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Gul, F.C.; Moradi, M.; Benedictus, R.; HADJRIA, RAFIK; LUGOVTSOVA, YEVGENIYA; Zarouchas, D.

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Delamination Size Prediction for Compressive Fatigue Loaded Composite Structures Via Ultrasonic Guided Wave Based Structural Health Monitoring

FERDA C. GÜL, MORTEZA MORADI, RINZE BENEDICTUS, RAFIK HADJRIA, YEVGENIYA LUGOVTSOVA and DIMITRIOS ZAROUCHAS

ABSTRACT

Under in-plane compressive load conditions, the growth of a delamination initially induced by an impact can be followed by a fast growth after a threshold level, which leads to a catastrophic failure in composite structures. To avoid reaching this critical level, it is essential to uncover the delamination size and growth pattern in real time. Ultrasonic Guided Waves (UGW) have a strong capability to interrogate and monitor the structure in real-time and thus track the growth of damage, which may occur during the flight cycles. Although various types of damage affect the monitored UGW signals, it is challenging to determine from the UGW signals what types of damage and at what rate of growth are occurring within the structure. UGW signals can be acquired at defined intervals and then analysed to possibly detect different types of damages, such as delamination, and to quantify the rate of damage growth over fatigue cycles. However, correlating the UGW-based Damage Indicators (DIs) with the specific type of damage, such as delamination, and damage growth is a challenging task as the relation between these DIs and the actual damage state is very complex. Therefore, in this study, a supervised Deep Neural Network-based (DNN) prediction model is proposed aiming to diagnose the delamination size of the composite structure by correlating the UGW-based DIs with the quantified time-varying delamination size. UGW data is collected through a network of permanently installed piezoelectric transducers (PZTs). The delamination size is obtained through ultrasonic C-Scan technique at defined cycles. DIs are extracted in time, frequency, and time-frequency domains and used as the input for the DNN-based regression model. Each sensor-actuator path is considered as an independent set of indicators, which are separated for training, validation, and testing purposes. The effect of the different paths on the delamination size prediction is presented along with the model performance on measured delamination growth in woven type composite sample.

Ferda C. Gül, Rafik Hadjria, Safran Tech, Paris, France, E-mail: F.C.Gul@tudelft.nl
Ferda C. Gül, Morteza Moradi, Dimitrios Zarouchas, Center of Excellence in Artificial Intelligence for Structures, Prognostics & Health Management, Aerospace Engineering Faculty, Delft University of Technology, Delft, The Netherlands
Ferda C. Gül, Morteza Moradi, Dimitrios Zarouchas, Rinze Benedictus, Aerospace Structures and Materials Department, Aerospace Engineering Faculty, TU Delft, Delft, The Netherlands.
Yevgeniya Lugovtsova, Federal Institute for Materials Research and Testing (BAM), Berlin, Germany

INTRODUCTION

In aerospace industry, composite materials have initiated major transformation in terms of bringing lighter and more fuel-efficient designs due to composite's high stiffness-to-weight ratio and fatigue resistance. The advantages of composite materials results in less environmental impact and less operational cost. Despite their numerous advantages, composites are anisotropic materials with complicated damage accumulation processes. Besides that, their vulnerability to out-of-plane loading conditions, such as impact, can cause a damage initiation, which may evolve stochastically over the lifetime of the aircraft due to fatigue. Therefore, to maintain the safe operation, evaluating the integrity of a composite structure at the time that aircraft in operation is crucial.

In the lifetime of composite structures, various damage mechanisms may occur depending on the operational and environmental conditions. Delamination is one of damage types, which has a critical role, especially in aircraft components that are subjected to complex loading conditions. Delamination initiation and propagation rate are affected by various factors such as layup orientation and loading conditions. Compressive loading conditions can lead to delamination, which grows very quickly after reaching a threshold level, which in turn may cause a failure [1, 2]. To diagnose and predict the delamination growth in composite structures are important tasks to allow aircraft to continue its safe operations. Considering condition-based maintenance strategy, UGW based structural health monitoring (SHM) can be applied to examine the structure and address the structural damage in the sense of diagnosis and prognosis [3]. Owing to their characteristic scattering and mode conversion phenomena originated at structural discontinuity produced by the damage, damage related information can be extracted from UGW signals [4, 5]. DIs can be obtained from GW signals through signal processing techniques in time, frequency, and time-frequency domain. Yet, obtained DIs may not reflect the actual damage size as UGWs interact with damage in a very complex way.

