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Crack Propagation Life Prediction of a Single Lap Shear Joint: A Linear Elastic Fracture Mechanics Based Machine Learning Approach

Zafer Yüce[a], Paşa Yayla[a], Alev Taşkın[b]

[a]*Marmara University, Maltepe, Istanbul 34840, Turkey*
[b]*Yildiz Technical University, Besiktas, Istanbul 34349, Turkey*

Abstract

Estimation of fatigue life in the aerospace industry plays a key role in terms of safety, certification, and inspection. Individual aircraft tracking programs aim to calculate the fatigue index for each aircraft based on its load history. Therefore, accurate estimation of fatigue life based on unique load spectra for each aircraft plays a crucial role. The purpose of this study is to predict the crack growth (CG) life of a single lap shear joint for an aircraft based on different spectral loads using random forest regression and k-nearest neighbors(k-NN) regression. A finite element model was built using the Huth fastener flexibility method to obtain fastener loads and stress values on the structure under maneuver loads. Then, finite element results were compared to analytical calculations. Based on Fighter Aircraft Loading Standard for Fatigue and Fracture (FALSTAFF) spectra, 90 different spectra were developed to be used for the calculation of CG life. The AFGROW software was used to calculate the CG life based on the load spectra and the findings of the finite element model. Analytical calculations of CG lives and features of individual load spectrums were fed to machine learning models. Finally, the CG life predictions of the machine learning models were compared with analytical calculations. According to the findings, a good correlation was observed between the analytical and predicted CG lives.

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Keywords: Fatigue; Crack; Machine Learning; Aircraft

1. Introduction

Machine learning methods are widely used in various industries, including automotive, aerospace, construction, medicine, and so on. The capabilities of machine learning methods in handling huge amounts of data and building complex relationships are attracting engineers and researchers to utilize them more and more. Estimation of fatigue

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life requires so many input parameters and it also has a statistical distribution, which makes it hard to calculate precisely. Previous studies have shown that with the aid of machine learning models, the fatigue life of engineering structures can be estimated with a good level of accuracy.

Pleune and Chopra (2000) studied artificial neural networks (ANN) to predict the fatigue life of carbon and low alloy-steels for different environmental conditions. In order to train the model, the results of 1,036 fatigue tests were used. According to the results, the model showed promising performance for environmentally assisted corrosion cases. Srinivasan et al. (2003) studied ANN to predict low cycle fatigue and creep-fatigue interaction behavior of 316L steel. Optimum results were achieved with 4 neurons in the hidden layer and using the sigmoid activation function. The results indicate that ANN can predict with a factor of two under low cycle fatigue (LCF) and creep-fatigue interaction. Genel (2004) studied ANN to predict strain life fatigue properties of steels using the input parameters as Young's modulus, reduction in area, hardness, yield stress, the ultimate tensile strength based on tensile test data for 73 steels. According to findings, ANN may predict strain life fatigue properties with 98-99% of accuracy. Marquardt and Zenner (2005) studied ANN to predict fatigue life by considering load spectra parameters as input such as maximum load, length of sequence, irregularity, and severity of the spectra. Their findings suggest that the accuracy of ANN is more reliable than damage accumulation-based life calculation methods such as Palmgren Miner. Vassilopoulos et al. (2007) studied ANN to predict the fatigue life of composite materials based on the input parameters such as angle of fibers, stress ratio, the amplitude of stress, and maximum stress. According to the results, 0.12 MSE was achieved. Mathew et al. (2008) set out a study to predict the low cycle fatigue life of 316LN stainless steel based on the input variables such as temperature, strain rate, strain range, etc. According to the results, feed-forward back propagation ANN may predict life with a factor of two of experimental data. Al-Assadi et al. (2011) studied to predict the fatigue life of composite materials using ANN. Findings indicate that RMSE varies between 6.1 and 40%. Also, to obtain a more accurate result, the number of hidden layers is suggested between 6 and 12. Barbosa et al. (2020) set out a study to develop a constant life diagram for metallic materials with the aid of ANN using P355NL1 test data. Mean stress and number of cycles were used as input and stress amplitude was determined as output. According to the findings, the multilayer perceptron model with a backpropagation algorithm gave accurate results for R-ratios of -0.5 and 0. Yang and his team compared the semi-empirical model with ANN in terms of predicting the low cycle fatigue life of polyamide-6 based on stress amplitude mean stress and stress rate parameters as input. They conclude that ANN outperformed the semi-empirical model (Yang et al., 2020).

