DEVELOPMENT OF A MACHINE LEARNING-BASED STRESS SPECTRUM ESTIMATION TECHNIQUE FOR FATIGUE MONITORING

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Abstract

Load monitoring of aircraft is essential for safe operation. By monitoring loads occurring on the aircraft during operation, fatigue life can be predicted, and structural damage and defects can be detected in advance to ensure the structural safety of the aircraft. For this, a study is conducted in this paper to accurately estimate loads based on flight parameters recorded during flight tests. Flight tests were previously conducted with load monitoring sensors attached to the aircraft to obtain flight parameters and sensor data. MLR (Multiple Linear Regression) and ANN (Artificial Neural Network) regression models are applied to predict load monitoring sensor data using the acquired flight parameters. The regression performance of the two models is quantitatively evaluated using RMSE (Root Mean Squared Error) and adjusted R-squared (Adj. R^2). As a result, the mean Adj. R^2 values for all targets were 0.9751 for ANN and 0.8858 for MLR, and the mean RMSE values were 0.0601 for ANN and 0.2043 for MLR. This indicates that the regression performance of ANN is higher than that of MLR. Additionally, the trained MLR and ANN models are tested using new flight test data. The performance of ANN is also higher than that of MLR for this new flight test data, confirming that the generalization performance of ANN is significantly superior. Through the correlation coefficients and variance inflation factors of the flight parameters, it is confirmed that multicollinearity exists among the flight parameters. Consequently, the ANN regression model is more suitable than the MLR model for load monitoring using flight test data.

Keywords: Fatigue Monitoring System, Machine Learning, Flight Test, Flight Parameter, Stress Spectrum

1. Introduction

Aircraft are subjected to complex and various loads repeatedly during the operational life, resulting in fatigue phenomena such as crack initiation and propagation and decrease of structural strength[1]. This causes catastrophic structural damage to aircraft[2], accounting for more than 50% of total mechanical structure failures[3]. Therefore aircraft with high cost, complex structure, and safety requirements must have high-reliability[4]. For this purpose, a fatigue monitoring system that detects structural damage and defects in advance and predicts fatigue life is essential. Load monitoring is an important method of fatigue life management[5]. Since it is impossible to directly measure load spectrum during flight, a lot of research has been studied to accurately estimate load spectrum based on flight parameters recorded during flight for fatigue monitoring[6]. Multiple linear regression equations have been used for load monitoring[7,8,9]. However, the prediction accuracy based on the multiple linear regression is low, and the nonlinear relationship between flight parameters and loads cannot be revealed and established[10]. To address this issue, recent research using machine learning has been actively conducted[5,11,12]. In particular, flight parameter based structural load monitoring systems using artificial neural networks are being developed to map the input flight parameters to the output strain measurements[13,14,15]. Aircraft structural load spectrum are calculated from the measured strain gauges attached to the aircraft[16]. However, strain gauges can fall off or have missing data[17], so it is necessary to accurately estimate sensor measurements from flight parameters recorded in the flight data recorder. Existing studies have been conducted on simple structures such as cantilever beams[14,15], and only aircraft wing prototype, excluding other structures[5,11]. Additionally, studies have been conducted using ground test data[5] or simulation data[1]. Therefore, in this study, regression models are developed to predict bending moment and strain sensor measurements attached to the aircraft wings, horizontal/vertical tails, and fuselage from flight parameters recorded during flight testing. The actual flight test data used in this study is not sequential vibration data collected at regular time intervals, but event trigger data in which all flight parameters and sensors are recorded when any flight parameter changes more than the gate value. So the flight test data can be considered as a snapshot. In order to utilize the flight test data with these characteristics, we applied not only multiple linear regression (MLR), which has been predominantly used for such problems until now, but also artificial neural network (ANN) to real flight test data, and compared and analyzed their performance.