In this study, to predict the delamination growth in woven type carbon fiber reinforced polymer (CFRP), a regression model has been developed by using DNN. In the experimental phase, delamination is first initiated by an impact and then it is subjected to compressive fatigue loading which is explained in the section of compression-compression fatigue experiment. Ultrasonic C-scans have been used to label the delamination length at discrete data acquisition steps and related steps are described at delamination quantification with ultrasonic c-scan section. DNN model is trained by using UGW based DIs as input where the target set contains the measured delamination length. DI extraction process is explained in ultrasonic guided wave based damage indicators section. The prediction model is tested by using the sensor-actuator paths, which are not involved in training phase, and the accuracy and sensitivity of these paths are tested on model. The section of regression model with deep neural network contains the DNN architecture hyper-parameters and input matrix properties. The results show that different paths show different sensitivities to the delamination growth and the related accuracy values are presented with the delamination length prediction results.

COMPRESSION-COMPRESSION FATIGUE EXPERIMENT

Composite structures have high stiffness-weight ratio which results in high fatigue resistance. A damage induced by out-of-plane load can reduce the strength of the structure drastically and lead a failure unless it is replaced or repaired. Therefore, in this study, to investigate the delamination growth under compressive loading condition, compression after impact (CAI) experiment has designed according the ASTM D7136 [6] for the CFRP samples obtained from one main plate-like structure. The sample dimension is 100 mm wide, 150 mm long with 5.5 mm thickness which is in accordance with the standard. On each sample, a PZT network was glued on its surface which enables to collect UGWs signals throughout the fatigue cycles. In Figure 1, the experimental setup is presented with the anti-buckling fixture and the PZT network installed. The UGW signal acquisition has been done for healthy state, impacted state, and cycle 0, which refers to impacted samples in clamped condition and from cycle 1 to cycle 70000 at each 10000 cycle steps. The fatigue force is applied with 5Hz frequency and the ratio of maximum applied force to minimum force is 10. Fatigue loading continued until the final failure occurred. At the final failure stage, no data acquisition could be applied because PZTs were debonded and broken.

DELAMINATION QUANTIFICATION WITH ULTRASONIC C-SCAN

To label the damage size of the sample under fatigue loading, ultrasonic C-scan measurements have been carried out at the same time steps as UGW acquisition. A pulse-echo ultrasonic transducer has been used which has 8 MHz centre frequency with 128 x 128 transducer elements and with 30 mm x 30 mm probe size. In Figure 2, ultrasonic C-scan measurement results are introduced. The measured length of delamination is the maximum length in the growth direction, which is perpendicular to the loading direction. The measured length information is organised as the target set in the prediction model.

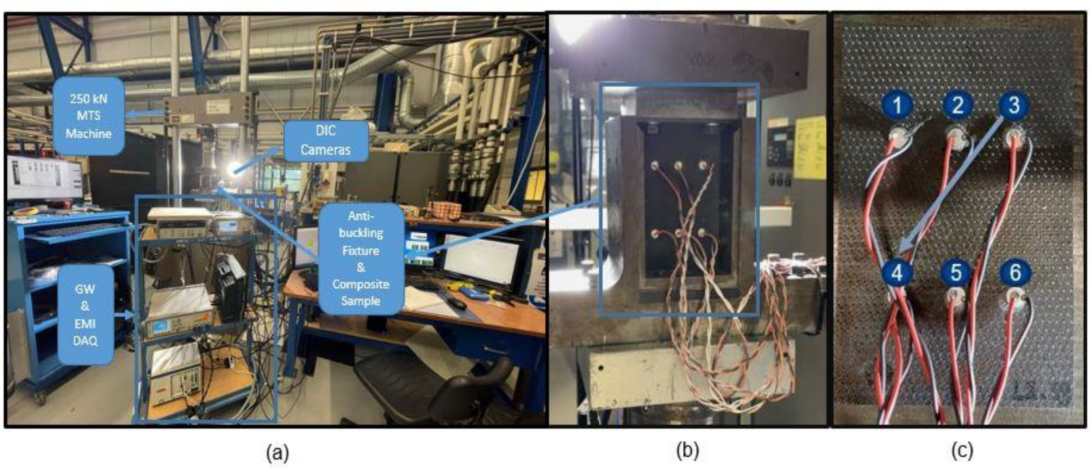


Figure 1. Photos of (a) fatigue testing setup, (b) anti-buckling fixture and (c) composite sample with PZTs with an indication of the path between PZT 3–PZT 4.

