Chapter 16
Estimating Damage Detection of an Aircraft Component with Machine Learning Models

Brandon Jones, Milton Jones, Stephen Keyes, Eamon Mott, and Thomas J. Matarazzo

Abstract Vibration measurements can assist with monitoring and inspecting the condition of aircraft components. This study uses a vibration-based sensor network to assess damage on a specific aircraft component, creating a system that can provide invaluable information to aircraft maintainers. The system implemented in this study used supervised machine learning methods to determine the existence and assess the severity of a specific damage case on an aircraft component. The method was validated experimentally using nondestructive and then destructive testing. Overall, the machine learning model was successful in distinguishing between five levels of damage and was able to predict a loss of mass with an error of 0.5 grams. Overall, the results indicated that the regression model had a strong ability to accurately predict different levels of damage, supporting the use of such a system for aircraft component damage detection.

Keywords Structural Health Monitoring · Damage Detection · Machine Learning

Introduction

Aircraft maintenance is often labor intensive, time consuming, and tedious, but it is an important requirement that must be fulfilled. Furthermore, proper maintenance has become increasingly important as aircraft incorporate advanced technologies with higher expectations in performance. To reduce operational cost and enhance performance of the next generation of aircraft, the development of affordable sensors, powerful algorithms, and stronger data processing technology has made the integration of structural health monitoring (SHM) into aircraft development more feasible [1]. Implementing a system that provides maintainers with valuable information could enhance safety and efficiency in the aviation industry. There are a multitude of techniques that can be used for SHM, which can include using vibration signatures, impedance based technology, limit strain measurement, and fiber optic sensors [2]. The main goal of this study is to develop a damage detection system that accurately and efficiently determines whether maintenance is necessary for an aircraft component. There are key advantages of having a detection system that shows the status of a component, whether it is slightly damaged or on the end of its life cycle. Previously, to standard existing methods for detecting damage on aircraft rely solely on visual inspections. However, structural damage is not always visible to inspectors and maintainers; that is, micro-cracks or internal defects can be difficult to detect during visual inspections.

The overarching method of structural health monitoring used in this study involves completing hypothesis testing to compare a proposed healthy state to a state where damage is introduced. If the means of the "healthy state" is statistically different from the "damaged state" it can be concluded that damage has been introduced, prompting maintenance of the structure [3]. Applying that methodology to the modular effects launcher (MEL), the component of interest, enables comparison of a baseline healthy state with an unknown state and an evaluation of structural condition [4]. The results of previous research illustrate the feasibility of creating a system to monitor the health of various civil and mechanical systems, while highlighting the inefficiencies in current maintenance practices.

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Brian Damiano et al. (eds.), *Structural Health Monitoring & Machine Learning, Vol. 12*, Conference Proceedings of the Society for Experimental Mechanics Series, https://doi.org/10.13052/97887-438-0157-3_16

Methodology

In order to create a system that meets the requirements set by the sponsors of this study,the computational process for identifying damage had to be determined. This process was narrowed down to three main objectives; determining whether the current state is different from the baseline, the quantity of the difference, and implementing a machine learning model that can predict damage (mass removed from structure). Following these three goals the end product will inform the maintainer about the health of the structure[5].

To find a change of state in the structure it must be excited and its responses recorded in this case acceleration responses were recorded from six sensors placed on locations of interest of the MEL. Once the data is collected from the structure it can be analyzed through damage sensitive features, which are statistical parameters that measure the change in response based on the state of the structure. The damage sensitive features are then trained on the machine learning model. The damage-sensitive features that were utilized prioritized the quantity of transmissibility, which measures the magnitude of frequency response function and relates it to an input-output dynamic [11]. The machine learning model that was used was a linear Support Vector Regression (SVR), which was used because it is simple and yielded the best results for classification problems like this. Once the data was collected and the machine learning model was trained, it can then make a prediction on whether or not the data it is being fed is from a healthy MEL or a MEL with a certain amount of damage. This process is shown in Figure 1 below. In order to quantify and differentiate the states of structure for the model, mass was added (non-destructive) and mass was removed (destructive). The methodology had to be validated through non-destructive techniques before actually damaging the MEL itself, since there was only one undamaged version of the MEL structure. Overall, once the model was validated and coupled with the destructive testing, the model would be able to accurately detect how much mass is removed from the structure based on the response it has received from the excitation.

Fig. 1 Methodology.