Estimation of accurate life for aircraft structures is very significant when it comes to individual aircraft tracking in the sense of aircraft structural integrity program. Each aircraft works under different load conditions that depend on the region, usage, pilot, and other parameters. Therefore, each aircraft has a unique fatigue index and should have a unique maintenance plan correspondingly. This paper examines the CG life prediction of a shear joint under different load spectra using random forest regression and k-NN regression. This study introduces a methodology for load analysis, machine learning model development, and optimization of the model.

Nomenclature

V	Fastener Load
C	Fastener Flexibility
P	Load
t	Thickness
d	Hole Diameter
E	Young's modulus
w	Width
σ	Stress
f	Flexibility
z_1	Top surface
z_2	Bottom surface

2. Methodology

In order to calculate CG life, a lap shear joint geometry was considered. Based upon FALSTAFF, 90 unique load spectra were developed for different load levels, and then CG life was calculated for each load spectra. After all, used load spectrums were cycle counted, and then calculated histograms were fed into machine learning models to predict CG lives. Figure 1 illustrates the methodology of this study.

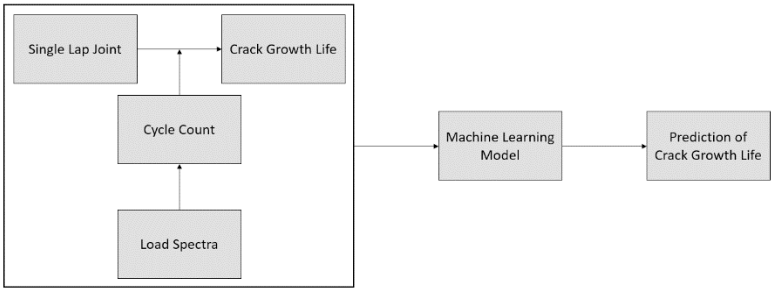

Fig. 1. Methodology of the study

2.1. Load Spectra

FALSTAFF was developed in 1976 based on the flight data of the Lockheed F-104G, Fiat G-91, Northrop NF-5A, and Dassault Mirage III S that were utilized in the German Air Force, Royal Netherlands Air Force, and Swiss Air Force. FALSTAFF consists of 32 different load levels where zero is set to 7.52 and one block of spectrum is representative of 200 flights or one year of typical usage (Aicher W, et al 1976).

In this study, the lap shear joint of a fighter aircraft with a 10,000 flight hours (FH) design service goal (DSG) was considered. Therefore, 90 unique load spectra were derived for different g envelopes ranging from -3g to 9g based on FALSTAFF.

2.2. Analysis of the joint

2.2.1. Fastener Load Calculation

The joint consists of two 7050-T7451 aluminum sheet metals with 3mm of thickness and 32mm of width, which are fastened by three steel bolts. Fastener loads were calculated based on compatibility, which assumes that displacements of opposite points between two fasteners on each plate are equal to deflection (*ESDU 98012,* 2002). The effects of secondary bending are not considered in this study. To simulate the worst-case scenario, pre-tension loads and friction between plates were not taken into account. It is assumed that the stiffness of the structure will not change under load. Figure 2 presents the load flow between plates.

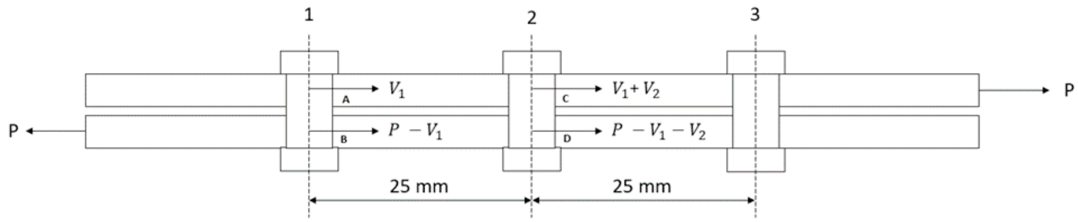

Fig. 2. Load flow of the joint

Following compatibility equations are used to calculate fastener loads.

$$V_1C_1 + P_A\left(f_A\right) = V_2C_2 + P_B\left(f_B\right) \tag{1}$$

$$V_2C_2 + P_C\left(f_C\right) = V_3C_3 + P_D\left(f_D\right) \tag{2}$$

Fastener flexibilities were calculated using the Huth fastener flexibility method (Huth, 1984). Huth equation is:

$$C = \left(\frac{t_1 + t_2}{2d}\right)^a \frac{b}{n}\left(\frac{1}{t_1E_1} + \frac{1}{nt_2E_2} + \frac{1}{2t_1E_1} + \frac{1}{2nt_2E_2}\right) \tag{3}$$

Where;
a=2/3 and b=3 for metallic bolts and n=1 for single lap joint.
Analytical calculation results of fastener loads and FEM findings are presented in Figure 3.