2. Procedure for Predicting Aircraft Load Based on Flight Parameters

2.1 Data Preprocessing

Seven flight tests were conducted on the same aircraft to obtain in-flight data from take-off to landing. All seven flight data were combined and randomly split into training/test data for MLR and training/validation/test data for ANN, as shown in Figure 1. Flight parameters and sensor data are standardized so that all features have a mean of 0 and a standard deviation of 1.

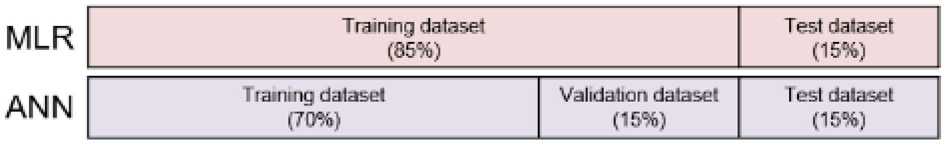

Figure 1 – Datasets for MLR and ANN training.

2.2 Multiple Linear Regression Model

The MLR equation expresses the dependent variable as a linear combination of the independent variables and the regression coefficients, as shown in Equation (1). $\boldsymbol{X}$ and $\hat{\boldsymbol{y}}$ represent independent and dependent variables, respectively. $\boldsymbol{W}$ is regression coefficients with bias and weights for the independent variables. In this study, $\boldsymbol{X}$ and $\hat{\boldsymbol{y}}$ are 30 flight parameters and 18 sensors, respectively. The least square method was used to find the regression coefficients that minimize the error between the predicted values derived from MLR and the measured values from the flight test.

$$\hat{\boldsymbol{y}} = \boldsymbol{W}\boldsymbol{X} \tag{1}$$

$$\hat{\boldsymbol{y}} = \begin{Bmatrix} \widehat{y_1} \\ \widehat{y_2} \\ \vdots \\ \widehat{y_n} \end{Bmatrix}, \boldsymbol{W} = \begin{bmatrix} w_{10} & w_{11} & \cdots & w_{1m} \\ w_{20} & w_{21} & \cdots & w_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n0} & w_{n1} & \cdots & w_{nm} \end{bmatrix}, \boldsymbol{X} = \begin{Bmatrix} 1 \\ x_1 \\ x_2 \\ \vdots \\ x_m \end{Bmatrix}$$

2.3 Artificial Neural Network Regression Model

Among the artificial neural network structures, the regression model is constructed with a multi-layer perceptron(MLP). An MLP consists of an input layer, one or more hidden layers, and an output layer, as shown in Figure 2. Input data are passed sequentially from the input layer to the output layer, where all neurons in each layer are fully connected. All input parameters are multiplied by the weights of the neurons composing the first hidden layer, biases are added, and then passed through an activation function. The output values of the first hidden layer are input into the second hidden layer and go through the same process as the first hidden layer. This process is repeated in all hidden layers, and dependent variables are calculated through the output layer. The weights and biases at each neuron are referred to as model parameters. To obtain model parameters that minimize the error between the predicted value of the ANN model and the measurement, the mean squared error in equation (2) was adopted as the cost function, and Adam optimization was adopted as the optimization algorithm. In equation (2), y_i is the measurement of the i-th sensor, and $\hat{y}_i$ is the predicted value of the i-th sensor. Additionally, an early stopping algorithm was applied to prevent overfitting.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (2)$$

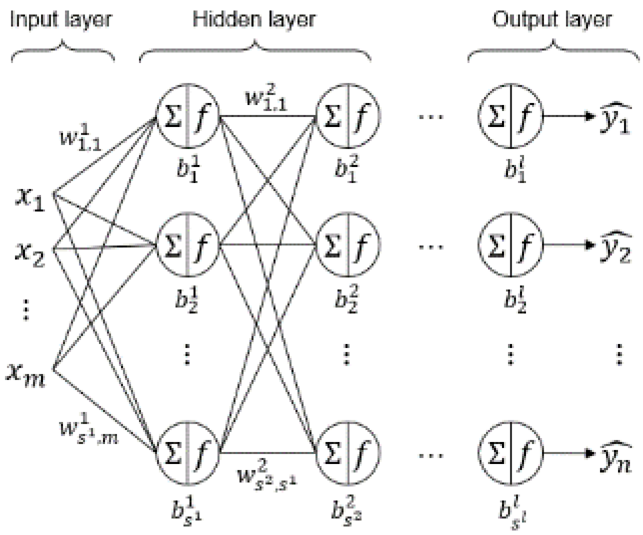

Figure 2 – Structure of MLP.