Experimental Setup

In designing the experimental setup, there were a couple of key components to consider. The first is how the MEL structure will be placed during testing. The MEL was oriented how it would be hung from an actual aircraft and hung from the lugs by a steel frame, which simulated the MEL's responses to vibrations more accurately to how it would in flight. Next, the sensor type, uniaxial accelerometers were selected as the sensor of choice as they had been proven to be simple and effective, from previous years of conducting similar experiments. These sensors also allowed for immediate testing without the need for the ordering of additional sensors. When considering sensor placement, locations were narrowed down through analysis of the MEL within FEA software, which included seeing the modal shapes and locations of high strain energy. In recording the frequency responses of structures placing sensors at locations of high strain energy and at locations of increased movement in the mode shapes allows for better frequency response.

For the experimental tests, 6 accelerometers were placed around the MEl measuring the response in each direction. When selecting an apparatus to excite the structure, a small piezo buzzer would be ideal for testing due to its low weight and controllable input. However, due to difficulties of manipulating the input signals into said piezo and the additional time needed to understand how to properly employ it, a mini-inertial shaker combined with a small amplifier was used instead to allow for immediate testing and was placed at the bottom of the legs of the MEL. This shaker is connected to a small amplifier, which takes inputs from the DAQ using DewesoftX's function generator. A force sensor is connected to the shaker to measure the input response from the actuator itself. Similarly, the accelerometers are connected to the DAQ as well, providing their response readings throughout testing. The input signal provided by the functions generator itself is also recorded, so that the input signal and the actual input of the actuator can be compared. Throughout testing, the mini shaker would perform a logarithmic sine sweep from a frequency of 10 Hz to 1000 Hz, and then loop back down in the span of 20 seconds. This process allowed for a simple and consistent data collection process due to the input being automated, whilst

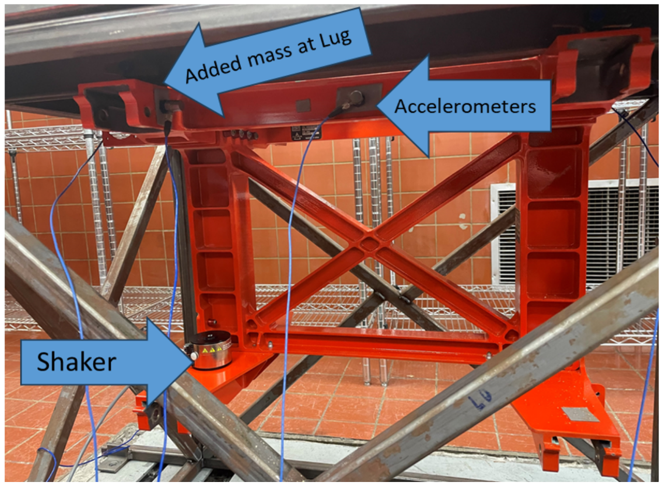


Fig. 2 Experimental Setup.

also being easily repeatable, allowing for the collection of large amounts of data sets at a time. A view of the experimental setup can be seen in Figure 2.

Experimental Results

Non-Destructive Cases

The damages cases for the non-destructive cases include the addition of 5, 7.5,10.15, 22.5, and 30 grams at the base of one lug. Non-destructive testing is a good way to validate our model without having to damage the MEL structure. The data collection process consisted of a sine sweep from the inertial shaker that lasted 20 seconds and accelerometers would record the response. Each testing case included 100 repetitions of acceleration response data. Then 20% of the data was used for training and 80% for evaluation in the SVR machine learning model. If the model is successful it will correctly predict how much damage a particular case has depending on the frequency response. Figure 3 shows that our model had a strong fit and

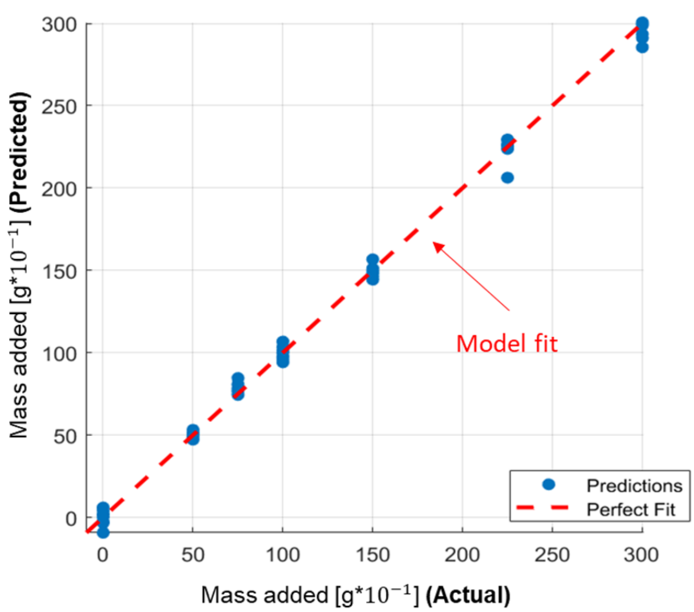


Fig. 3 SVR for Non-destructive Cases.

was able to classify the amount of damage that was present, with a root squared mean error (RSME) of less than 0.5g which means that our model had a high predictive accuracy of how much mass is removed from the MEL.