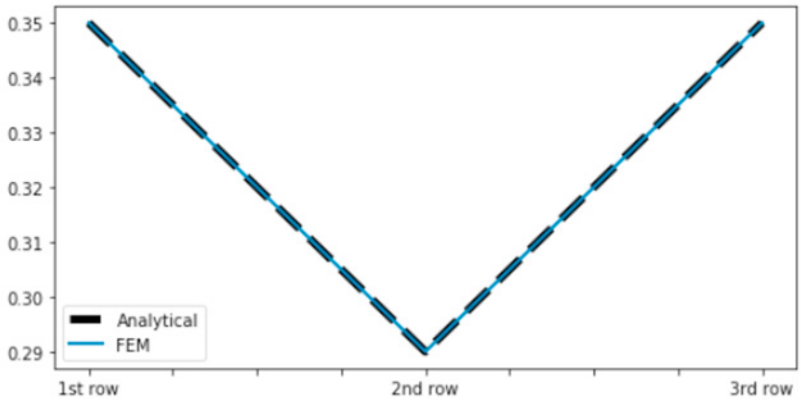

Fig. 3. Results of analytical and FEM calculations of fastener loads

As it can be seen from the chart above, analytical calculation and FEM results are almost the same.

2.2.2. Crack growth analysis

It's assumed that the crack will propagate perpendicular to the tensor direction of the first principal stress near the most critical region. In our model, the most critical region is calculated as the edge of the first hole. During CG life calculation, a linear elastic fracture mechanics based approach was utilized, and to stay in conservative side retardation effects were not taken into account.

For the CG analysis, gross, bearing(Br), thru, and bending stress are calculated as following;

$$\sigma_{Gross} = \frac{P_{Gross}}{wt} \tag{4}$$

$$\sigma_{Br} = \frac{P_{Br}}{dt} \tag{5}$$

$$\sigma_{Thru} = \frac{\sigma_{z_1} + \sigma_{z_2}}{2} \tag{6}$$

$$\sigma_{Bending} = \frac{\sigma_{z_1} - \sigma_{z_2}}{2} \tag{7}$$

Based on the gross, bearing, thru, and bending stress components, the CG life of the joint was calculated for each spectrum. The initial crack size was chosen as 1.27 mm as suggested in Joint Service Specification Guide (*JSSG-2006,* 1998). CG life calculations were performed using AFGROW software.

2.3. Machine Learning Model

2.3.1. Preparation of data

Cycles of developed load spectrums were calculated using the rainflow cycle count method (Matsuichi & Endo, 1968). The results of the rainflow cycle count histogram consisting of maximum, minimum, and cycle values were fed to a machine learning model with statistical features of the spectrum such as mean and standard deviation of the spectrum. Regarding train and test split size, 20% of the data was utilized as a test, and the rest of the part is used as training data.

Figure 4 illustrates the machine learning process.

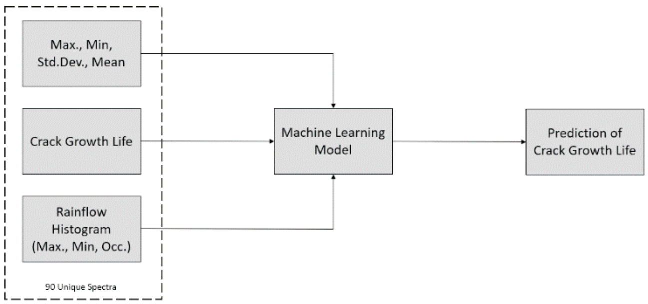

Fig. 4. Outline of the machine learning model

To measure the effect of extreme values on results, two data sets were created as original full data and data without outliers. A scatter factor of 4 was utilized during filtering. So, the filtered data set consists of CG life values below 40,000 FH (1 DSG x 4).

2.3.2. Random Forest Regression Model

Random Forest is a decision tree-based algorithm. The algorithm creates multiple decision trees and calculates the output by averaging the results of individual trees. Also, the interaction between individual trees is not allowed. In this study, the initial run was performed with 100 estimators, which correspond to individual trees, then using hyperparameter optimization, the number of estimator values was fine-tuned.

2.3.3. k-NN Model

The k-NN algorithm makes predictions based on searching the closest data points for corresponding input. The number of closest data points is determined by the user, and the result is calculated by averaging the values of the closest points. In this study, an initial run was performed with 5 neighbors, and then using hyperparameter optimization, the number of neighbor values was fine-tuned.