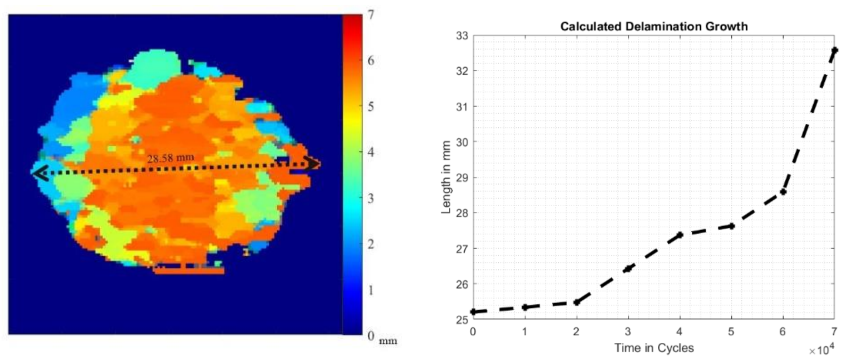
ULTRASONIC GUIDEDWAVES BASED DAMAGE INDICATORS

UGW acquisition has been performed at defined intervals. GW excitation signals are 2 cycle tone-burst signals in the frequency range of 100 kHz, 120 kHz, 140 kHz, 160 kHz and 180 kHz. A network of PZTs is already attached on the surface for exciting and sensing the UGWs within the structure, which is the active approach where one PZT acts as an actuator and the rest of the network as sensors. The thickness of the PZT transducer is 0.5 mm and the diameter is selected as 8 mm. The signal is collected with the sampling frequency at 5MHz in the pitch-catch mode. GW based DI extraction process have been conducted by following multiple signal processing steps. At the first stage the crosstalk in the signal is removed. A denoising procedure is applied to clear the noise effects in the signal which contains a band-pass filtering and a discrete wavelet filter (DWF). Band-pass filter range is determined considering the excitation signal's frequency range. The DWF is applied by verifying and selecting the best signal-to-noise ratio for different wavelets which are namely Haar, Daubechies, Symlets, Biorthogonal, Morlet, Coiflets wavelets. In Figure 3, denoised GW signals at different frequency and different cycles are presented both in time and frequency domain.

After the denoising step, DIs are determined using cross correlation (CC), envelope energy, power spectral density (PSD) and signal average power (SAP). CC is applied to time domain signals, considering the GW signal acquired from the impacted state under clamped-loaded condition as the reference state, and later growing cycle signals are compared with the reference signal, where the change in maxima of CC is determined as the CC based DI. The envelope energy of the signal is calculated in the time domain after Hilbert transform within a time window where the envelope has its maximum in the first arriving wave packet. PSD based DI is defined by calculating the change in the PSD spectrum by comparing the PSD of the reference signal with the PSD spectrum of the growing cycle signals. The total power change in the spectrum is assigned as the PSD based DI. SAP-based DI is defined in the time-frequency domain, where the SAP is calculated at each time step after the Continued Wavelet Transform (CWT). For SAP based DI, a time window is applied to the reference signal where the SAP has its maxima and the area of later SAPs from higher cycles is calculated and compared with the SAP area of the reference state. As a result of the DI extraction process, a matrix containing the DIs obtained for all paths and frequencies is prepared for the training and testing purposes of the DNN-based regression model. In Figure 4, four DIs are presented for the paths between PZT3 (actuator) to PZT 4, 5 and 6 (sensors) and for the frequencies of 100 kHz, 140 kHz and 180 kHz.

REGRESSION MODEL WITH DEEP NEURAL NETWORK

DNN model is designed to correlate UGW-based DIs with measured delamination length and then predict the delamination length by using the DIs based on excluded actuator-sensor paths. The target set of the model consists of measured delamination lengths at 8 different cycle steps. The input dataset size for training at one cycle equals to 15x20, which contains 15 paths from 5 actuator to 3 different sensors where feature number is 20, 4 different types of DI domain with 5 different frequency. The model consists of 4 layers that contain 360, 240, 60, 40 neurons, respectively, apart from the input layer which has 20 neurons whereas the output layer has 1 neuron. Activation function for the first layer is tanh function, for the second layer is sigmoid function, third and fourth layers is ReLU and the last layer is linear activation function. Optimization of the model has been done with Adam optimizer. The dataset is separated into training, validation, and testing sets. The testing set is selected as one actuator to three sensors paths and the training step is repeated for 6 times for 6 different dataset which contains different actuator-sensor paths at each training step. In Figure 5 and Figure 6, the prediction results are presented. The prediction intervals are provided by random re-initiation of weights and for repeated training process. In Table I, mean squared error values (MSE) are shown for predicted delamination length vs. measured delamination length.