Destructive Cases

The same methodology and experimental setup was applied for the non-destructive case. The only difference is that the MEL would be damaged by removing mass around the lug. To execute this the MEL was cut by a milling machine, carefully and not excessively damaging the structure. To measure the amount of mass removed from the structure we weighed the MEL before and after it was cut. The first cut removed 1.6 grams and increased to 2.3 grams and ended with 4.1 grams. The cuts that were made on the structure are pictured in Figure 4. Using the same SVR model to see if the machine learning algorithm could predict how much mass was removed from the MEL. In Figure 5, the SVR predictions show a strong correlation in our model identifying how much damage is on the MEL. At this point the model was proven successful and yield promising results.

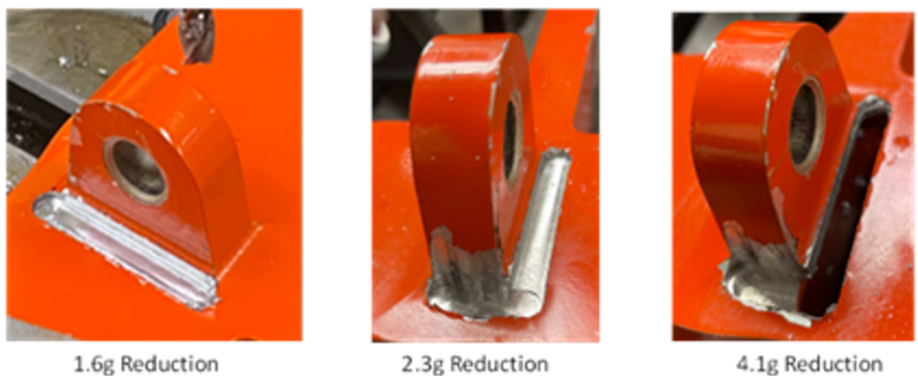


Fig. 4 Damage Test Cases.

