Development of an Artificial Intelligence (AI) for the Prediction of Fatigue Failure in Naval Structures: A Digital Twin Application

SOURAV BANERJEE, NAFISA MEHTAJ
and BENJAMIN L. GRISSO

ABSTRACT

Many of the high speed and high-performance naval vessels use aluminum as a primary structural material. Welded aluminum stiffened structures are very common in these vehicles, but even with much research, performance of these structures under fatigue is not completely known. Many experimental investigations on similar structures were performed over the past two decades. Meanwhile, the desire for a comprehensive naval structural health monitoring (SHM) system is receiving greater interest. Recently, with re-advent of machine learning and artificial intelligence (AI) for structural digital twin, older experimental sensor dataset from crack growth in welded aluminum structure could be better utilized and exploited for crack predictions with few interventions from the sensor data. In this study, piezoelectric wafer active sensors are utilized for SHM of a welded aluminum structure and sensor data were collected at multiple frequencies from multiple specimens. Crack initiation to growth pattern were also recorded. Through machine learning, sensor data from four specimens were exploited to develop an AI algorithm for predicting the crack growth. It is shown that ML and AI frameworks are suitable for ship structure digital twin applications.

INTRODUCTION

Aluminum welded joins are frequently used in the design and fabrication of marine and naval vessels. High speed and high-performance vessels require light weight hulls to meet operational requirements, and thus aluminum is a natural material choice for these ships. Although much research has been dedicated to understanding aluminum behavior under fatigue, aluminum sensitization, fatigue performance and strength of aluminum welded structures are still unknown. A primary concern in aluminum structures is the heat-affected zone (HAZ) induced during the welding process [1].

Sourav Banerjee, Professor, Mechanical Engineering, University of South Carolina, 300 Main Street, Columbia 29208, U.S.A. email: banerjes@cec.sc.edu
Benjamin Grisso, SHM Research Engineer, Naval Surface Warfare Center, Carderock, 9500 MacArthur Blvd., West Bethesda MD 20817, U.S.A.

These structures are susceptible to fatigue cracks which may grow continuously under operational loading. Wide uncertainty in crack paths and crack lengths over a broad range of environmental fatigue loading make it extremely difficult to predict crack length. Thus, real time structural health monitoring (SHM) [2-3] is one approach for long term monitoring of welded aluminum structures. Structural details can be instrumented with piezoelectric transducers to probe the material state in real time via a range of passive and active SHM. This article is primarily focused on Guided wave based active mode of SHM. Typically, the transducers are installed and ultrasonic Guided waves are collected through an active SHM system. Factors such as operational environmental conditions, transient material properties (aluminum sensitization), and inconsistent behavior of the installed sensors sometime makes the interpretation of the crack length from the sensor data difficult. However, advances in machine learning (ML) based data modeling and implementation through an artificial intelligence (AI) framework for crack prediction of welded aluminum joints would be a valuable means to enhance the usage of SHM for complex structures.

Research described in this paper utilized several representative welded aluminum test specimens. These specimens were instrumented with Guided wave SHM system using four surface mounted piezoelectric sensors. Data from one of these specimens were analyzed and presented in ref. [4]. In this study, a total of six of these specimens were analyzed, for which a complete set of Guided waves SHM data were available.

MATERIALS AND SPECIMENS

Detailed descriptions of the specimens can be found in [4], however, a few details are reiterated herein. In this study, the test structures are aluminum fatigue specimens constructed with typical Navy ship design details (Figure 1). All connections are welded. The base plate and bulkhead material consist of 3/8 and 1/4 inch thick 5083-H116 aluminum, while the stiffeners are made of extruded 6061-T6 aluminum. Thick end plates are welded to the specimen to allow for placement of the plate in a tensile fatigue machine. Using the fatigue machine, different loading profiles are applied to groups of specimens in an effort to characterize the S/N curve for this type of plate intersection. The results from monitoring one of these stiffened plate specimens are presented in this paper. Sixteen strain gauges were applied to the specimen to assist in balancing the structure in the fatigue machine, as well as monitor the loading through the fatigue process. Specimen name and details are shown in Table I.

