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A Comparative Investigation of Random Forest Regression and Artificial Neural Networks for Predicting Crack Growth Life of a Fighter Aircraft Wing Joint Under Spectrum Loading

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ABSTRACT

Estimating fatigue life is challenging due to the input parameters' statistical natures, such as the manufacturing process, scatter of service loads, microstructure, etc. Regarding fatigue life calculation in the aerospace industry, the importance of an accurate estimation becomes more critical due to strict safety, certification, service costs, and competitiveness regulations. The ability of soft computing methods to reveal complex relationships between multiple parameters and their computational speed could help predict fatigue life, especially in the service. This study compares random forest regression and artificial neural network methods to estimate the crack growth life of a fighter jet aircraft wing joint in terms of their computational time and accuracy. In addition, permutation feature importance and hyper parameter optimisation studies are conducted to extract essential features, investigate their effects on estimation performance, and fine-tune model parameters. The analysed joint is made of 7050-T7451 aluminium, widely used as a structural element in the aerospace industry. Since a hole is one of the major sources of stress concentration, and there may be many holes involved in any engineering structure, it is reasonable to assume that fatigue cracks may initiate at some of these holes during the service life of engineering structures. The crack type considered is a thru-crack around a hole, which is more severe than a corner crack. Load spectra are derived using the Fighter Aircraft Loading Standard for Fatigue (FALSTAFF) to calculate crack growth life. Considering particular service load conditions, ninety different spectra are developed, and the crack growth life of the joint is calculated based on linear elastic fracture mechanics correspondingly. Also, to simulate the worst-case scenario, friction between members and the retardation effect of load spectra are not considered when calculating crack growth life. Python's Tensor Flow and Scikit-learn libraries are utilised to build machine learning models. Then, ninety different load spectra are input for the thru-crack configuration to predict the crack propagation life. Eventually, the crack propagation life predictions of random forest regression and artificial neural network models are compared. The findings indicate that permutation feature importance and hyperparameter-optimisation significantly affect the model's accuracy and processing time performance.

Keywords: Fatigue; Machine learning; Random forest; Prediction; Crack

NOMENCLATURE

V	:	Load of fastener
C	:	Fastener flexibility
P	:	Applied load
t	:	Sheet metal's thickness
d	:	Fastener hole diameter
E	:	Elasticity modulus
w	:	Sheet metal's width
σ	:	Stress
f	:	Sheet metal flexibility
z_1	:	Upper surface
z_2	:	Lower surface
Br	:	Bearing
K	:	Stress intensity factor
Y	:	Geometric factor

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1. INTRODUCTION

Machine learning (ML) methods provide a wide scope for dealing with problems consisting of multiple variables and nonlinearity. Each aircraft has a unique load history and its own fatigue life. Scheduling the planned maintenance based on a generic spectrum for all the fleets may result in catastrophic failure and financial loss. Instead of using a single spectrum for the fleet, with the assistance of ML algorithms, it may be possible to estimate the fatigue life for each aircraft using flight data recordings in a short time.

Abdalla and Hawileh[1] set out a study to predict the endurance of steel bars with the aid of an Artificial Neural Network (ANN) for different strain amplitudes and load ratios. Maximum axial strain and load amplitude are utilised as inputs for the model. The authors conclude that the prediction results of ANN comply with test results with a correlation coefficient of 0.98. Pujol and Pinto[2]utilise ANN to obtain a probability function to estimate endurance. Findings indicate that an ANN-based model has better accuracy than standard models. Twala[3] investigates space system software fault prediction using ML techniques. Bhekisipho points out that among proximity, decision tree, and hyperplane-based alternatives, the naive bayes classifier has higher accuracy[3].

Mohanty, *et al.*[4] compared ANN, adaptive neuro-fuzzy inference system (ANFIS), and exponential models in predicting the crack growth life of 7020 aluminium alloy for constant amplitude loading with different load ratios. According to the findings, the estimation of the ANN and ANFIS models was less conservative than the exponential model. Moreover, the performance of the exponential model outperformed that of ANN and ANFIS[4]. Mishra, *et al.*[5] studied ANN to predict the endurance in the low-cycle region of Al-Si-Mg alloy based on parameters such as the percentage of alloy elements, heat treatment, and strain amplitude. Mishra, *et al.*[5] suggest utilising ANN to estimate endurance in low-cycle regions.