3. Results

As presented in Section 2, the rainflow histogram and statistical features of load spectra were fed to the machine learning model to predict the CG life of the joint. Regarding error metrics, the root mean square error (RMSE) was employed. Which is;

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \left(\mathrm{Predicted}_i - \mathrm{Actual}_\mathrm{i}\right)^2}{N}} \tag{8}$$

3.1. Random Forest Regression

Using the results of 90 load spectra, a random forest regression model was built with 100 estimators. The RMSE for this model was calculated as 9,926 FH. The actual CG life and predicted CG life of this model are presented in Figure 5.

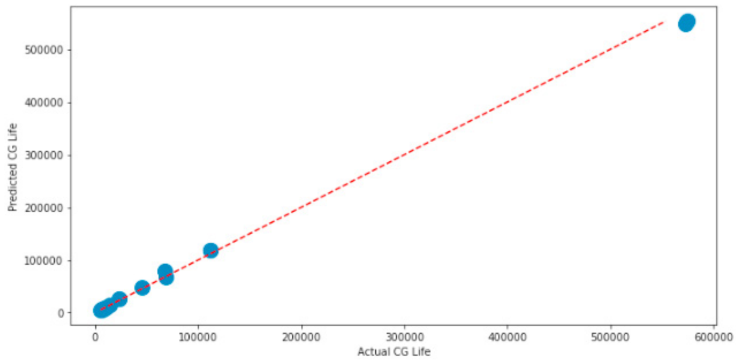

Fig. 5. Comparison of predicted and actual values for random forest regression with original data

To remove outliers, input data was filtered while keeping spectrums with CG life lower than 40,000 FH. RMSE of the filtered model was calculated as 383 FH. The actual CG life and predicted CG life of this model are presented in Figure 6.

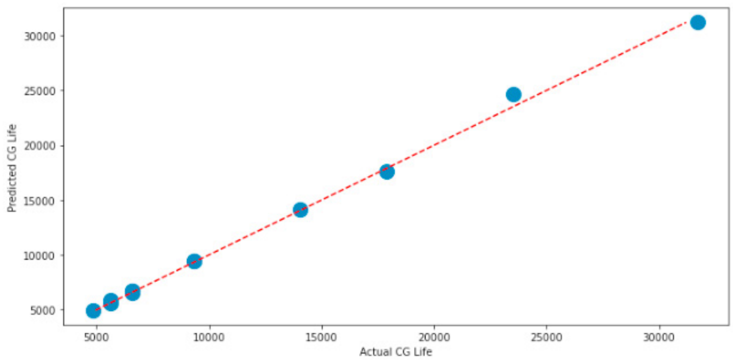

Fig. 6. Comparison of predicted and actual values for random forest regression with filtered data

Finally, a grid search algorithm was utilized to filter data to find optimum parameters and reduce the RMSE. According to grid search algorithm results, the number of estimator values should be 292. The RMSE error of the optimized model by grid search was calculated as 327 FH. The actual CG life and predicted CG life of this model are presented in Figure 7.

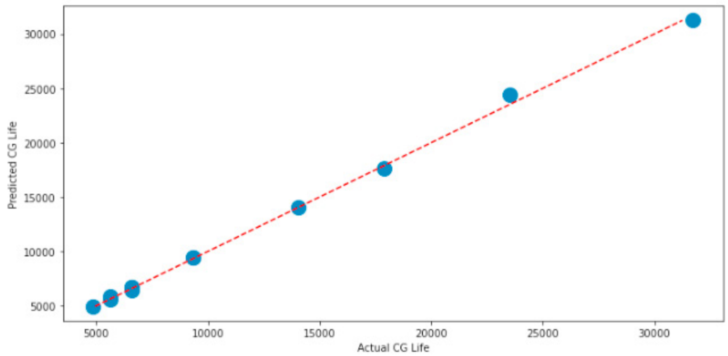

Fig. 7. Comparison of predicted and actual values for hyperparameter optimized random forest regression with filtered data

3.2. k-NN

Using the results of 90 load spectra, a k-NN model was built with 5 neighbors. The RMSE for this model was calculated as 174,294 FH. The actual CG life and predicted CG life of this model are presented in Figure 8.