TABLE I: SPECIMEN NAMES AND IDENTIFICATION

Item No	Specimen no.
1	MAHI Spec 1
2	MAHI Spec 2
3	MAHI Spec 4
4	MAHI Spec 8
5	MAHI Spec 12
6	MAHI Spec 22

EXPERIMENTAL DESIGN

A 550-kip MTS machine was used for the specimens under investigation. Fatigue loading with 5 Hz loading rate, constant amplitude and R = -1 was applied to the specimens. The specimens were subjected to cyclic loading until an onset of crack is detected visually. Initiation of a crack in a specimen is considered failure of the specimen. However, the cracks were allowed to grow further by continuing the cyclic loading. The loading continued until the crack propagated through one side of the plate.

Four piezoelectric wafer active sensors (PZTS) were bonded to the surface of the base plate (Figure 1). The average diameter of the sensors was 0.5-inch. PZTS were 0.02 inch thick made of 851 materials. PZTS were supplied by APC, International and bonded to the plate with Vishay Micro-Measurements M-Bond 200 adhesive [4]. Acellent Technologies Inc. Smart Suitcase Lamb wave data acquisition system was used [4]. Designations of PZTS are shown in Figure 1. All possible combinations of paths were utilized to acquire the data. A Krohn-Hite 7602M wideband amplifier is used to amplify the excitation signals from the DAQ system [4]. A typical tone-burst consists of 5 cycles of a Hanning-windowed sine wave that was used as an actuation signal. 20,000 data points at a rate of 25 mega samples per second were recorded with 20 averages to increase signal to noise ratio.

The machine was stopped at a regular interval to collect the data from the sensors. A detailed protocol can be found in ref [4]. Guided wave signals were collected at 50, 75, 100, and 150 kHz. Different specimens, when inspected visually, show the sign of initiation of crack after a certain number of fatigue cycles. For example, visual indication of onset of crack in specimen 4 shows after 167,300 cycles. The crack was located in the heat-affected zone adjacent to the main plate butt weld. Similar was observed for all other specimens.

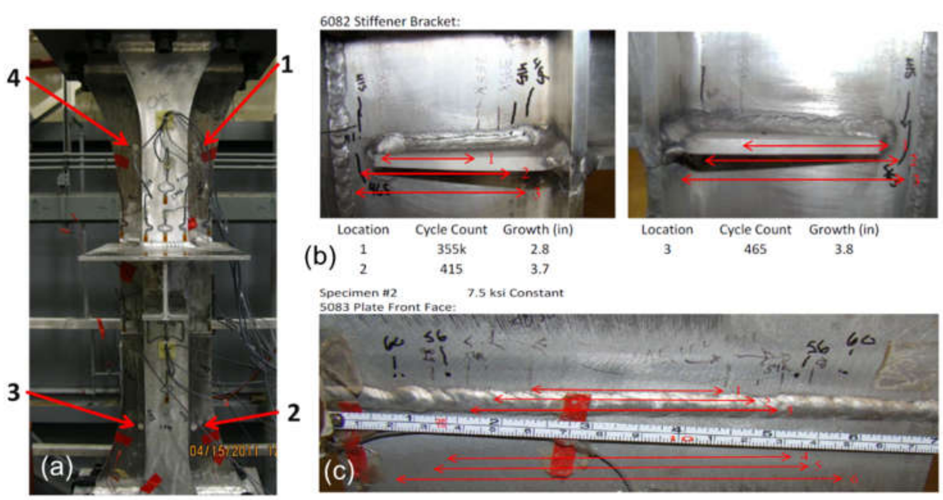

Figure 1. a) The front side of a specimen (Specimen No. 4) is shown, and the four piezoelectric discs bonded to the plate are labeled. b) Crack growth in Specimen No. 8 c) Crack growth in Specimen no. 2