Mohanty[6] studied to estimate the crack growth life of 6061 aluminium using the input parameters of load ratio, stress intensity range, and maximum Stress Intensity Factor (SIF) by an ANFIS model. The ANFIS model's prediction performance is acceptable based on the results. Durodola, *et al.*[7] investigate ANN for time domain and frequency domain fatigue life prediction regarding random fatigue loading. The results indicate that the accuracy of ANN with time domain methods is greater than ANN with frequency domain methods[7]. Verma & Peyada[8] compare extreme ML with classical methods to predict the parameters of an unstable aircraft. They propose extreme ML in combination with the Gauss-Newton method instead of classical alternatives.

Durodola, *et al.*[9] investigate ANN in the frequency domain with mean stress to estimate fatigue life for metallic materials. Spectral moments and material parameters such as fatigue strength, fatigue exponent, and ultimate tensile stress values are used as inputs. Durodola, *et al.*[9] suggest that ANN performs promisingly compared to current time domain approaches. Sanwale and Sing[10] work on predicting aerodynamic parameters. They conclude that radial basis function neural networks converge better than multi-layer perceptron. Ganesh kumar, *et al.*[11] compared random forest regression (RFR), k-nearest neighbour (k-NN) and support vector regression (SVR) in terms of estimating tool wear. The findings show that RFR has almost 92 per cent accuracy in predicting tool wear. Wang, *et al.*[12] examined knowledge-based ANN with a radial basis function, a support vector machine (SVM) and back propagation neural network to predict the surface roughness of ball-end milling. Outcomes indicate that knowledge-based ANN with radial basis function outperformed others. Kong, *et al.*[13] examined ANN for predicting the endurance of coil springs using vertical acceleration and resonance frequency as input. The Morrow, Coffin-Manson, and Smith Watson Topper methods are considered to make a prediction. The findings show that the Morrow method with three hidden layers of ANN gives the minimum mean squared error[13].

Liu, *et al.*[14] compare SVM and ANN in predicting fatigue life for vibration isolation rubber based on strain, temperature, hardness and rubber compound. To optimise the parameters of SVM, modified gravity search algorithm (MGSA), genetic algorithm (GA), particle swarm optimisation (PSO), and simulated annealing (SA) algorithms are compared. It is concluded in the paper that SVM outperforms ANN, and MGSA shows better performance compared to other methods[14]. Jimenez-Martinez and Alfaro-Ponce[15]compared Miner's damage rule and ANN to estimate the endurance of S420MC as a chassis component. Several load sequences and different temperature values, such as 23, 35, and 45 ^{o}C, are considered. According to the findings, the ANN model makes better predictions than Miner's damage rule[15].

Ramachandra, *et al.*[16] compared ANN with experimental results regarding fatigue life for Manten and RQC-100 materials using stress histories developed by the Society of Automotive Engineers for brackets, transmissions, and suspensions. According to the findings, the ANN method correlates well with experimental results. Voet, *et al.*[17] worked on estimating solder joint failure using ANN. They build two sub-models to estimate if a joint failed or not and predict crack length if it failed. Results indicate that the performance of the classification part has a huge effect on the model's overall performance. When estimating the crack growth life of corner crack types, Yüce, *et al.*[18] compared RFR and k-NN regression. According to the findings, the predictions from RFR have higher accuracy than k-NN regression.

This study aims to assess RFR and ANN to estimate the crack propagation life of an aircraft wing joint. RFR from machine learning algorithms is preferred here as a very successful bagging method, and backpropagation (multi-layer perceptron) from ANN is a high-performance algorithm. This paper presents a methodology for fatigue loading spectra, analysis of load, an ML model, an investigation of features, and hyper parameter optimisation. This is the first study that explores and compares the benefits of ML algorithms in predicting the crack growth life of a fighter aircraft wing joint in a thru-crack configuration. The importance and originality of this study are that it investigates the effects of outliers and feature selection by employing the permutation feature importance (PFI) technique and hyperparameter optimisation.

