https://dx.doi.org/10.22161/ijaers/3.12.48 *ISSN: 2349-6495(P) | 2456-1908(O)*

Low Temperature Fatigue Crack Growth Test and Life Estimation of 7475-T7351 Al-ally by ANN

J. R. Mohanty

Department of Mechanical Engineering, Veer Surendra Sai University of Technology, Burla, 768018, India,

***Abstract*— *In the present wok fatigue crack growth tests have been performed under interspersed mode-I overload on 7475-T7351 Al-alloy. The overloads with an overload ratio of 2 were given at 0℃, –30℃, –45℃, –60℃, and –75℃ at a loading rate of 7 KN/min after the crack had grown to a/w ratio of 0.4. The crack growth tests have been continued in mode-I at a frequency of 5 Hz and load ratio (R) of 0.1 till fracture. From the fatigue tests it has been observed that the crack growth rate decreases and consequently fatigue life increases as the overload temperature decreases. The experimental data generated have been subsequently used to formulate the ANN model to predict the fatigue crack growth rates and the fatigue life of 7475-T7351 Al-alloy. It has been observed that the proposed model predicts the fatigue life with reasonable accuracy having + 0.919% deviation from experimental results.*

Keywords*— *Fatigue crack growth, Low temperature overload; Load ratio, Artificial neural network, Normalized mean square error.

I. INTRODUCTION

Engineering materials don't reach theoretical strength when they are tested in the laboratory. Therefore, the performance of the material in service is not same as it is expected from the material. Hence, the design of a component frequently implores the engineer to minimize the possibility of failure. Most of the material damage**s/**failures occur mainly due to cyclic/fatigue loading. It is a progressive and localized material damage that occurs without any obvious warning and leads to catastrophic failure. It not only causes loss of human life but also pays penalty on economy. Hence, it is essential to estimate the life of components/structures subjected to fatigue loading in order to schedule timely inspections of machine parts to avoid catastrophic failure.

Fatigue life is influenced by a variety of factors, such as loading histories, material properties, operating temperatures, environmental conditions etc. Load cycles may consist of constant amplitude, variable amplitude, band loads etc. The load interactions during fatigue may occur in terms of single spike/band over/under loads. The single spike overload in constant amplitude loading retards a growing crack whereas; its corresponding counterpart i.e. under load accelerates the crack growth. Earlier, several works [1-4] have been undertaken to study the effect of spike overload on fatigue crack growth as it has got beneficial effect by increasing the residual life of the machine parts. This type of loading situation may occur in presence of low temperatures e.g. aircrafts, ships, off-shore structures, ships, oil pipe lines etc.

As far as fatigue crack growth at low temperature is concerned, few works have been done till date. Zambrow and Fontana [5] have studied the effect of working temperature on fatigue life and found that fatigue life of magnesium and aluminum alloys and also some stainless steels increase with lowering the temperature due to increase in fatigue strength. Stephens et.al [6] have conducted variable amplitude fatigue crack initiation and fatigue crack growth on some carbon and low-alloy steels. They have observed that the fatigue crack growth life tends to increase as the temperature is lowered. Further, it has been observed that [7] fatigue life of most FCC materials increase with decrease in temperature. As far as spike overload at low temperature is concerned almost no work has been done to verify its effect on constant amplitude fatigue crack growth. In the present investigation, the effect of mode-I fatigue crack growth under interspersed low temperature spike overload at various temperatures such as 0°C, –30°C, –45°C, –60°C, and –75°C on 7475-T7351 aluminium alloy has been studied. It has been observed that a growing fatigue crack retards as the temperature decreases. Back-propagation neural network has been applied to predict the fatigue life of the alloy and observed that the model predicts the life with reasonable accuracy with + 0.919% deviation from experimental results.