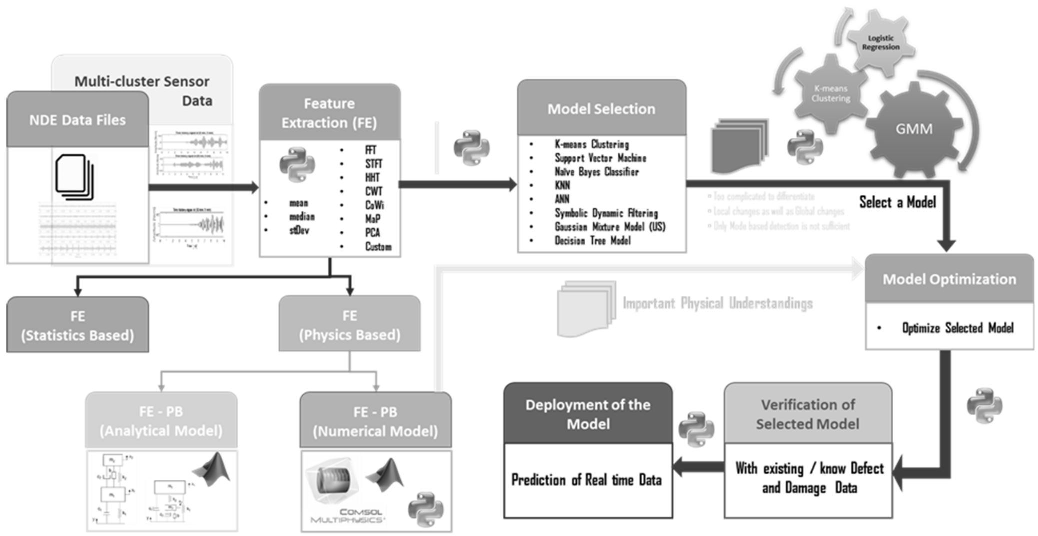

Figure 2: A schematic showing the philosophy adopted for the data analysis through feature extraction, model selection, model optimization, verification and model deployment.

OVERALL ML PROCESS FOR DATA ANALYSIS

To maximize understanding from the data sets, it was not possible to perform the manual analysis. Hence, an automated data analysis process was adopted. Figure 2 shows the overall flow chart of how the data analysis and machine learning methods were adopted to develop the final algorithm, model training, and predictive capability.

The first step was to extract the features from the Guided wave signal that are relevant to quantify the damage (crack length) size. Guided wave signal consists of several wave modes with different velocities at different frequencies. The underlying physics must be captured through the features to be extracted. Feature extraction is the step where long 20,000 data points signals are reduced to a few features that facilitate fast and efficient interpretation of the data. To explore these features a software portal was built in MATLAB. A class called 'GuidedWaveFeatures' was created with multiple internal functions that are responsible for calculating specific features. Automated signal analysis objects were created from the class to generate multiple features. The following features extraction algorithms were used. A total of 38 features were extracted, including principal components, nonlinear parameters, nonlocal parameters, frequency content and amplitudes, Kurtosis, average and moving average signal energy to name a few. Hence, each Guided wave signal of 20,000 data points along any path was reduced to only 38 data points.

Figure 3 shows the software portal that was built to perform this analysis. The software portal is capable of loading full datasets captured during the fatigue experiments on all six specimens. The user is able to select any specific specimen, select individual excitation frequencies, and automatically have visuals of all the signals collected along the four sensor paths. Please note that in this analysis only four paths were considered, those between sensors 1 and 2, 3 and 4, 1 and 3, and 2 and 4. After frequency selections, users may explore the signals from the Baseline Data and Fatigue

Data dropdown menu. Next, a Fatigue Analysis is performed. Clicking the 'Load All Data Fatigue Analysis' button, the feature extraction algorithms are initiated. Giving equal weightage, a Damage Index (DI) is formulated using the following equation.

$$DI = \sqrt{\sum_{i=1}^{38}(f \times f^*)} \tag{1}$$

DI was calculated over the entire fatigue test for each specimen at all frequencies mentioned before. An evolution of the Damage index in specimen 4 at 100 kHz is shown in Figure 3. File 12, which is a representative of the data after 110k loading cycles, shows significant increase in the DI as an indication of onset of crack. Please note that the crack was not visible on the surface until 167,300 cycles.