2. METHODOLOGY

Ninety load spectra are generated using FALSTAFF for various load levels to determine the crack development life. Then, these load spectra are used to calculate the crack growth

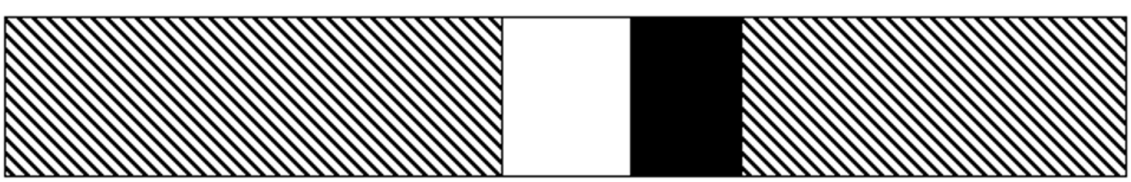

Figure 1. Geometry of thru-crack.

lives of a wing joint for a thru-crack configuration, which is more severe than a corner crack since the load-carrying section is smaller. Figure 1 illustrates the geometry of a thru-crack.

After that, crack growth calculations are performed using Air Force Grow (AFGROW) software developed by the Air Force Research Laboratory. Later on, based on the rain flow cycle counting technique, the cycles in the spectrum are calculated, and then these rain flow histograms are fed to RFR and ANN models for training and prediction. After all, a hyperparameter optimisation study is performed to fine-tune the model parameters.

2.1 Load Spectra

FALSTAFF is a load spectrum for the wing root region and was developed for fighter aircrafts in 1976. Load data from four different types of aircraft operated in the air forces of three different countries is used during the development process. Three others are used during the development process. The block length of the spectra is considered to be 200 flights, which are categorised into three levels based on severity and repetitiveness. Some missions that FALSTAFF covers can be listed as high/low navigation, instrument flying, combat patrol, etc. FALSTAFF consists of thirty-two discrete load levels, and level zero was set to 7.52[19].

This study considers a splice joint located under the wing of a fighter jet designed to operate for10,000 flight hours (FH). Accordingly, to derive load spectra for this study, load levels of FALSTAFF are scaled to the envelope of -3g to 9g. Finally, with the aid of the FALSTAFF, ninety fatigue load spectra are derived for exceptional load levels to be used for the crack growth life calculation.

2.2 Assessment of the Joint

2.2.1 Calculation of Fastener Loads

This study focuses on a single lap shear joint of 7050-T7451 aluminium with three steel fasteners. The thickness of the aluminium sheets is 1 mm, and the width is 32 mm. The relationship between fasteners is established based on compatibility conditions. Compatibility suggests that the deflection of the plates between two fasteners equals the displacement of counterpoints[20]. Secondary bending is not considered in this study. Even though friction between sheet metals helps reduce the load on the fasteners, pretension loads are not considered when analysing the worst-case scenario. Also, stiffness is assumed to remain the same under deflection. Figure 2 demonstrates the load transfer among sheets.

Fastener loads are calculated with the aid of compatibility. Eqns. (1-2) present the Eqns. to calculate fastener loads.

$$V_1 C_1 + P_A(f_A) = V_2 C_2 + P_B(f_B) \tag{1}$$

$$V_2 C_2 + P_C(f_C) = V_3 C_3 + P_D(f_D) \tag{2}$$

where, C is the bolt flexibility constant calculated using the Huth Eqn., V is the load on the fastener, P is the load on the sheet, and f is the flexibility if the sheet is idealised as a bar in this study.

The Huth method was employed to obtain fastener flexibility[21]. Eqn. (3) shows the Huth method's mathematical expression.

$$C = \left(\frac{t_1 + t_2}{2d}\right)^a \frac{b}{n}\left(\frac{1}{t_1E_1} + \frac{1}{nt_2E_2} + \frac{1}{2t_1E_3} + \frac{1}{2nt_2E_3}\right) \tag{3}$$

where, d is the bolt shank diameter, t is the thickness of the sheet, E is the modulus of elasticity of the sheets and fasteners, and n is the number of shear surfaces, which is one in this study. Besides, the constants a, b, and n are driven by material, type of fastener, and several shear surfaces.

2.2.2 Calculation of Crack Propagation Life

Tensor directions determine the path crack path. The maximum principal stress tensor estimates the crack path near the most critical hole. The crack is assumed to propagate from the hole edge to the sheet metal edge based on the first principal stress tensor directions. The directions of the principal stress tensors are presented in Fig. 3.