II. EXPERIMENTAL PROCEDURE

The material used in this study is 7475-T7351 aluminium alloy. The chemical compositions and mechanical properties of 7475-T7351 Al-alloy are listed in Tables 1

https://dx.doi.org/10.22161/ijaers/3.12.48 **ISSN: 2349-6495(P) | 2456-1908(O)**

and 2, respectively. The compact tension (CT) specimen has been cut from 15 mm thickness plate and designed as per the requirements of ASTM E647-05 [8]. The specimens have been made in the longitudinal transverse (LT) direction. The detail geometry of the specimens is shown in Fig 1. The fatigue crack growth tests have been conducted 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. The tests have been performed in air and at room temperature except during overloading. The test specimens have been fatigue pre-cracked under mode-I loading up to a crack length to width (a/w) ratio of 0.3 and then subjected to constant load test (i.e. progressive increase in ΔK with crack extension) maintaining a load ratio of R=0.1 up to a/w ratio of 0.4. Sinusoidal loads have been applied during the test at a frequency of 7 Hz. The crack growth has been monitored with the help of a COD gauge mounted on the face of the machined notch.

Table.1: Chemical composition of Al 7475-T7351 (wt%)

Zn	Mg	Cu	Cr	Fe	Si	Mn	Ti	V	Al
5.79	2.13	1.37	0.2	0.07	0.04	0.01	0.04	0.01	Bal

Table.2: Mechanical properties of Al 7475-T7351

Young's modulus (GPa)	Yield strength (MPa)	Tensile strength (MPa)	Elongation (%)
71.70	429.00	502.00	9.00

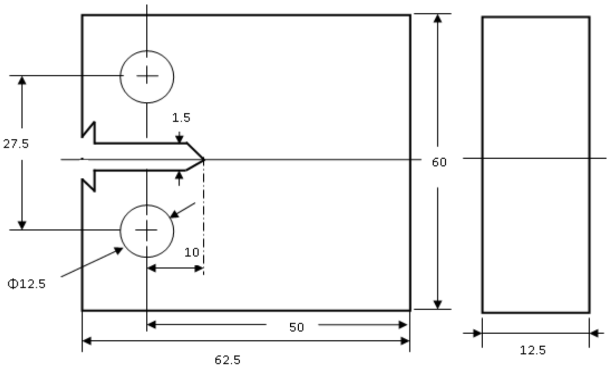

Fig.1: Compact tension (CT) specimen geometry

After the crack has grown to the specified length (i.e. a/w = 0.4), the specimens have been subjected to single spike overload with an overload ratio of 2 ($R_{ol} = K_{ol}/K^{B}_{max}$ = 2) at a rate of 7KN/min maintaining different temperatures of 0°C, –30°C, –45°C, –60°C, and –75°C where, K^{B}_{max} 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 consists of two inlet ports in lower end and two outlet ports in upper end connected by blind holes as shown in Fig 2.

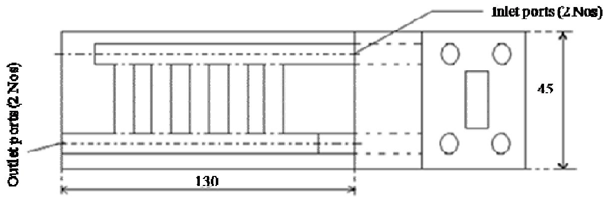

Fig.2: Cooling Chamber

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. The 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.

III. EXPERIMENTAL RESULTS

The machine generated data of crack length (a) and number of cycles (N) obtained from the fatigue crack growth tests at different low temperature overload cases as well as base line contain much scatter. The determination of crack growth rates from those data is very difficult due to scattering of data points. Therefore, to smoothen the a ~ N raw data, exponential equation method has been followed as proposed in the author's earlier work [9]. After data smoothening, the modified superimposed a ~ N curve for different low temperature overload cases along with base line data has been plotted in Fig. 3. From the smoothened a ~ N data, the crack growth rates (da/dN) have been calculated directly by using the following equation.

