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SHM to detect and characterize impact events in metallic aircraft structure

Shashank PANT [1], Jack WOOLDRIGE [1], Emma SEABROOK [1],
Julio VALDES [1], Marc GENEST [1]

[1] National Research Council Canada, Ottawa, Ontario, Canada
shashank.pant@nrc-cnrc.gc.ca

Abstract. This paper presents findings related to the detection and characterization of foreign object impact events on a Metallic Aircraft Structure (MAS) using two passive Structural Health Monitoring (SHM) sensor systems. The MAS is a cut-out from an aircraft's fuselage with riveted doublers, stringers and frames. Two sets of four sensors from Mistras Inc. and Acellent Inc., were installed on the opposite sides of the MAS. Both sets of sensors were directly connected to two separate digital oscilloscopes. A multi-use tapper was developed to calibrate the system and to record the impulse energy (force versus time) of the impact events. Impact detection and characterization were defined by two regression tasks: position prediction and energy prediction. The features used for prediction were selected based on the results from a feature selection algorithm. The study found that a Gradient Boosting model excelled in localizing the impact site to within an average error of 1.2 inches [30.48 mm], demonstrating a strong correlation of 0.98. In terms of impulse energy prediction, the optimal Gradient Boosting model achieved an average prediction error of 5.8 mV.ms, with a correlation of 0.90. These results highlight the potential of this approach for detecting and characterizing impact events to be explored for potential application for aircraft SHM.

Keywords: impact detection, machine learning, SHM, aircraft structure

1. Introduction

Aircraft structures are susceptible to foreign object impacts, which can occur during manufacturing, maintenance and in-service. Examples of foreign object impacts include rock strikes and debris kicked up from the runway during take-off / landing, hail, bird strikes, and accidental tool drops during maintenance. Common ways to detect such impacts are based on flight / ground crew observations and reports leading to examination of the structures in question using non-destructive evaluation (NDE) techniques. If left undetected and/or unrepaired, these types of damage may grow and potentially compromise the integrity of the structure, jeopardizing the safety of crews, passengers and cargo [1]. Therefore, timely detection of impact damages is critical so that proper maintenance actions can be taken. The aim of this ongoing research is to develop methodologies for Structural Health Monitoring (SHM) that can automatically detect and characterize foreign object impact events using physics-based and machine learning (ML) techniques. The focus of this paper is on the ML technique.

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Machine learning (ML) has become increasingly popular due to improvements in computational capabilities, data storage, and the accessibility of ML algorithms. These algorithms can successfully mimic human intelligence, automate complex tasks, and predict future outcomes. However, the interpretability of these algorithms is often restricted due to the multitude of defining parameters, which can constrain the adaptability of ML models in new settings or situations. Additionally, the optimization process may require extensive datasets that may not be easily accessible and can be challenging to collect. Researchers have used ML to detect and characterize impact events. Tabian et. al. [2] converted the recorded time-series signal into 2D images and used convolution neural networks to detect and characterize impact in composite structures. They collected the data by dropping a hemispherical impactor from different heights. Damm et. al. [3] also used convolution neural network to detect impact events in a composite plate by passing 2D spectrograms generated using short-time Fourier transform of the sensors' signals. They used a robotic impact bench for collecting the data. Li et. al. [4] used random forest and deep learning techniques on a thermoplastic aircraft elevator. They collected the data by dropping a steel ball inside a tube. Dipietrangelo et. al. [5] used polynomial regression and shallow neural network to detect impact events generated by a steel ball dropped inside a tube in an aluminum panel. Hu & Albertani [6] employed support vector machine (SVM) for the purpose of identifying impacts on full-scale wind turbine blades using vibration data collected during the impact events. Saki et. al. [7] investigated the potential of using surface profiles (dent profilometry) from low-velocity impact events on carbon fibre composite laminates. Impact characteristics including: impactor shape, delamination area, and delamination length were estimated using a variety of ML techniques including ridge regression, logistic regression, and random forest. Muflih et. al. [8] employed pulsed thermography on carbon fibre composites for the detection of impact damage, leveraging the Cubic SVM model.

The majority of techniques for detecting impact events depend on supervised ML, which necessitates data for training the ML models. For practical implementation, data from an existing structure is required to train the ML model without causing any damage to the structure. This can be challenging as each Structural Health Monitoring (SHM) setup is unique and requires data from that specific setup to train the ML models for accurate predictions. This paper uses a method that collects data from an existing aircraft structure without inflicting damage, using a multi-use tapper. The data obtained from this multi-use tapper is then used to train the ML models, enabling them to predict both the location and impulse energy (force vs. time) of impact events on an actual metallic aircraft structure.