Based on this assumption, a crack growth scenario is established with a linear elastic fracture mechanics approach. Bearing stress, thru stress, and bending stress values are needed to calculate crack growth life. For gross stress, Eqn. (4) is used. P is the applied load on the sheet, w is the sheet's width, and t is the sheet's thickness. Bearing stress is calculated using Eqn. (5). P is the fastener load, d is the hole's diameter, and t is the sheet's thickness. Thru stress is calculated based on Eqn. (6), and bending stress is calculated using Eqn (7).

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

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

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

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

For each of the ninety unique load spectra, the crack growth life of the joint is calculated using the values and the fraction of stress components. To conduct a damage tolerance evaluation, it is assumed that the most critical hole already has a crack at its start. According to the Joint Service Specification Guide, the initial crack size is 1.27 mm, corresponding to a

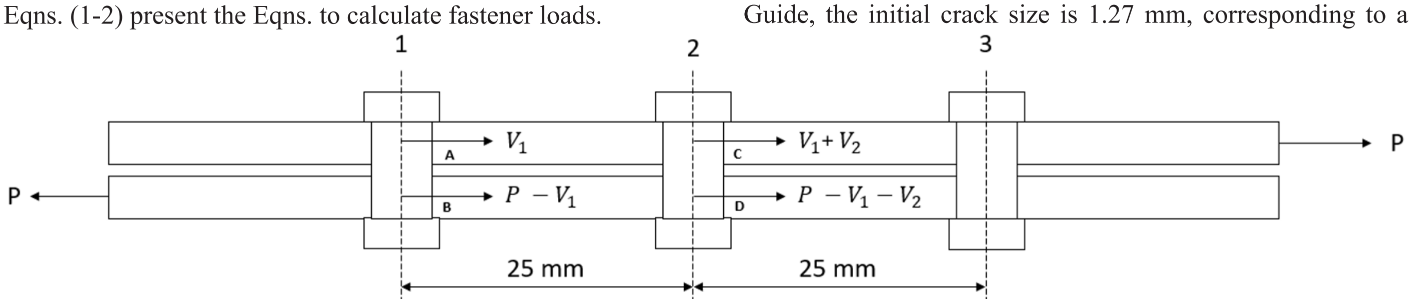

Figure 2. Load transfer among sheets.

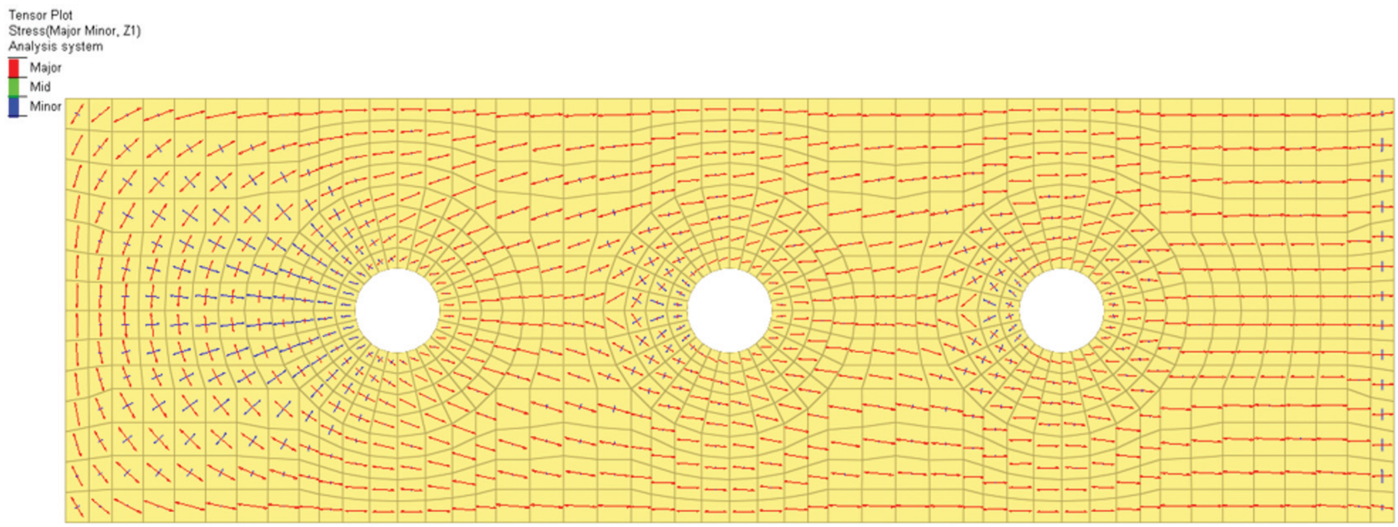

Figure 3. Directions of principle stress tensors.

thru-crack for a 1 mm sheet component[22]. Later on, AFGROW software is employed to calculate crack growth lives.