(a) (b)

Figure 2. (a) Ultrasonic C-scan result for delamination quantification at 60000th cycle (b) measured delamination length vs cycles.

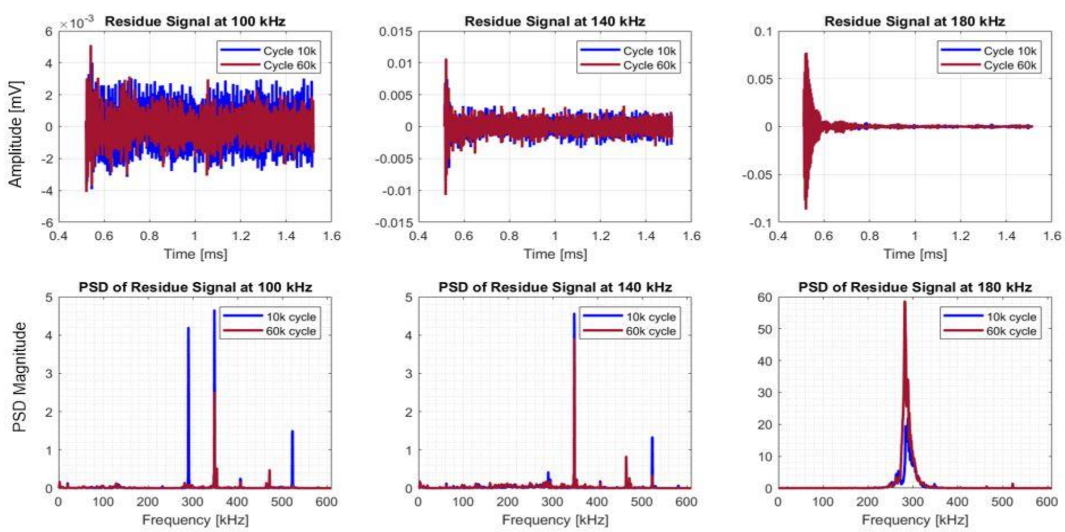


Figure 3. Denoised GW signal in time domain and PSD spectrum for a) b) 100 kHz, c) d) 140 kHz and e) f) 180 kHz at Cycle 10000 and Cycle 60000.