BUILDING MACHINE LEARNING MODEL

Using the tool above, six sets of data where prepare to initiate the Machine Learning of damage index and crack length. Table II shows an example of a feature table created for each specimen. Table II shows the data from specimen 1.

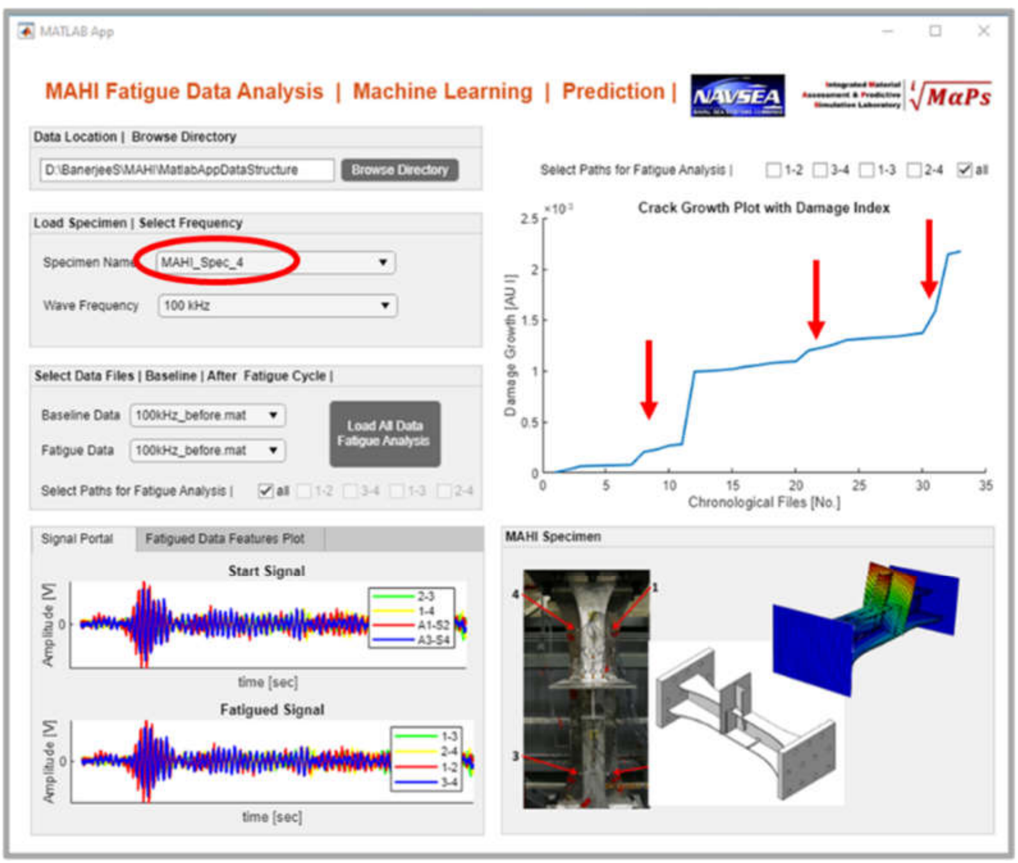

Figure 3: Data analysis toolbox for feature extraction and calculating damage index.