$$\frac{da}{dN} = \frac{(a_j - a_i)}{(N_j - N_i)} \quad (1)$$

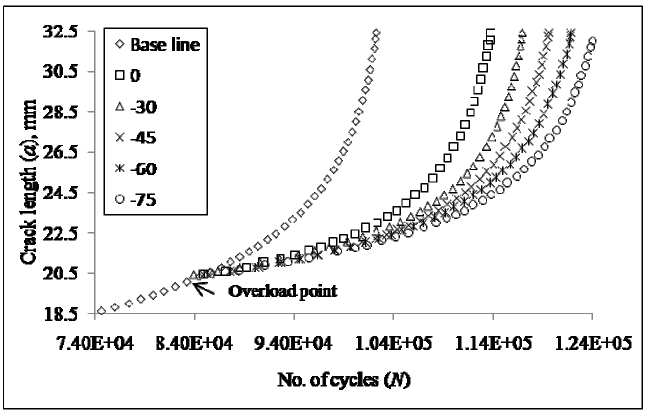

Fig.3: Superimposed a ~ N curves at different low temperature overloads

https://dx.doi.org/10.22161/ijaers/3.12.48 ISSN: 2349-6495(P) | 2456-1908(O)

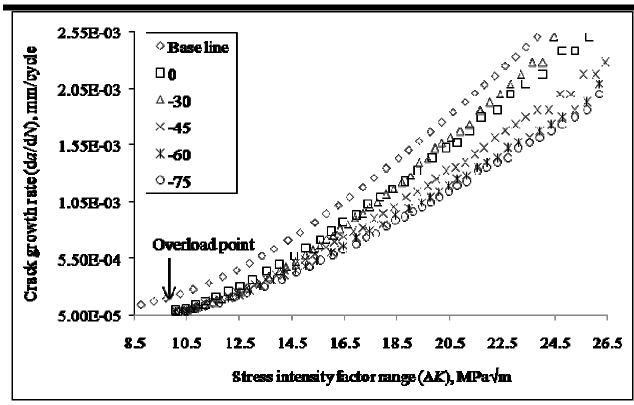

Fig .4: Superimposed da/dN ~ ΔK curves at different low temperature overloads

IV. NEURAL NETWORK APPLICATION AND DESIGN

In the present work, the back-propagation neural network (BPNN) has been adopted. It is a supervised, multi-layer, feed-forward network with an error-back propagation algorithm (error minimization technique). Its architecture consists of a collection of nodes distributed over a layer of input neurons, one or more layers of hidden neurons and a layer of output neurons. Neurons in each layer are interconnected to subsequent layer neurons with links, each of which carries a weight that describes the strength of that connection. Various non-linear activation functions, such as sigmoidal, tan*h* or radial (Gaussian) are used to model the neuron activity. Training involves moving the patterns forward through the network layers, then propagating the errors backward, and then updating the weights. This is done in order to decrease the errors.

In the present investigation, a nine-layer perceptron ANN with back-propagation neural controller 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 input parameters to the neural network controller are as follows: Stress intensity factor range = "ΔK"; Maximum stress intensity factor = "K_{max}"; Low temperature overload = "T_{ol}". The output from the controller is: Crack growth rate = "d*a*/d*N*" The proposed ANN has been written in the C^{++} programming language and all the training tests have been performed on a Pentium 4 (2.0 GHz). The activation function chosen in this work is the hyperbolic tangent function:

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{2}$$

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

$$E_{rr} = \frac{1}{2} \sum_{\substack{all \\ training \\ patterns}} (\theta_{desired} - \theta_{actual})^2 \tag{3}$$

where, θ_{actual} represents crack growth rate ("cgr")

While developing an ANN model, proper selection of input and output parameters and also the structure of the network are very much essential in achieving better results. It is considered that the most suitable combinations of input and output sets are those which would give the least normalized mean square error (MSE). The stress intensity factor range (ΔK), maximum stress intensity factor (K_{max}), and (1) low temperature overload (T_{ol}) have been considered as the input parameters whereas crack growth rate $\left({da}/{dN} \right)$ has been chosen as the output parameter for the present investigation. To make the input amenable for successful learning to minimize the overall mean square error, the two input parameters (i.e. ΔK and K_{max},) have been normalized between 1 and 4, while the other one, low temperature overload (T_{ol}) has been normalized between 0 and 1. Similarly the output $\left({da}/{dN} \right)$ 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 3×350 experimental values of ΔK, K_{max} and $\left({da}/{dN} \right)$ data for each of the low temperature overloading cases (0°C, –30°C, –60°C and –75°C). The other experimental set i.e. at –45°C overload data have been kept for testing.

