of conditions in the antecedent sections. Another name of this layer is firing strength layer. This level of determination fulfils using the following expression [14]:

$$O_i^2 = W_i = \beta_{Ai}(X) \beta_{Bi}(X)$$

 $O_i^5 = Y = \sum_i \overline{W_i} f_i = \overline{W_1} f_1 + \overline{W_2} f_2 = \frac{\sum_i W_i f_i}{\sum W_i}$

Layer 3 – In this layer, the calculated values of W_i (firing strengths) in the previous layer are normalized to easily discriminate between the firing strengths of each rule from and the total firing strengths of entire rules as below: $O_i^3 = \frac{W_i}{\sum W_i}$ (10)

Layer
$$4^{4}$$
 – This layer characterizes the linguistic terms of the output of model, which is the thermal conductivity in the present work. The degree of influence of each rule on the output of model is determined through following relation:

$$O_i^* = W_i f_i = W_i (m_i X_i + n_i X_2 + r_i)$$
 (11)
In which, n_i , m_i and r_i are linear variables. These variables as well as the variables of the first layer are adjusted and optimized by ANFIS model to provide a better consistency between model outcomes and target values.

Layer 5 – This layer sums up the entire rules attributed to an output parameter and transfers it to a numerical form using the weighted average sum approach formulated as following:

III.MODEL DEVELOPMENT

In the present work single spike overload has been applied at different low temperature to study the fatigue crack growth in mode-I. Here, three parameters are responsible for crack growth in the given loading situations. The first parameter is stress intensity factor range (ΔK) which is the main crack driving force which controls the crack growth. In addition to that maximum stress intensity factor (K_{max}) is also responsible for crack growth as per 'unified approach' [15-17] which take into account the mean stress effect. The third parameter is the various temperatures during overloading (T_{ol}) depending upon which the retardation of crack growth occurs after overloading. So, these three parameters have been selected as linguistic input variables whereas, crack growth rate (da/dN) has been taken as output variable during formulation of ANFIS model. 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 five sets of fatigue crack growth data having low temperature overloads (T_{ol}) of 0°C, -30° C, -45° C, -60° C, and -75° C. Each set for a particular low temperature overload case contains approximately 300 data sets with K_{max} and ΔK values along with their corresponding da/dN values. The training set (TS) has been constructed from the four experimental input/output data sets low temperature overloads (T_{ol}) of 0°C, -30° C, -60° C, and -75° C. The remaining data set (i.e. for $T_{ol} = -45^{\circ}$ C) has been kept for testing 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. T_{ol} , K_{max} and ΔK) as well as output variable (i.e.

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da/dN to unity. The numbers of membership functions (MF) have been chosen to be 4-4-4 corresponding to the inputs T_{ol} , K_{max} and ΔK respectively. The $4 \times 4 \times 4 = 64$ 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 1000 epochs.

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:

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

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

$$MPE = \frac{1}{2} \sum_{i=1}^{p} \left(\frac{t_i - o_i}{2} \times 100 \right)$$
(13)
(14)

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

 $p \sum_{i=1} \left(t_i \right)$

IV.MODEL VALIDATION

The formulated ANFIS model has been trained by feeding the input/output data of TS. After training, the RMSE, R^2 , and MPE values obtained are 0.000175, 0.98998 and 0.19857 respectively. Then, the input data for validation set i.e. for $T_{ol} = -45^{\circ}$ C 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 mention above, 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 $T_{ol} = -45^{\circ}$ C (i.e. VS). The predicted crack growth rates (for $T_{ol} = -45^{\circ}$ C) obtained from ANFIS model have been compared with experimental results in Fig. 6 and found to be in good agreement.



Fig. 6.Comparison of $da/dN \sim \Delta K$ curves for $T_{\rm ol} = 45^{\circ} \rm C$



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The numbers of cycles (i.e. fatigue life) have been calculated as per the following equation and presented Fig. 7.

$$N_{i+1} = \frac{a_{i+1} - a_i}{\frac{da}{dN}} + N_i \tag{16}$$

From the result it has been observed that the fatigue life obtained from the ANFIS model was 118×10^3 cycles whereas its corresponding experimental value has been 120×10^3 cycles. Comparing the results it is found that the percentage deviation of fatigue life obtained from the proposed model is -1.67%. The prediction ratio of the model which is defined as the ration of experimental fatigue life to predicted fatigue life is 1.017 which is nearer to 1.0 and is acceptable as per the literature [18].



Fig. 7. Comparison of predicted and experimental a ~N curves for $T_{\rm ol} = 45^{\circ} \rm C$

V. 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 6082 T651 aluminum alloy under the effect of low temperature spike overload. From the results it has been observed that the predicted fatigue life from the proposed model is 118×10^3 cycles with percentage deviation of -1.67% and prediction ratio of 1.017 in comparison to experimental result of 120×10^3 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 underestimates the life.

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