3. Performance of trained model

3.1 Performance Comparison of MLR and Ann Model

To evaluate the regression performance of MLR and ANN models, the test data in Figure 1 were input to the trained models and the predicted values were compared with the actual measurements. Figures 3 and 4 are cross plots of MLR and ANN model, respectively, where the x-axis is the measurement obtained from the flight test and the y-axis is the predicted value derived from the trained model. A cross plot closer to a linear trend indicates higher regression performance. Comparing Figures 3 and 4, the graph in Figure 4 is closer to linear than that in Figure 3, so the regression performance of ANN is better than that of MLR.

Table 1 shows the quantitative evaluation of regression performance using Adj. R^2 and RMSE. For all sensors, the regression performance of ANN is superior to that of MLR. In particular, the mean Adj. R^2 for the 18 sensors in ANN is a high value of 0.9751, while that in MLR is 0.8858, which is lower than the ANN. For sensor 9, which has the lowest performance among all sensors in both models, the ANN is 0.9244 and the MLR is 0.6948. The mean RMSE of ANN is 0.0601 and that of MLR is 0.2043, indicating that the error of MLR is about 70% greater than that of ANN.

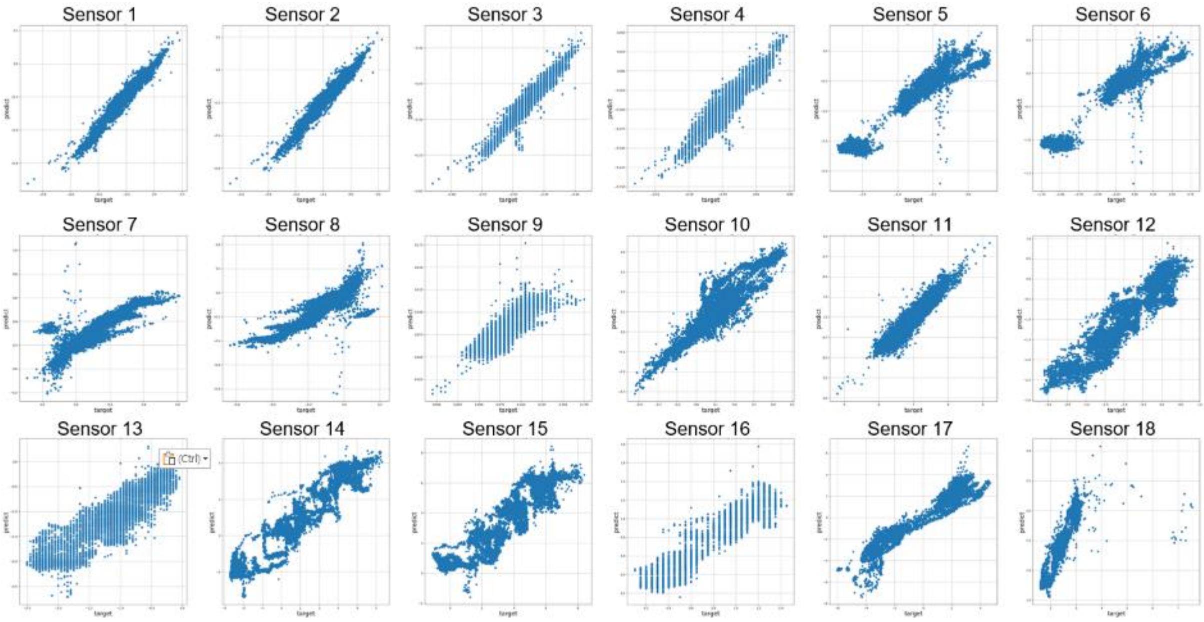

Figure 3 – Cross-plot of MLR Model on the Test Data.