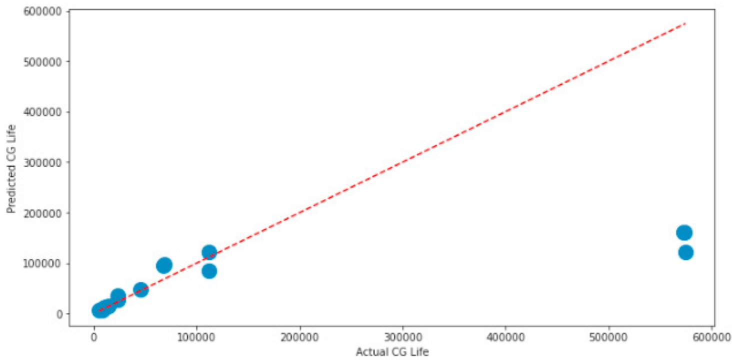

Fig. 8. Comparison of predicted and actual values for k-NN regression with original data

To remove outliers, input data was filtered while keeping spectrums with CG life lower than 40,000 FH. The RMSE of the filtered model was calculated as 4,499 FH. The actual CG life and predicted CG life of this model are presented in Figure 9.

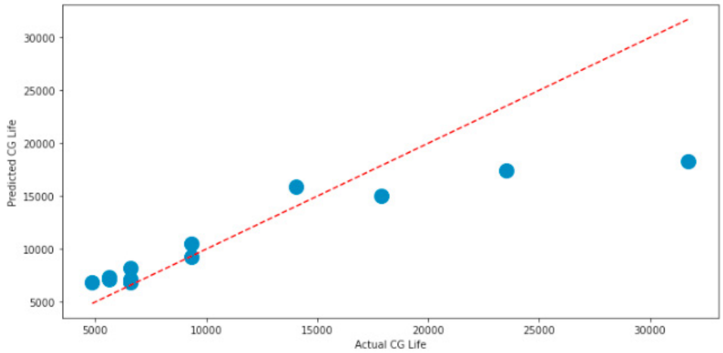

Fig. 9. Comparison of predicted and actual values for k-NN regression with filtered data

Finally, a grid search algorithm was utilized to filter data to find optimum parameters and reduce the RMSE. According to grid search algorithm results, the number of neighbors value was calculated as 2. The RMSE error of the optimized model by grid search was calculated as 3,795 FH. The actual CG life and predicted CG life of this model are presented in Figure 10.

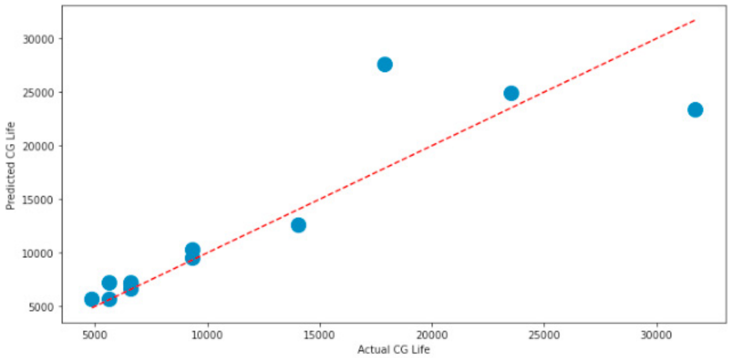

Fig. 10. Comparison of predicted and actual values for hyperparameter optimized k-NN regression with filtered data

4. Discussion

In this study, random forest regression and k-NN methods were investigated in terms of CG life prediction of a single lap joint for a fighter aircraft. One interesting finding is that the error value was increased when the original input data was used. Considering the CG life values of used 90 spectra, which range between approximately 4,800 FH and 770,000 FH, it seems possible that input data contains outlier values, and these extreme values may lead to an increase in the error. When the input data was cleaned from the outliers, the error of the random forest regression model was decreased by approximately 97% and the error of the k-NN model was decreased by 98%. According to these data, we can infer that data without outliers tends to give more accurate results. Also, after the hyperparameter tuning with the aid of the grid search algorithm, the error value of the random forest regression model decreased by 15%, and the error value of the k-NN model decreased by 16%. A possible explanation for these results may be that hyperparameter tuning found better parameters than initial ones to get more accurate results. Another important finding was that, even after hyperparameter tuning and removal of the outliers, the error value of the k-NN method was calculated as 0.37 DSG and 0.03 for the random forest regression model.

These findings suggest that outliers of input data should be considered during the estimation of CG life and also that the random forest regression model gives more promising results than k-NN in the prediction of CG life of a lap shear joint. The obtained results are encouraging when the 0.03 DSG RMSE value of the random forest regression model is taken into consideration. It has been shown that the fatigue index of individual aircraft can be calculated, and predictive maintenance programs may be launched with a low error value.

Additional studies, such as investigating thru crack configuration and including the effects of secondary bending, will be required to develop a complete picture of joint CG life estimation.

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