2.2.2.1 Stress Intensity Factor Approach

Depending on the loading condition, crack propagation can be classified into mode-I, mode-II, and mode-III. Due to the formation of tensile stress, mode-I can be accepted as the most critical scenario. Also, mode-I creates more damage and has a higher occurrence than others. In this study, the mode-I crack propagation scenario is considered. Griffith observed that stresses near the crack tip are proportional to the $\sqrt{\pi a}$. The Eqn. for the SIF is presented in Eqn. (8)[23].

$$K_1 = Y\sigma\sqrt{\pi a} \tag{8}$$

Y is a geometric constant, σ is stress, and a is half of the crack length. Because of the material yield, excessive stresses will not occur near the crack tip due to the redistribution of the stresses. This region is called the crack tip plastic zone (CTPZ). Since the CTPZ of the plane stress condition is higher than the plane strain condition, the fracture toughness value of the plane strain is less than the plane stress fracture toughness value. During hand calculation, plane strain fracture toughness value can be preferred to stay conservative. However, most recent software can dynamically evaluate the stress state based on material thickness and yield stress. High loads on the fatigue spectra may help to increase the plastic region near the crack, and then the crack propagation speed reduces[23]. This phenomenon is called the retardation effect. In this paper, the retardation effect is not considered to simulate the worst-case scenario.

2.2.2.2. Fatigue Life Calculation with Fracture Mechanics

The first systematic study in the fatigue field was published in 1837 by Wilhelm Albert about conveyor chains. Then, August Wöhler proposed a fatigue limit concept for railway vehicle axles. After that, many publications have been made to develop stress and the number of cycle curves for materials. At the end of these studies, it has been found that fatigue is built upon both initiation and propagation processes[23].

In the case of fatigue crack, the SIF at the crack tip alters. This change can be calculated using Eqn. (9)[23].

$$\Delta K = K_{\max} - K_{\min} \tag{9}$$

To calculate maximum and minimum SIF, Eqns. (10-11) can be utilised.

$$K_{\max} = Y\sigma_{\max}\sqrt{\pi a} \tag{10}$$

$$K_{\min} = Y\sigma_{\min}\sqrt{\pi a} \tag{11}$$

In the case of damage tolerance investigation, crack propagation speed can be calculated by Eqn. (12), known as the Paris-Erdoğan law[23].

$$\frac{da}{dN} = C\left(\Delta K\right)^m \tag{12}$$

where, C and m are material constants and $\frac{da}{dN}$ is the rate of crack propagation[23].

If the change in the SIF is below the limit value, the crack is expected to not propagate[23].

2.3 Machine Learning Model

The cycle counting of the load spectrums is made using the rain flow cycle counting method[24]. Flattened histograms of the rain flow method composed of the highest value, the lowest value, and several cycles are utilised for training the ML model, with the aid of average value, standard deviation, and maximum and minimum values of the load spectra. Twenty per cent of the data set is used as test data, and 80 per cent is utilised for model training purposes.

Two datasets are produced, one with all the data and the other without outliers, to examine the effects of the outliers on prediction performance. The threshold for filtering outliers is determined as a scatter factor of four. Therefore, values above 40,000 flight hours are considered outliers.

2.3.1 Random Forest Regression Model

Breiman[25] developed the random forest method for classification and regression, combining the output of numerous decision trees to calculate the result.

The initial run of this study is made with a hundred estimators, which correspond to the total number of decision trees in the random forest algorithm. Later, a hyperparameter optimisation study is performed to fine-tune the model parameters to improve model accuracy.

2.3.2 *Artificial Neural Network Model*

The origin of neural networks lies in the working principle of the human brain in terms of biological signal transfer among neurons. ANNs consist of bunches of nodes, or in other words, artificial neurons, which receive input from a previous neuron and then process it with weight and transfer functions. The output of an individual node is evaluated based on its threshold value to decide whether to transfer the data to the next node. In this study, a dropout layer is utilised to prevent overfitting. The ANN model is also trained using two data sets: one with the entire dataset and one without outliers. Then, using PFI, the features with the highest impact on results were determined. Finally, a hyperparameter optimisation study is conducted to fine-tune the model parameters.