TABLE II: DAMAGE INDEX AND CRACK LENGTH DATA

Cycle (k)	DI 100 kHz	DI 150 kHz	DI 75 kHz	DI 50 kHz	Crack Length (in.)	Temp (°F)
0	1.61E-06	2.48E-06	1.57E-06	1.57E-06	**0**	79
0	0.000294	5.56E-06	4.55E-05	4.55E-05	**0**	79
68	0.000428	4.89E-05	6.55E-04	0.000655	**0**	84
68	0.000627	9.92E-05	6.63E-04	0.000663	**0**	84
110	0.001002	0.000106	6.71E-04	0.000671	**1**	86
110	0.001007	0.000114	7.59E-04	0.000759	**1**	86
128	0.001011	0.000327	2.97E-03	0.002967	**1.1**	82
128	0.002475	0.000402	0.002968	0.002968	**1.1**	82
135	0.003371	0.000447	0.002968	0.002968	**1.25**	80
135	0.003549	0.000464	0.002968	0.002968	**1.25**	80
154	0.003627	0.000479	0.003154	0.003154	**2.24**	80
154	0.003744	0.000706	0.003298	0.003298	**2.24**	80
195	0.003781	0.000781	0.003315	0.003315	**3.75**	80
195	0.003783	0.000782	0.003336	0.003336	**3.75**	80
216	0.003784	0.000784	0.003563	0.003563	**4.87**	80
216	0.005386	0.00081	0.003571	0.003571	**4.87**	80
228	0.005443	0.000897	0.003579	0.003579	**5.50**	80
228	0.005494	0.000912	0.008145	0.008145	**5.50**	80
228	0.005745	0.000917	0.008198	0.008198	**5.50**	80
228	0.006456	0.000926	0.008255	0.008255	**5.50**	80

To train the ML algorithm, four sets of such data were used where the DI data at different frequencies were the inputs, and the crack length data were the output. Before creating the model, all data were scaled to themselves. That means the data from each specimen were scaled individually. Following the steps shown in Fig. 2, different models were developed. An Artificial Neural Network (ANN) model was found to be most suitable with the least error. A four-layer dense network with RELU activation was created sequentially in Python employing Keras. 'adam' optimizer and 'mse' loss methods were used. The best optimized model was found when the four sequential layers 38, 76, 38 and 16 nodes were used. A 500 epoch loss curve is shown in Fig. 4. Mean square error with respect to the iteration number is shown.

After the model is developed, a specimen used in the training set was chosen to determine if the model correctly predicted the damage index. As there were other specimens with various different scaled damage index values used to develop the model, prediction was not hundred percent accurate but ranged between 96% – 98%. After the model verification for validation, specimen test data were fed into the predictive model without true crack length data. Different trainings were performed with various combinations of 4 and 2 specimens where 4 specimens were used for training and 2 specimens were used for testing the model.

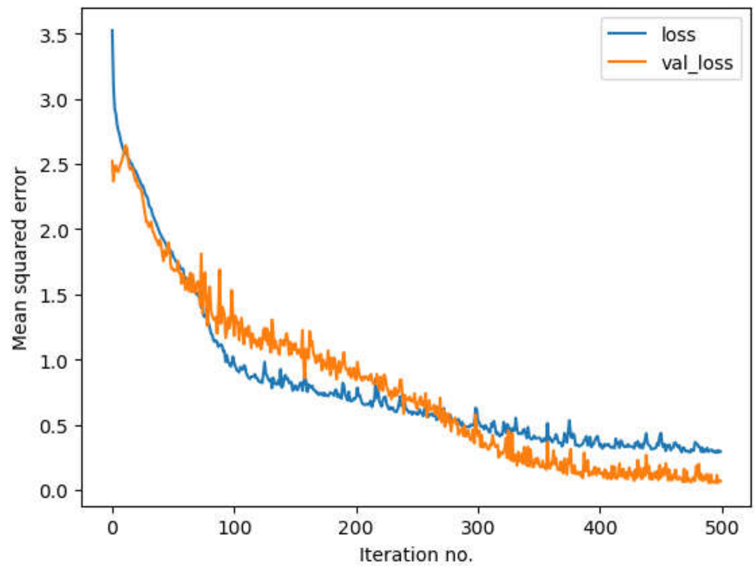

Figure 4: Mean square error with respect to iteration number.

For example, when Specimen nos. 1, 2, 4 and 22 were used as the training specimens, Specimen no. 8 and 12 were used for testing the prediction. Figure 5 shows the outcome of all the result when 55 different cases with different specimen and at different loading cycle was tested for crack size. The figure shows the actual crack size and the predicted crack sizes in inch.