The multi-layer perceptron (MLP) neural network architecture has been applied to simulate the crack growth rate of an unknown set of low temperature overload case of, –45°C as validation set (VS). The network has been trained by error back-propagation learning method and error during training and testing has been shown in Fig. 5. Table 3 and 4 show various Learning algorithms' parameters and statistical performances respectively during training.

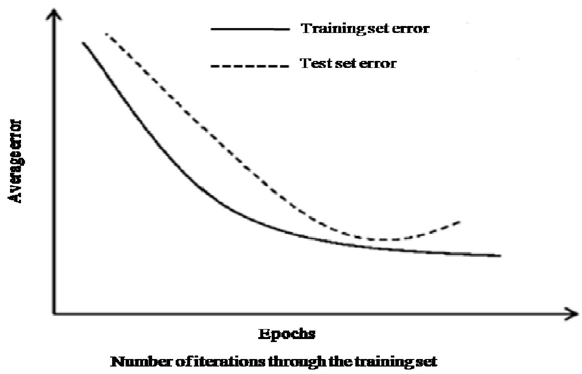

Fig. 5: Training set error and test set error during training

https://dx.doi.org/10.22161/ijaers/3.12.48 ISSN: 2349-6495(P) | 2456-1908(O)

Table.3: Learning algorithms' parameters of the network

Momentum Coefficient	Learning rate	Hidden neurons	Training epochs	Computational Time (Min.)
0.2	0.32	179	6.532×10^{5}	850

Table.4: Statistical performance of ANN during training

R^2 value	Correlation coefficient (r)	MSE	Maximum absolute error	Minimum absolute error
0.997	0.8976	1.237×10^{-6}	1.432×10^{-5}	0.003×10^{5}

V. MODEL VALIDATION

After training, the three input parameters i.e. stress intensity factor range (ΔK), maximum stress intensity factor ($K_{\max}$) and low temperature overload (T_{ol}) for the suppressed overload temperature –45°C have been fed to the trained ANN model in order to predict the corresponding crack growth rate $\left(da/dN\right)$. Table 5 gives the statistical performances of the network during testing.

Table.5: Statistical performance of ANN during testing

R^2 value	Correl-ation coeffi-cient (r)	MSE	Maximum absolute error	Minimum absolute error
0.998	0.965	1.365×10^{-6}	1.983×10^{-5}	0.012×10^{5}

The predicted crack growth rate results of the tested specimen have been presented in Fig. 6 along with experimental data for comparison. It is observed that the simulated da/dN–ΔK points follow the experimental ones quite well.

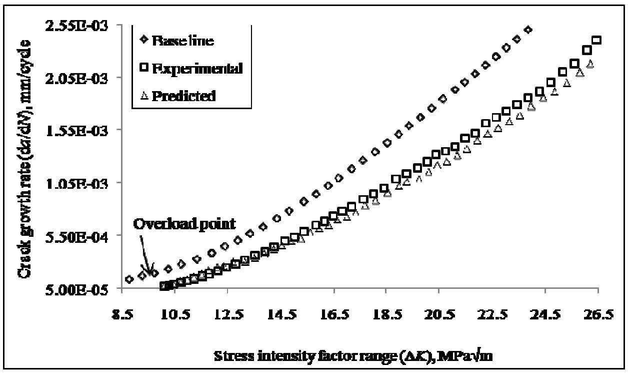

Fig.6: Predicted and experimental da/dN~ΔK plot, –45 ℃

The number of cycles has been calculated from the simulated $\left(da/dN\right)$ values by taking the post-overload experimental 'a' and 'N' value as the initial value and assuming an incremental crack length of 0.005mm in steps in excel sheet as per following equation:

$$N_{i+1} = \frac{a_{i+1} - a_i}{da/dN} + N_i \qquad (4)$$

The predicted a–N values of the ANN model have been compared with the experimental data in Fig. 7.