The architecture of the ANN model used in this study is built upon one input layer, one output, and two hidden layers.

2.3.3 *Permutation Feature Importance*

The PFI algorithm investigates the effects of individual features in terms of overall model performance. The algorithm shuffles the features and compares the model's performance with the shuffled features and the original setup. If feature shuffling reduces the model's accuracy, the corresponding feature is assumed to be an essential feature for the model and suggested to be kept during prediction. On the other hand, if shuffling a feature increases the model's accuracy, then that feature can be assumed as not essential for the model. Employing PFI enables boiling down the model to a more refined version.

With PFI, it is ensured that features that do not have a high impact on the output are eliminated before the analyses begin, thus enabling the analyses to be carried out faster and more focused.

2.3.4 *Hyperparameter Optimisation*

Hyperparameter optimisation is used to fine-tune the parameters of ML models. For instance, finding the optimum number of estimators in the RFR model or the neuron's number in the ANN's hidden layer can be investigated by designing experiments. The best number of estimators or neurons can be calculated according to the objective function, which is our study's minimum mean absolute error. Also, the assessment of multiple parameters at the same time is possible. To prevent overfitting, a cross-validation technique may be used. The cross-validation divides the input data into pieces, whose number is determined by the user, instead of using the entire input dataset as it shuffles the pieces while training the model. For n number of cross-validation requests, n number of error metrics is calculated. An average of n number of errors is calculated for each grid to determine the best-performing model. This study uses the number of estimators and maximum feature parameters to fine-tune the RFR model. Other parameters of the RFR model are kept as defaults. Regarding the artificial neural network model, the number of neurons in the hidden layer and dropout rate values are used to optimise the model.

With the hyperparameter optimisation, while the algorithms are running, it is tried to determine the combination of the most suitable values of the critical hyperparameters. While this is a factor that can increase CPU time, it has the effect of improving the performance of algorithms. The load spectrum should be provided as an attachment.

2.3.5 *Model Evaluation*

The mean absolute error (MAE) metric is utilised to measure model performance. The mathematical expression of the MAE is shown in Eqn. (13)[26].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x| \tag{13}$$

where, n is the number of evaluation instances, x_i is the estimated value, and x is the actual value.

3. RESULTS

As explained in the introduction and model evaluation sections, this study compares RFR and ANN models based on the MAE metric to predict crack growth life based on pre-generated crack growth life data using FALSTAFF.

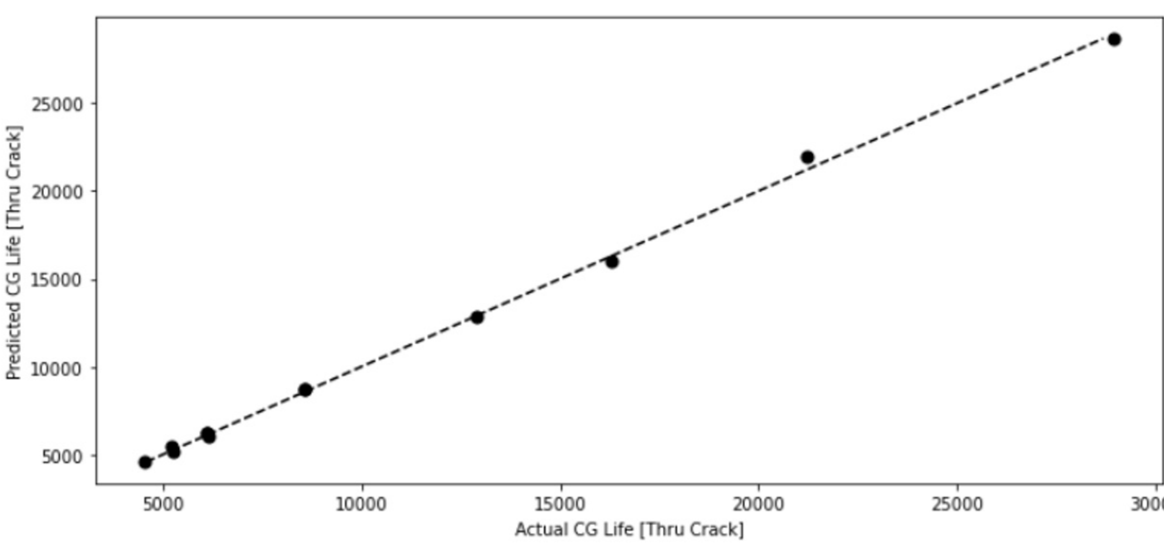

Figure 4. Actual and predicted life of hyperparameter optimised RFR model.