CONCLUSION

A machine learning approach is demonstrated using fatigue test data for future prediction of crack growth using Guided wave sensor data collected online. The approach is useful for the development of digital twins of naval structures with in situ SHM. In the future, multiple datasets including in situ SHM, visual or remote inspection, nondestructive evaluation (NDE) data, and more can be fused for a comprehensive understanding of platform condition.

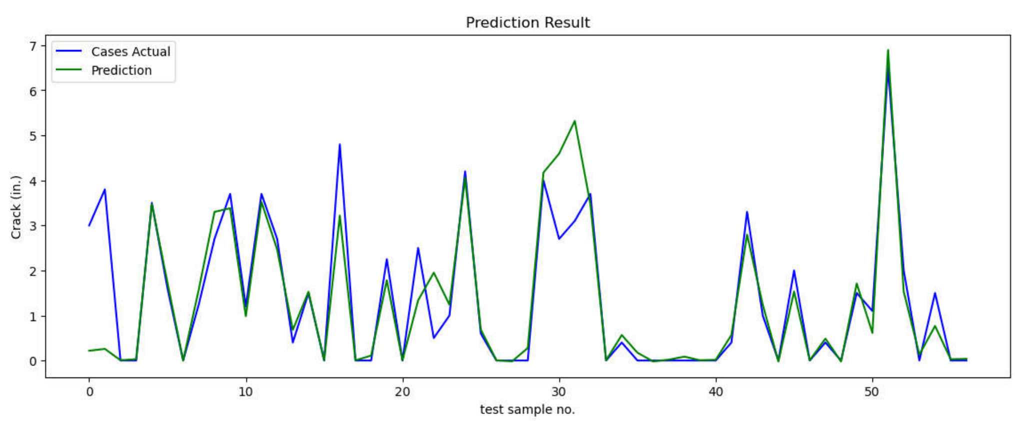

Figure 5: A summary of prediction results

Online sensor data can be utilized for real time updating of digital twins. At that scale, it would be necessary to employ ML and AI for real time prediction of material state from the sensor data. Although Guided wave sensors data are used in this study, future efforts will focus on data fusion between these local sensors and global health monitoring data using accelerometers, strain gauges, etc. to understand ship response to operational (wave) conditions. As the use of local, crack monitoring SHM grows, it will not be possible to perform all possible scenarios of experiments in the laboratory and train the model. At that point of time, it will be beneficial to employ fully verified and validated computational model [5-6] for data generation that could be used in training the ML models.

REFERENCES

1. Shankar, K and W. Wu. 2002. "Effect of welding and weld repair on crack propagation behaviour in aluminium alloy 5083 plates," *Materials & Design*, 23(2):201-208.
2. Lynch, J. P., R. A. Swartz, A. T. Zimmerman, T. Brady J. Rosario, , L. W. Salvino, and K. H. Law. 2009. "Monitoring of a High-Speed Naval Vessel using a Wireless Hull Monitoring System," Proceedings of the 7th International Workshop on Structural Health Monitoring, Sept. 9-11, Stanford, CA,
3. Hess, P. E. 2007. "Structural Health Monitoring for High-Speed Naval Ships," Proceedings of the 6th International Workshop on Structural Health Monitoring, Sept. 11-13, Stanford, CA, 3-15.
4. Grisso. B., Park, G., Salvino, L. W., Farrar, C. F., Structural Damage Identification in Stiffened Plate Fatigue Specimens Using Piezoelectric Active Sensing., Proceedings of the International Workshop on Structural Health Monitoring, Stanford, CA, 2011.
5. Patra, S., Ahmed, H., Saadatzi, MS., Banerjee, S., Experimental Verification and Validation of Nonlocal Peridyanmic Approach for Simulating Guided Lamb Wave Propagation and Damage Interaction, *Structural Health Monitoring* Journal, Vol 18(5-6), pp. 1789-1802.
6. Patra, S., Ahmed, H., Banerjee, S., (2018) Peri-Elastodynamic Simulations of Guided Ultrasonic Waves in Plate-Like Structure with Surface Mounted PZT, Sensors, Vol. 18, No. 274, pp. 1-16.