2. Experimental Setup

This experiment employed a cut-out from an aircraft fuselage, with dimensions of 31 by 26 inches [787.4 by 660.4 mm] and a skin thickness of 0.032 inches [0.81 mm]. This metallic aircraft structure (MAS) was fabricated from an aluminium alloy and featured riveted overlapping panels, stringers, and frames, as depicted in **Fig. 1**. To administer impact, the MAS was segmented into 1 by 1 inch [25.4 by 25.4 mm] grid patterns over an area of 22 by 20 inches [558.8 by 508 mm].

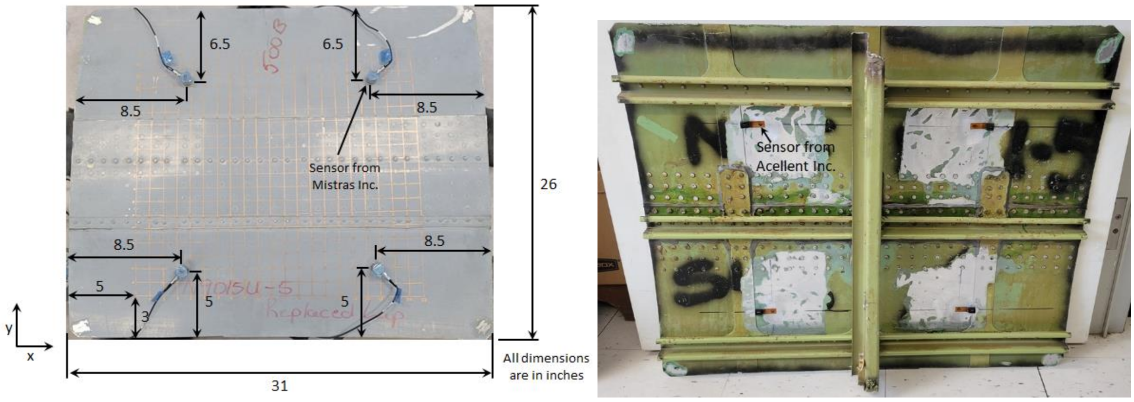

Fig. 1. Metallic aircraft structure used in the experiment - dimensions in inches [x25.4 mm].

Two different sensor systems were used to collect data during the impact events - acoustic emission (AE) sensors from Mistras Inc. and lead zirconate titanate (PZT) sensors from Acellent Inc. Mistas and Acellent sensors will be denoted as Mis and Acl, respectively from herein. For acquiring the data, the Mis and Acl sensors were bonded to the panel using Loctite silicone and M-bond 200 adhesive, respectively. Both sensors were directly connected to two individual digital oscilloscopes (Picoscope 4824), without any amplifications and filtering.

To impact the MAS and to calibrate the system, a configurable multi-use tapper with a force feedback capability was developed. The tapper consisted of an interchangeable hemispherical head in which a load cell was inserted between two metallic discs. The multi-use tapper was fabricated out of aluminum alloy and can be converted to a tap hammer by attaching a handle. By detaching the handle, the tapper can be used as a drop-weight impactor by adding or removing desired weights, which can be dropped inside a guide-tube from discrete heights. For acquiring the force-feedback signal from the tapper, the tapper was connected to a strain gauge box (P-3500 from Vishay). The force-feedback signal from the strain gauge box was sent to both Mis and Acl data acquisition system to collect the impulse energy data.

For detecting an impact event, a triggering threshold of 10 mV was set on the force-feedback signal from the tapper for both the Mis and Acl sensors. Once triggered due to an impact, 50,000 samples were recorded over a duration of 100 milliseconds, corresponding to a sampling frequency of 0.5 MHz for both the Mis and the Acl sensors. The recorded samples were saved in .mat (Matlab matrix) file format for further processing. Typical signals acquired from the Mis sensors and the tap-hammer is shown in **Fig. 2**.