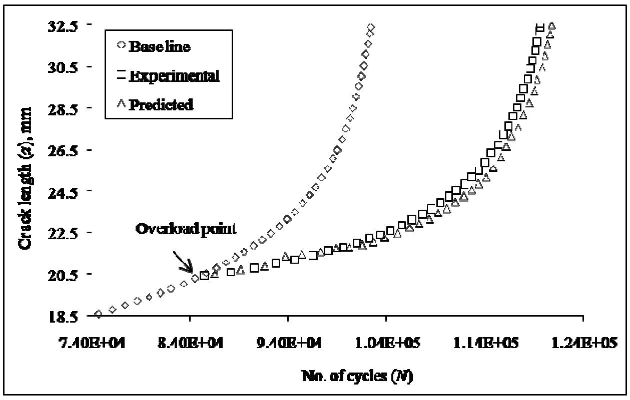

Fig. 7: Predicted and experimental a~N results (–45 ℃)

The predicted and experimental post overload fatigue lives (i.e. No. of cycles) along with its percentage deviation are presented in Table 6. As observed from the table, the percentage deviation of predicted results from the experimental findings is + 0.025.

Table.6 - Predicted and experimental results

Predicted Post overload fatigue life	Experimental post overload fatigue life	% Dev
120.77×10^{3}	119.67×10^{3}	+0.919

VI. CONCLUSION

The current research work presents a novel approach for the formulation of fatigue crack growth rates and subsequently the fatigue life of Al 7475-T7351 under low temperature overload condition using ANN. The proposed ANN model is an empirical formulation based on experimental result collected from fatigue crack growth tests. The model shows very good agreement with the experimental findings having + 0.919% deviation. This work proves that the back-propagation neural network technique can successfully be applied to low temperature overload fatigue loadings by substantially reducing the time consuming and costly fatigue tests.

REFERENCES

[1] V. V. Bolotin and V. L. Lebedev, "Analytical model of fatigue crack growth retardation due to overloading," International Journal of Solids Structure, vol. 33, pp. 1229-1242, 1996.

[2] A.U. DeKoning, "A simple crack closure model for prediction of fatigue crack growth rates under variable amplitude loading," ASTM Specific Technical Publication, vol. 743, pp. 63-85, 1981.

[3] J. Schijive, "Fatigue crack propagation in light alloy steel material and structures," in: Advances in Aeronautical Sciences, Pergamon Press, New York, pp. 387-408, 1961.

[4] O. E. Wheeler, "Spectrum loading and crack growth. Journal of Basic Engineering," vol. 94, pp. 181-186, 1972.

[5] J. L. Zambrow and M. G. Fontana, "Mechanical properties, including fatigue of aircraft alloys at very low temperatures," Transaction of American Society of Metallurgy, vol. 41, pp. 480-518, 1949.

[6] R. I. Stephens, A. Fatemi, H. W. Lee, S. G. Lee, C. Vacas-Oleas, C. M. Wang, "Variable amplitude fatigue crack initiation and growth of five carbon or low-alloy cast steels at room and low climatic temperatures," ASTM, STP, vol. 857, pp. 293-312, 1985.

[7] J. Polak and M. Klesnil, "Thermodynamics of cyclic plastic deformation and fatigue life of low carbon steel at low temperatures," Material Science Engineering, vol. 26, pp. 157-166, 1976.

[8] Standard test methods for measurement of fatigue crack growth rate, ASTM, vol. E 647-05, 2005,

[9] J. R. Mohanty, B. B. Verma and P. K. Ray, "Determination of fatigue crack growth rate from experimental data: A new approach," International Journal of Microstructure & Material Properties, vol. 5, pp. 79–87, 2010.