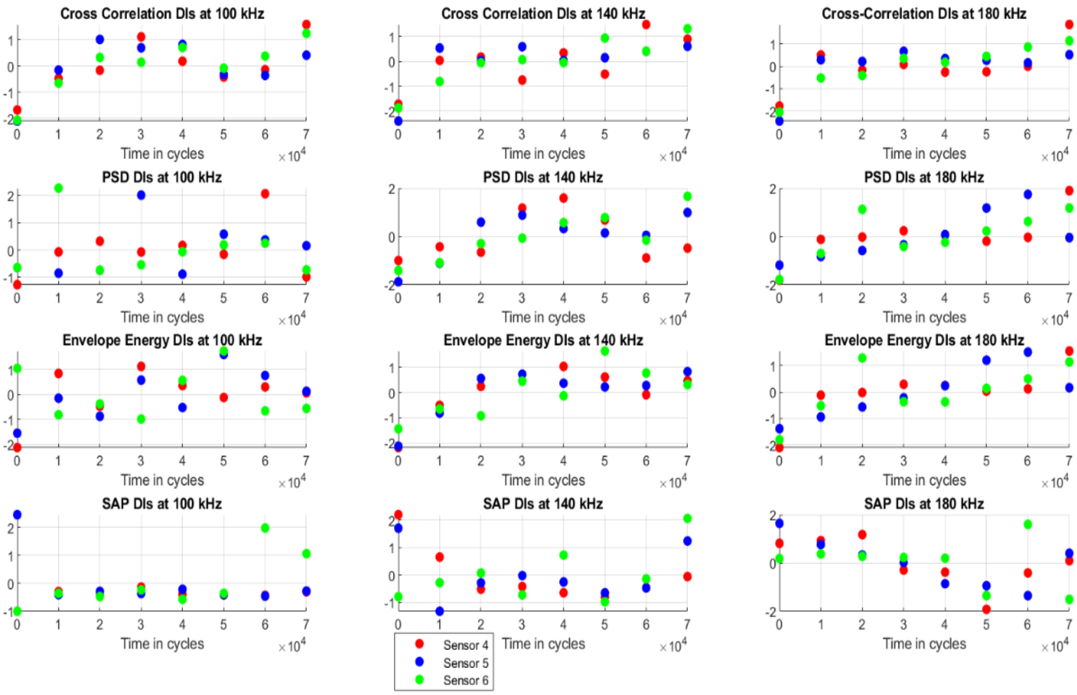


Figure 4. Four DIs for 100 kHz, 140 kHz and 180 kHz for PZT 3 – PZT 4,5,6

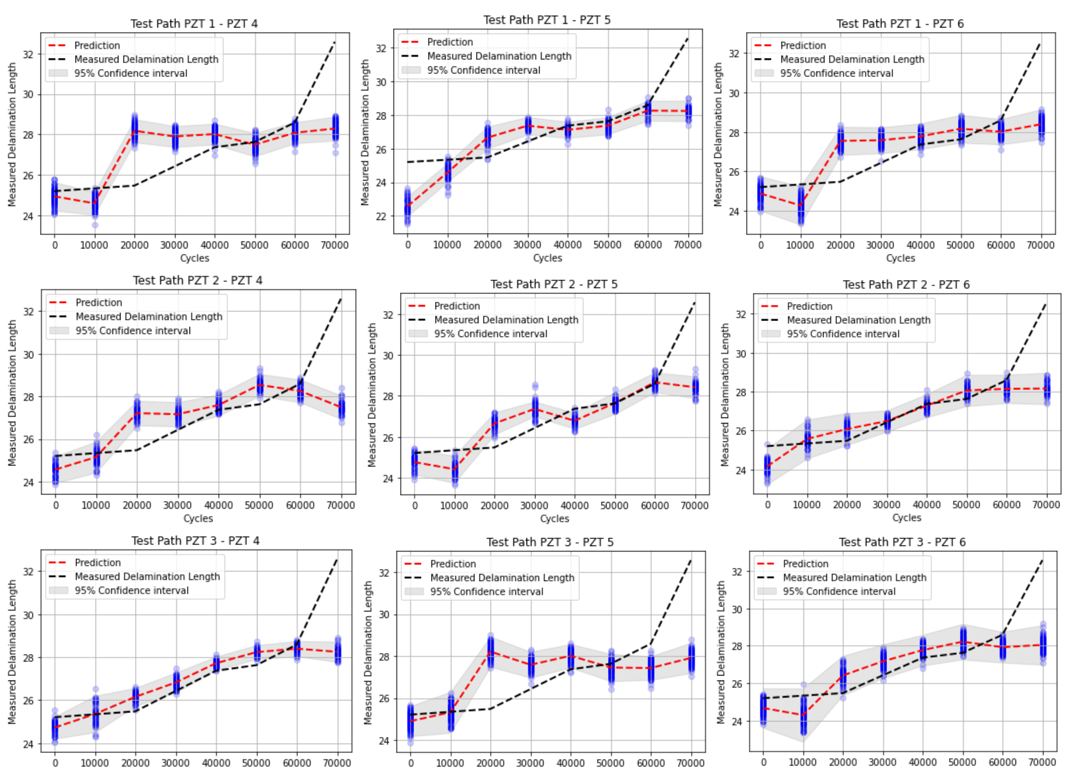


Figure 5. Delamination length prediction by using sensor paths after removing the actuator paths: 1, 2, 3, respectively.