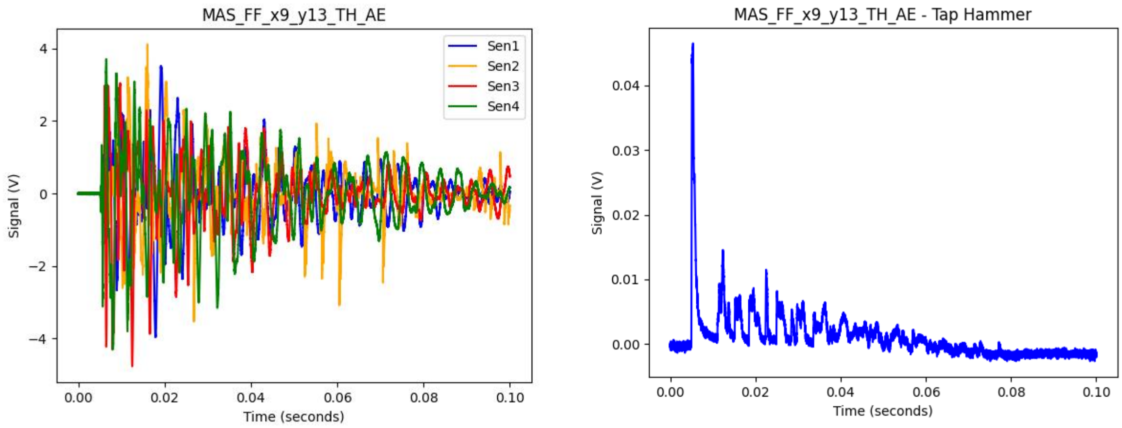

Fig. 2. Typical signals recorded by: left - Mis sensors, and right – tapper.

Two sets of experiments were performed: (i) the calibration and (ii) the drop-weight impacts. In the calibration experiment, the multi-use tapper was used in the tap hammer configuration to impact each location 5 times with varying levels of force. In the drop-weight experiment, an additional mass of 102 grams was added to the tapper, for a total mass of 136 grams, which was dropped inside a guide-tube from four discrete heights of 100 mm, 150 mm, 200 mm, and 250 mm. A total of 2080 datapoints were gathered during the calibration experiment from both the Mis and Acl sensors. In the case of the impactor experiment, a total of 1588 and 1668 datapoints were gathered from the Mis and Acl systems, respectively.

3. Analysis, Results and Discussions

In the realm of machine learning, 'features' in the data denote individual measurable properties or characteristics of a phenomenon being observed. The features extracted in this study included time of arrival (ToA) using the Akaike information criterion (AIC), root mean square (RMS), energy, maximum amplitude, maximum range, start and end time of the maximum range, time delay, peak frequency, frequency centroid, etc. This resulted in 48 potential features from both the Mis and Acl sensors' datasets. A Gamma test was performed to determine whether these features could effectively predict the target outcome. The Gamma test is a non-parametric procedure to estimate the amount of residual variance in a dataset composed of a set of predictor features and a target variable. This is the variance component of a target variable that does not come from the predictor variables and represents an estimate of the ideal mean squared error of a model relating the predictor and the target variables, obtained directly from the data. Accordingly, it provides an assessment of the quality of the data from the point of view of its modelling potential [9][10]. The Gamma test scrutinizes the inherent relationship between the input (features) and output (target) data without any pre-existing knowledge. A Gamma test result (V_{ratio}) close to zero suggests that the output can be predicted with a high degree of accuracy using the given set of input data [11]. The results of this test, provided in **Table 1**, show V_{ratios} for positions (x and y) less than 0.08, and V_{ratios} for impulse energies of less than 0.14, indicating that the input features can effectively predict the impact position and impulse energy.

Table 1. Gamma test results.

		V_{ratio}	
Sensor	**Target**	**Tap Hammer**	**Drop-Weight Impactor**
Mis	Position (x)	0.0430	0.0444
	Position (y)	0.0130	0.0715
	Impulse Energy	0.0603	0.133
Acl	Position (x)	0.0135	0.0283
	Position (y)	0.00418	0.0160
	Impulse Energy	0.0940	0.106

After establishing that the extracted features were appropriate for predicting the target, the significance of these features was assessed through a feature selection procedure using the Permutation Feature Importance (PFI) algorithm [12]. The PFI algorithm operates by repeatedly shuffling the feature values in the training set and fitting a model to the data each time to monitor changes in the model's performance. The importance of each feature is then determined based on its correlation with the target. The results of the PFI algorithm are depicted in **Fig. 3**, where it is evident that ToA and RMS had the most significant influence on predicting position and impulse energy, respectively.