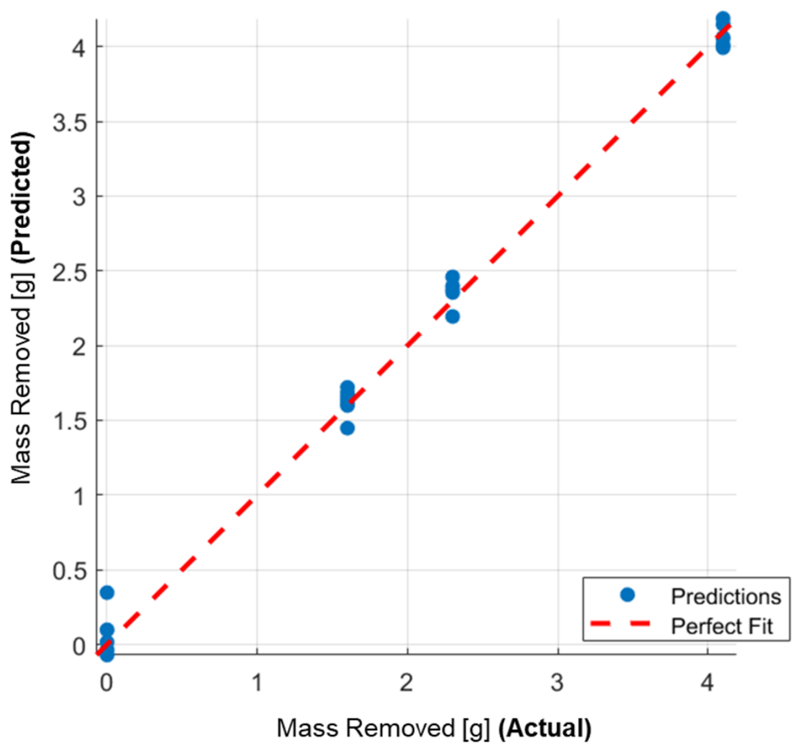
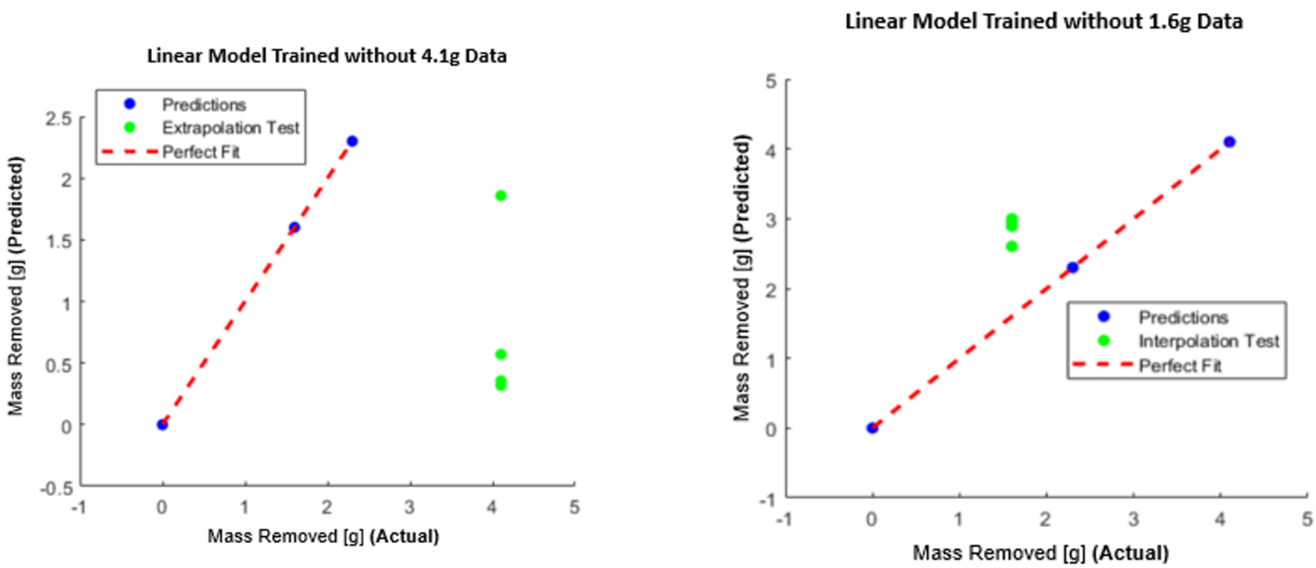


Fig. 5 SVR Results Destructive Case.

Limitations

The regression models developed demonstrated promising results; however it is important to test their robustness. In order to make sure that our model is able to identify if the structure is damaged and not just matching patterns, more analysis is required. One way to examine this, is to to test the performance of the model with regard to unseen data classes. Therefore two scenarios of our destructive cases were tested, damage cases of 1.6 grams and 4.1 grams removed from the structure were removed from the training data. These tests were done separately, not simultaneously, to see if the model could still predict those damage cases, even though they were left out of the training data. In completing this analysis that is shown in figures 6 and 7, the predictions of damage were not accurate. These results can be interpreted that the model will perform well under the circumstance that it has data from every damage case possible. This also indicates that there is a possibility the model was not identifying the physics of the model and rather trying to pattern match and does poorly when it has not seen similar cases in the training data.



Figs. 6 & 7 SVR INTERPOLATION RESULTS.

Conclusion

The results demonstrate the application of a damage detection system to an aircraft and practicability of utilizing structural health monitoring for damage detection. However, there are still clear limitations of the models used in these experiments, and still have significant room for improvement. Although a regression model can be fit to experimental testing data with a strong correlation, the model fails to accurately predict data it has not seen before. There are a few ways to mitigate the effects of this flaw in the model. The first is to increase the amount of training data. The experimental damage cases only included 3 different test cases, if increased would likely lead to more robust results. Additionally, if there were more cases given as training data for the model, the less the model must interpolate new data. The second method is to change the damage sensitive features implemented in the machine learning model. The purpose of the damage sensitive features is to extract characteristics of the frequency data that are sensitive to damage. The features used in these regression models are not extracting the necessary information from the frequency data and should be changed to ensure stronger results. Aside from improving the accuracy of this system, another area for improvement would be to expand the capabilities of this system to be able to determine the location of damage alongside severity.

Acknowledgments The team would like to acknowledge the support from US Army Program Executive Office - Aviation, PM FARA, and Fulcrum. Specifically, express our gratitude to Dr. Danny Parker, Mr. Kevin McGonigle, Mr. James Hale, Mr. Mike Pollut, Ms. Monna Moser and Mr. Evan Stringer for their advice and support throughout the project. Finally, we would like to acknowledge capstone advisors Dr. Matarazzo and LTC Bellocchio for their unending support for this project and team.

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