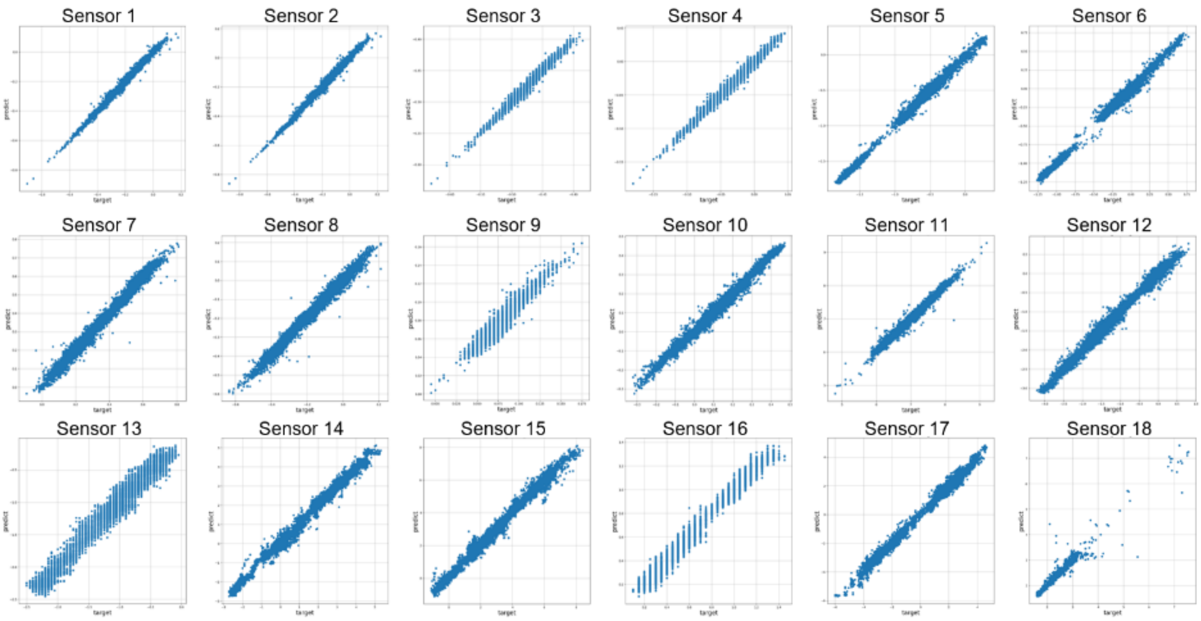

Figure 4 – Cross-plot of ANN Model on the Test Data.

Table 1 – Performance of Regression Model on the Test Data.

	Adj. R^2		RMSE	
	ANN	MLR	ANN	MLR
Sensor 1	0.9934	0.9560	0.0098	0.0254
Sensor 2	0.9934	0.9598	0.0101	0.0248
Sensor 3	0.9865	0.9366	0.0032	0.0070
Sensor 4	0.9890	0.9081	0.0034	0.0097
Sensor 5	0.9951	0.9240	0.0339	0.1330
Sensor 6	0.9943	0.9207	0.0322	0.1201
Sensor 7	0.9876	0.8740	0.0193	0.0614
Sensor 8	0.9870	0.8722	0.0186	0.0584

Sensor 9	0.9244	0.6948	0.0049	0.0098
Sensor 10	0.9879	0.8524	0.0163	0.0569
Sensor 11	0.9845	0.8893	0.0632	0.1688
Sensor 12	0.9904	0.8969	0.0888	0.2915
Sensor 13	0.9735	0.8368	0.0987	0.2448
Sensor 14	0.9933	0.9213	0.1732	0.5931
Sensor 15	0.9908	0.8517	0.2071	0.8329
Sensor 16	0.9863	0.9141	0.0406	0.1017
Sensor 17	0.9932	0.9123	0.2030	0.7288
Sensor 18	0.9804	0.8228	0.0693	0.2087
Mean	0.9851	0.8858	0.0601	0.2043

The generalization performance of the previously trained ANN and MLR models was assessed using new flight test data from additional flight test, not included in the training dataset as shown in Figure 1. The flight parameters from the new flight test data were input into the trained models and the predicted values were compared to the measurements. Figures 5 and 6 are scatter plots of measurements and predicted values over time for MLR and ANN, respectively, where blue dots are measurements and red dots are predicted values. This shows that the predicted values of the ANN follow the trends of the new flight data better than MLR.