3.1 Random Forest Regression Model

The initial RFR model is configured with a hundred predictors. The initial model's MAE is calculated to be 4,326 flight hrs. The MAE of the model without outliers is calculated as 246 flight hours. Later on, a PFI study is performed on the model without outliers, and predictions are made by just keeping the essential features of the model. Then, the effect of the input variables on prediction performance is calculated using the PFI technique. According to the results, eight out of twenty-nine features are selected based on their contribution to model performance. The MAE of the model with essential features is calculated as 216 flight hrs.

Finally, a hyperparameter optimisation study is conducted with the model and its essential features. Figure 4 depicts the actual crack growth life and predicted crack growth life of the hyperparameter-optimised RFR model. MAE of the hyperparameter optimised model is calculated as 184 flight hrs.

Regarding computational cost, the initial model, the model without outliers, the model with essential features, and the hyperparameter-optimised model took 78.1 ms, 62.5 ms, 46.9 ms, and 188 ms, respectively.

3.2 Artificial Neural Networks Model

The initial ANN model is built with twenty-nine neurons in hidden layers. The initial ANN model's MAE is calculated to be 37,289 flight hours. Then, the data without outliers is input to estimate crack growth life for the initial model. The MAE of the model without outliers is calculated as 6,374 flight hrs. Later on,a PFI study is conducted on the ANN model. Ten out of twenty-nine features are selected based on contributions to overall model performance. The learning rate is determined to be 0.5. The MAE of the model with essential features is calculated as 5483 flight hours. After all, the hyperparameter-optimised model had an MAE of 5344 flight hours. Figure 5 depicts the actual crack growth life and predicted crack growth life of the hyperparameter-optimised ANN model.

The CPU time of the initial model, the model without outliers, the model with essential features, and the hyperparameter-optimised model are calculated to be 25,600 ms, 4,380 ms, 5,660 ms, and 5910 ms, respectively.

3.3 DISCUSSION

The calculated lives of ninety load spectra range from 4,525 to 496,256 flight hrs. Furthermore, with the aid of the PFI study, the most contributing parameters for the RFR and ANN models are determined. The model with essential features yields an approximately 12 per cent increase in inaccuracy for the RFR model and a 14 per cent increase for the ANN model. Therefore, keeping all input parameters without any investigation of their importance may create disturbances in the prediction performance. Moreover, hyperparameter tuning based on the grid search algorithm improved the accuracy of ANN and RFR by almost 3 per cent and 15 per cent, respectively. In terms of accuracy, one intriguing finding of this study is that the MAE of the ANN model is calculated to be 53 per cent of the design life, whereas the MAE of the RFR model is calculated to be 1.8 per cent of the design life.

The initial RFR model requires 99.7 per cent less CPU time than the ANN model regarding computational cost. Also, regarding calculation time, the RFR model without outliers performed 98 per cent better than the ANN without outliers. Later on, after the PFI study, the computational cost of RFR is calculated to be 99 per cent cheaper than the ANN model. Finally, the hyperparameter-optimised RFR model outperformed the hyperparameter-optimised ANN model by almost 97 per cent.

A closer inspection of the computational cost shows that outliers, PFI, and hyperparameter tuning affect CPU times for ANN and RFR models.

In general, the RFR model outperforms the ANN in terms of accuracy and computational cost when predicting the crack growth life of the wing splice joint. It should be noted that the ANN model's success depends on various factors, including its