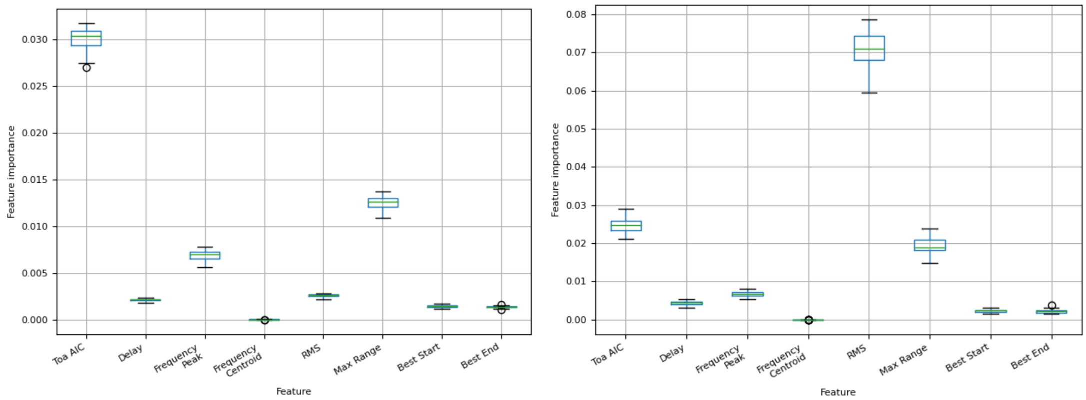

Fig. 3. Feature importance plot processed using Mis sensor data from tap-hammer experiment: left – position, and right – impulse energy.

In this study, the division of training and testing subsets varied between the two conducted experiments due to the quantity of data available. For the tap hammer experiment, the data was split into a 3:2 ratio, where three out of every five impacts at each point were allocated for training purposes, and the remaining two impacts were reserved for testing. In the case of the drop-weight experiment, the data was separated into a 3:1 ratio, with three out of every four impacts at each point was used for training and the fourth impact was used for testing. This approach was adopted to improve the model's ability to generalize impact detection performance by ensuring that it is exposed to each impact point three times in the course of the training phase.

The ML models used in this study were selected from the Scikit-Learn machine learning library and were executed in Python. For predicting the impact location, Random Forest [13] and Gradient Boosting (GB) [14] were implemented, while for predicting impulse energy, GB along with Multi-Layer Perceptron (MLP) [15], and Support Vector Machine (SVM) [16] were used. These ML models were selected based on the success from the previous experiments conducted on a simple metallic flat-panel specimen for predicting similar regression tasks (position and energy) [17]. These ML models were executed twice, once with the non-optimized hyper-parameters and another by optimizing the hyper-parameters using a halving grid search algorithm for hyper-parameter tuning [18]. The performance of these ML models was evaluated using commonly used metrics such as: Root Mean Squared Error (RMSE) and Pearson correlation coefficient (corr) [19]. The results of the ML models trained and tested on tap-hammer and drop-weight data are provided in **Table 2** and **Table 3**, respectively, where the best preforming models are highlighted by bold letters.

For impact position prediction, the non-optimized GB model trained on Acl sensor data, yielded the best results with a correlation of 0.98 and a RMSE of 1.413 inches [35.89 mm] for the tap-hammer setup (**Table 2**). For the drop-weight impactor setup, the non-optimized GB trained on Mis sensors provided the best results with a correlation of 0.98 and a RMSE of 1.176 inches [29.87 mm] (**Table 3**).

For energy prediction, the performances of the ML models were slightly inferior as compared to location prediction. The best model for the tap-hammer data was the non-optimized GB trained on Mis sensor data, achieving a correlation of 0.90 and a RMSE of 5.847 mV.ms (**Table 2**). For the drop-weight data, the best model was the optimized GB trained on Acl sensor data, achieving a correlation of 0.91 and a RMSE of 8.664 mV.ms (**Table 3**).

Overall, the determination of the impact location was highly accurate, but there is a need for further work to improve impact energy prediction. This could involve shifting the energy prediction approach from a regression model to a categorical classification such as: low, medium, and high-energy impacts. Moreover, to simulate an operational environment, the multi-use tapper should be used in tap-hammer mode to collect calibration data for the SHM system and to train the machine learning model to predict scenarios from drop-weight impactor that are new and have not been used for training the ML models.

Table 2. Results of the ML models trained on tap-hammer data.