Table 2 shows the quantitative evaluation of the regression performance of MLR and ANN on the new flight data. For ANN, Sensors 9, 12, 13, 14, and 15 have Adj. R^2 below 0.8, which is relatively low compared to other sensors. However, for MLR, most of the sensors have Adj. R^2 below 0.8 except for Sensor 1, 2, and 8. It was confirmed that MLR had lower generalization performance compared to ANN.

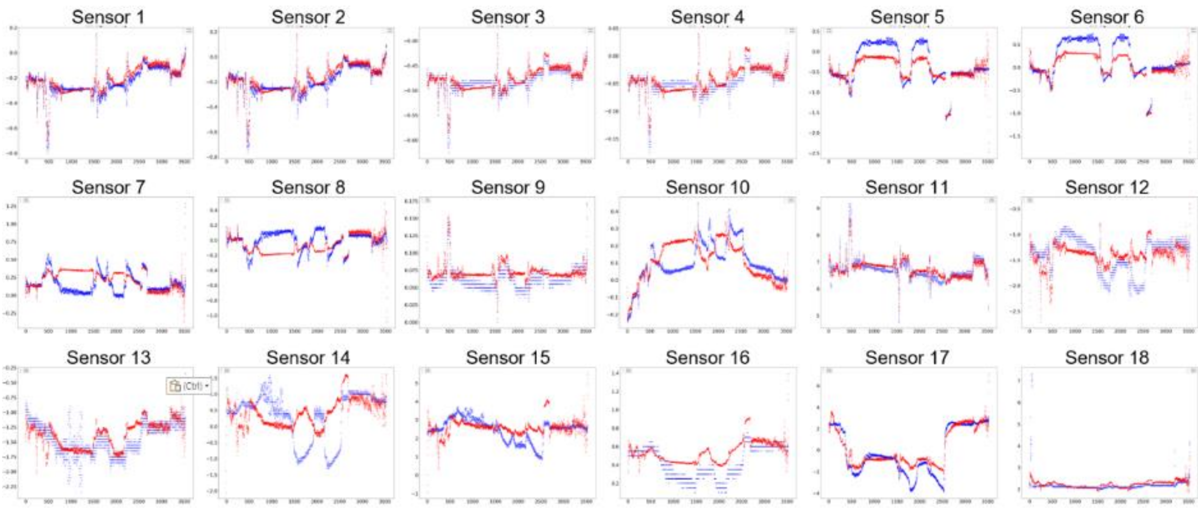

Figure 5 – Scatter Plot of MLR Model on the New Flight Data.