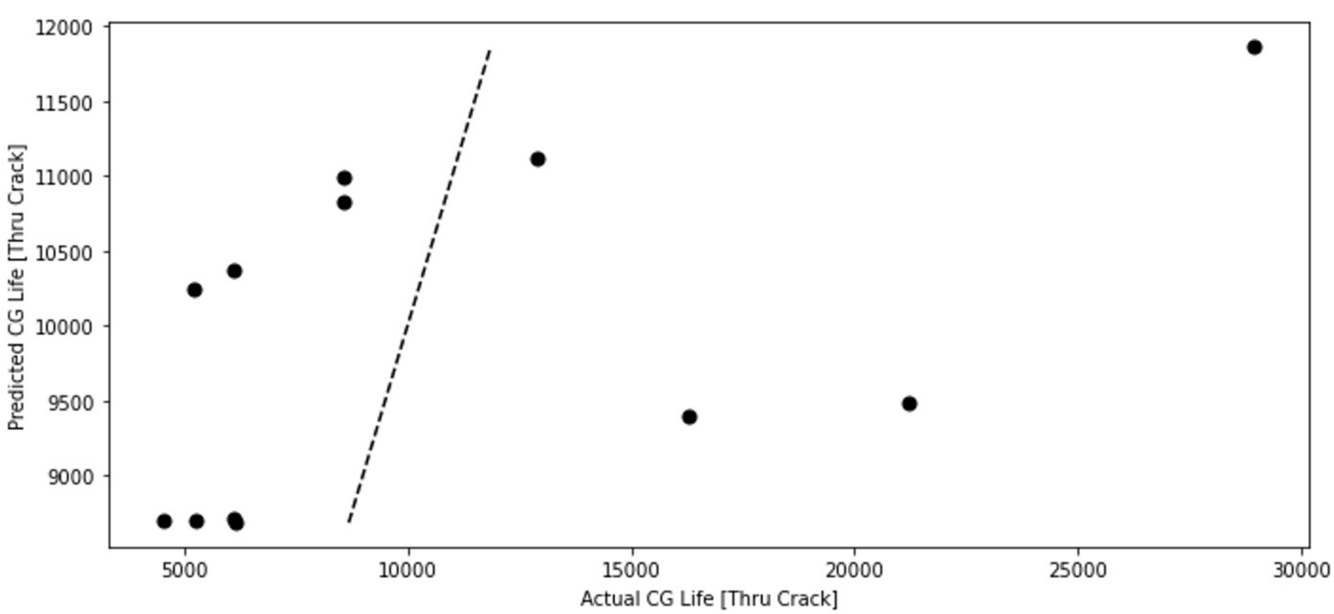

Figure 5. Actual and predicted life of hyperparameter optimised ANN model.

architecture and the neuron's number. It might be possible to improve ANN models' accuracy by altering the hidden layer's number and other factors. However, the random forest model's accuracy was better than the current ANN model.

4. CONCLUSION

Using a single load spectrum to calculate the fatigue life of an entire product range may lead to catastrophic failures, over-engineered designs, and inaccurate inspection plans. Therefore, calculating fatigue life under a unique load history is crucial for conducting tailor-made operations and reducing service costs. Conventional approaches, such as the finite element method, may take a long time to calculate each component's fatigue life dynamically. Accordingly, computational intelligence methods may be utilised to overcome the time cost of conventional techniques. This paper critically examines the performance of ANN and RFR in predicting crack growth life for the thru-crack case of an aircraft wing joint under spectrum loading. The calculated lives of ninety load spectra range from 4,525 to 496,256 flight hrs.

The current study finds that filtering the data for outliers increases accuracy for ANN and RFR methods. When the data is cleaned of outliers, the MAE error of the ANN model is dropped by almost 83 per cent, and the MAE of the RFR is reduced by nearly 94 per cent. The most prominent finding to emerge from this analysis is that mild spectrums without extreme loads tend to yield highly high crack growth lives, and these values may create noise for prediction algorithms. Also, these extreme crack growths do not contribute to scheduled inspections or maintenance. It is suggested that input data be processed before utilising it and that the effect of the outliers be investigated.

The present study raises the possibility that the crack growth life of individual aircraft for thru-crack configuration can be calculated with approximately 1 per cent deviation from design life. Therefore, the accumulated damage of each jet in the fleet can be predicted using ML algorithms. With ML methods, predictive maintenance programs can be planned precisely and quickly. This work has provided a deeper insight into the prediction of fatigue life with the aid of soft computing methods and their promising potential in accuracy and computational cost. This potential may be helpful in in-situ calculations and innovative material development studies. The present study provides the first comprehensive assessment of outliers and their effects on crack growth life prediction. Moreover, the study contributes to understanding feature assessment in predicting crack growth life. There is ample room for further progress in determining the effects of secondary bending, considering contact nonlinearity between sheet metals and ANN architecture in predicting crack growth life.

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