Sensor	Prediction	Model	Configuration	RMSE	Corr
Mis	Position	Random Forest	Non-optimized	1.563 in [39.7 mm]	0.976
			Optimized	1.761 in [44.73 mm]	0.973
		Gradient Boosting	Non-optimized	1.454 in [36.93 mm]	0.981
			Optimized	1.437 in [36.50 mm]	0.980
	Impulse Energy	MLP	Non-optimized	9.011 mV.ms	0.763
			Optimized	8.980 mV.ms	0.758
		SVM	Non-optimized	8.189 mV.ms	0.783
			Optimized	9.116 mV.ms	0.727
		Gradient Boosting	**Non-optimized**	**5.847 mV.ms**	**0.896**
			Optimized	6.566 mV.ms	0.875
Acl	**Position**	Random Forest	Non-optimized	1.508 in [38.30 mm]	0.975
			Optimized	1.618 in [41.10 mm]	0.973
		Gradient Boosting	**Non-optimized**	**1.413 in [35.89 mm]**	**0.980**
			Optimized	1.798 in [45.67 mm]	0.966
	Impulse Energy	MLP	Non-optimized	8.445 mV.ms	0.809
			Optimized	8.360 mV.ms	0.805
		SVM	Non-optimized	8.256 mV.ms	0.792
			Optimized	6.986 mV.ms	0.854
		Gradient Boosting	Non-optimized	6.561 mV.ms	0.878
			Optimized	7.143 mV.ms	0.873

Table 3. Results of the ML models trained on drop-weight data.

Sensor	Prediction	Model	Configuration	RMSE	Corr
Mis	**Position**	Random Forest	Non-optimized	1.268 in [32.21 mm]	0.976
			Optimized	1.314 in [33.38 mm]	0.977
		Gradient Boosting	**Non-optimized**	**1.176 in [29.87 mm]**	**0.982**
			Optimized	1.215 in [30.86 mm]	0.982
	Impulse Energy	MLP	User defined	11.134 mV.ms	0.830
			Optimized	12.184 mV.ms	0.800
		SVM	User defined	15.234 mV.ms	0.665
			Optimized	14.211 mV.ms	0.697
		Gradient Boosting	User defined	9.570 mV.ms	0.881
			Optimized	9.626 mV.ms	0.864
Acl	Position	Random Forest	User defined	1.334 in [33.88 mm]	0.982
			Optimized	1.423 in [36.14 mm]	0.979
		Gradient Boosting	User defined	1.476 in [37.49 mm]	0.982
			Optimized	1.259 in [31.98 mm]	0.986
	Impulse Energy	MLP	User defined	16.195 mV.ms	0.698
			Optimized	13.441 mV.ms	0.770
		SVM	User defined	14.318 mV.ms	0.683
			Optimized	13.954 mV.ms	0.722
		Gradient Boosting	User defined	9.529 mV.ms	0.873
			Optimized	**8.664 mV.ms**	**0.906**

4. Conclusions

This paper investigated techniques for detecting and characterizing impact events using machine learning (ML) methods. The experiments were performed on a metallic aircraft structure (MAS) extracted from a commercial airliner fuselage. Four acoustic emission sensors from Mistras Inc. (Mis) and four piezoelectric sensors from Acellent Inc. (Acl) were affixed to the structure's opposing sides to record the impact events. A multi-use tapper was designed and developed to collect data without causing any damage to the structure. Data was collected in two ways: one using the tapper in a tap-hammer mode, and the other by dropping the tapper in a drop-weight mode inside a guide tube.

A Gamma study was conducted using several features extracted from the sensors signal. The results form the Gamma test, showing V_{ratios} for positions less than 0.08, and V_{ratios} for impulse energy less than 0.14, indicated that the input features could effectively predict the impact position and impulse energy. Following this, the significance of these features was evaluated through a Permutation Feature Importance (PFI) study. The results from PFI showed that time of arrival (ToA) had the most significant influence on position prediction, while root-means square (RMS) was most influential in predicting impulse energy.

Two ML models - Random Forest (RF) and Gradient Boosting (GB) were employed to predict the position, while three machine learning models - Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), and GB were used to predict the impulse energy. The best results for impact position prediction were achieved by the hyperparameter tuned GB model trained on Mis sensor data for the tap-hammer setup, with a correlation of 0.98 and a RMSE of 1.437 inches [39.5 mm]. For the drop-weight setup, the user-defined GB model trained on Acl sensors yielded the best results with similar correlation but a lower RMSE of 1.176 inches [29.87 mm]. In terms of energy prediction, the models performed less effectively compared to position prediction. The user-defined GB model trained on Mis sensor data provided the best results for the tap-hammer data, achieving a correlation of 0.90 and a RMSE of 5.847 mV.ms. For the drop-weight setup, the optimized GB model trained on Acl sensor data yielded the best results with a similar correlation but with a higher RMSE of 8.664 mV.ms.

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