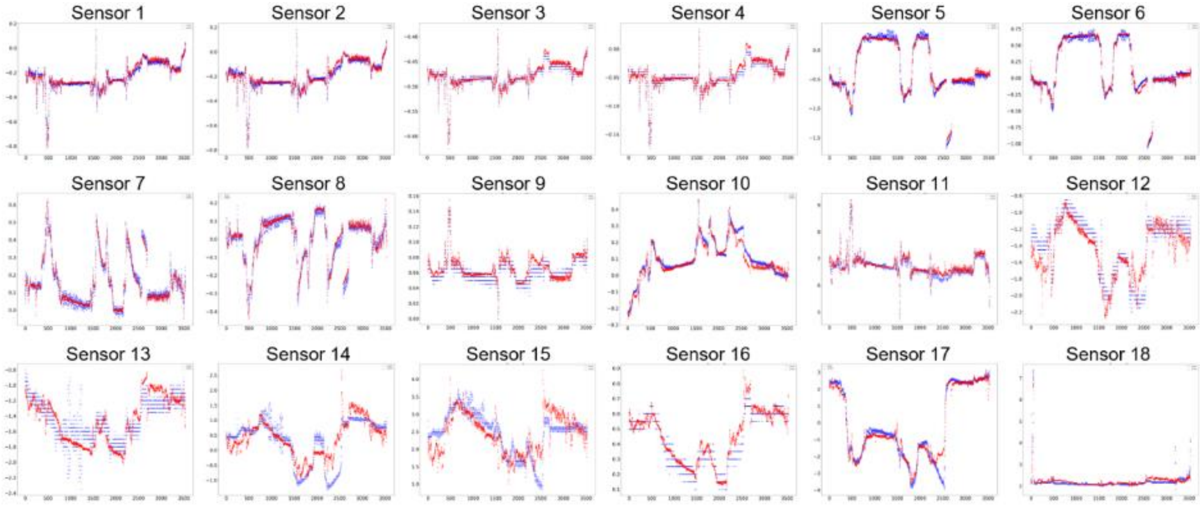

Figure 6 – Scatter Plot of ANN Model on the New Flight Data.

Table 2 – Performance of Regression Model on the New Flight Data.

	Adj. R^2		RMSE	
	ANN	MLR	ANN	MLR
Sensor 1	0.9682	0.8708	0.0185	0.0373
Sensor 2	0.9672	0.8767	0.0195	0.0378
Sensor 3	0.9529	0.7849	0.0049	0.0104
Sensor 4	0.9356	0.6734	0.0055	0.0124
Sensor 5	0.9846	0.6679	0.0559	0.2599
Sensor 6	0.9876	0.6321	0.0438	0.2387
Sensor 7	0.9718	-0.8927	0.0216	0.1768
Sensor 8	0.9662	-0.9393	0.0220	0.1667
Sensor 9	0.7210	0.1436	0.0077	0.0136
Sensor 10	0.9278	0.2463	0.0307	0.0992
Sensor 11	0.9233	0.7895	0.1082	0.1792
Sensor 12	0.7557	0.1877	0.1665	0.3035
Sensor 13	0.5112	0.2895	0.1728	0.2083
Sensor 14	0.6213	-0.1849	0.4512	0.7982
Sensor 15	0.4881	-0.1091	0.4211	0.6197
Sensor 16	0.8689	0.0646	0.0601	0.1604
Sensor 17	0.9600	0.8467	0.4253	0.8323
Sensor 18	0.8395	0.1362	0.1541	0.3574
Mean	0.8528	0.2824	0.1216	0.2507

3.2 Performance Analysis

Multicollinearity in the flight test data is investigated to analyze why the ANN model has better regression performance than the MLR model. Multicollinearity occurs when the regression model includes several variables that are significantly correlated not only with the dependent variable but also to each other[18]. Multicollinearity increases variance of the regression coefficients making them unstable[19]. Figure 7 shows a color map of Pearson's correlation coefficients for pairs of input variables. Many components, except for the diagonal component, have Pearson's correlation coefficients close to 1 or -1, confirming the existence of many highly correlated input variable pairs. Table 3 shows the variance inflation factor (VIF) of each input variable. 18 of the input variables have a VIF greater than 10, which is a common diagnostic for multicollinearity. The Pearson's correlation coefficients and VIFs confirm that multicollinearity occurs in the flight parameters used for training.

From this analysis result, it can be confirmed that the multicollinearity of the flight test data used in this study prevents MLR from accurately estimating the load spectrum from flight parameters, while ANNs provide relatively accurate estimates of the load spectrum despite the presence of the multicollinearity. This means that for data with multicollinearity like the flight test data used in this study for fatigue monitoring based on flight parameters, ANN is a more suitable choice.

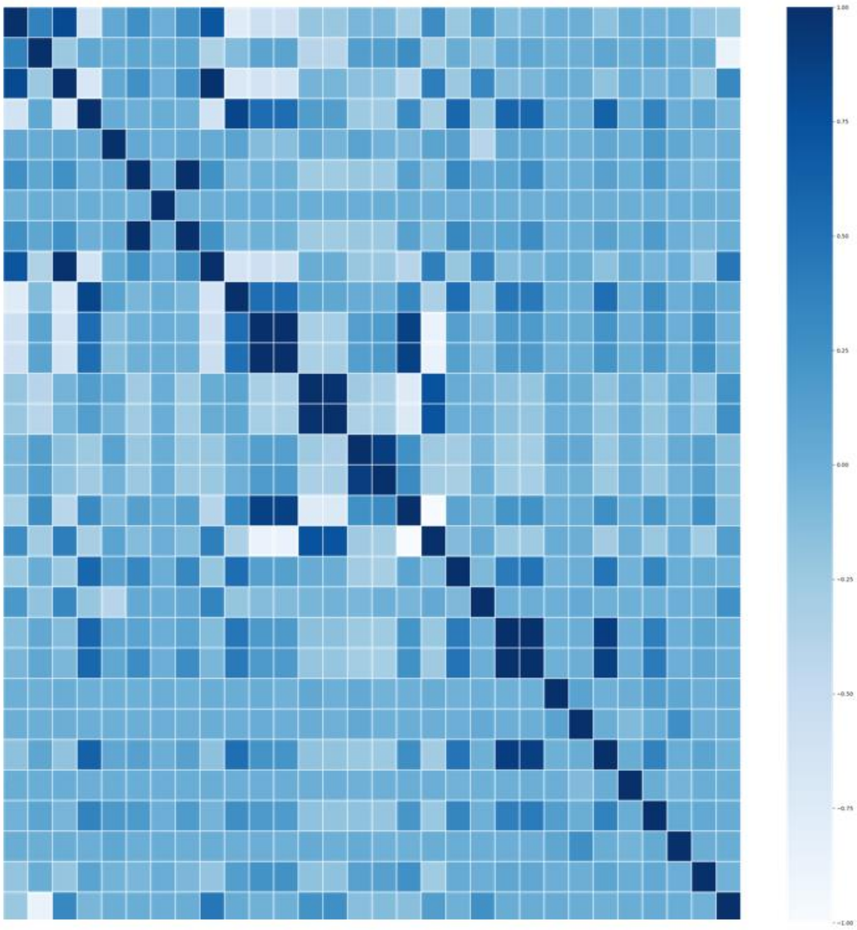

Figure 7 – Correlation Matrix of Input Variables.

Table 3 – VIF Results.

Features	VIF Factor
1	32099.35
2	808.8099
3	563.2947
4	493.1282
5	329.0442
6	299.2042
7	289.1409
8	278.0586
9	232.3188
10	215.8488
11	169.6191

12	159.6653
13	120.7618
14	109.0287
15	67.19487
16	30.47343
17	26.37923
18	17.9257
19	7.983609
20	6.147515
21	5.771975
22	2.197556
23	1.723659
24	1.659886
25	1.646627
26	1.483857
27	1.149743
28	1.135374
29	1.120338
30	1.018936

4. Conclusion

In this study, machine learning techniques were employed to estimate the load spectrum for aircraft fatigue monitoring from flight parameters. A MLR model and an ANN regression model were constructed to predict bending moment and strain sensor data from flight parameters obtained from actual flight tests, and the regression performance of the trained models was evaluated using test data that was not used for training. Additionally, the generalization performance of both models was assessed using new flight test data from additional flight test. The results show that the accuracy of ANN is superior to MLR. Multicollinearity was investigated in the flight parameters of the flight test data through Pearson's correlation coefficient and VIF, and this shows that MLR is not suitable for constructing a regression model for flight test data. ANN also simplifies the load monitoring process as it does not require variable selection to eliminate flight parameters with multicollinearity, which is required for MLR. Through this study, it was confirmed that the ANN regression model can accurately generate load spectrum for aircraft fatigue monitoring from flight parameters.

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