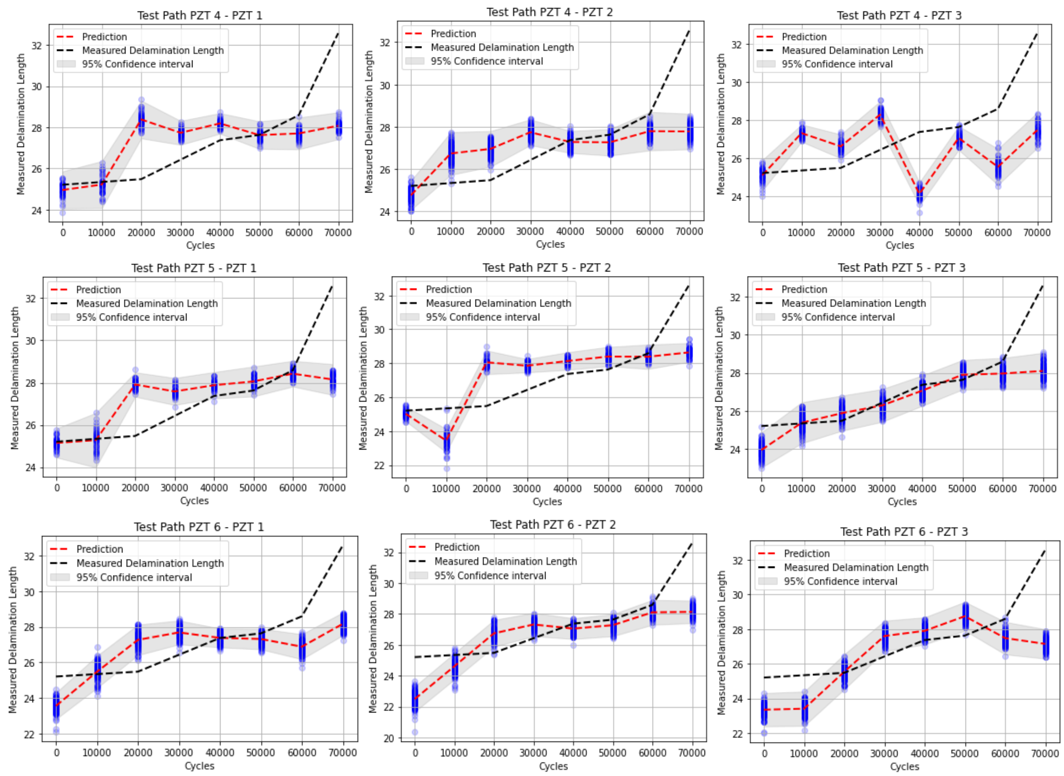


Figure 6. Delamination length prediction by using sensor paths after removing the actuator paths: 4, 5, 6, respectively.

TABLE I. PERCENTAGE VALUE OF CALCULATED MSE PER ACTUATOR-SENSOR PATH.

	MSE Values	**Actuator Mode**					
		PZT1	**PZT 2**	**PZT3**	**PZT4**	**PZT5**	**PZT6**
Sensing Mode	**PZT 1**	-	-	-	7.19	7.25	7.55
	PZT 2	-	-	-	6.94	6.92	7.49
	PZT 3	-	-	-	7.16	6.01	7.60
	PZT 4	7.25	7.15	6.40	-	-	-
	PZT 5	7.48	7.37	6.61	-	-	-
	PZT 6	7.22	7.27	6.95	-	-	-

DISCUSSION AND CONCLUSION

Predicting the increasing delamination length under compressive fatigue condition is critical for the application of condition-based maintenance strategies in aerospace industry. In this study, woven type composite samples are subjected to the compression-compression fatigue loading and the delamination length is quantified by ultrasonic C-scan. A DNN-based regression model is trained using four different DIs calculated for UGW signals recorded at specific fatigue cycle steps. The model is tested with actuator-sensor paths, which are not included in training process. The results show that some paths are slightly more sensitive to the delamination growth than the others. Among all actuator-sensor pairs, PZT 3 – PZT 4, 5, 6 present minimum MSE values; 6.40, 6.61, and 6.95, respectively, which demonstrates higher sensitivity to delamination growth. It should be noted that there has been significant increase in the delamination growth rate from cycle step 6 to cycle step 7, which indicates 60000th to 70000th cycle, and the model has limited capacity to capture that sudden change. Therefore, the main source of the error is originated from the prediction at the last cycle step. However, it is important to be able to capture drastic changes in delamination growth, as it can be considered as the threshold level in terms of the delamination length. Consequently, the results show that the presented UGW based DIs methodology is effective to predict growing delamination length under compressive fatigue loading and proposed supervised DNN based regression model is capable to predict delamination length with presented accuracy levels.

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REFERENCES

1. Sadighi, M., & Alderliesten, R. (2022, October). Impact fatigue, multiple and repeated low-velocity impacts on FRP composites: A review. Composite Structures, 297, 115962.
2. Uda N, Ono K, Kunoo K. Compression fatigue failure of CFRP laminates with impact damage. Compos Sci Technol 2009, 69(14): 2308–2314.
3. Janapati, V., Kopsaftopoulos, F., Li, F., Lee, S. J., & Chang, F. K. (2016). Damage Detection Sensitivity Characterization of Acousto-Ultrasound-Based Structural Health Monitoring Techniques. Structural Health Monitoring, 15(2), 143–161;
4. Yue, N., Broer, A., Briand, W., Rébillat, M., Loutas, T., & Zarouchas, D. (2022, August). Assessing stiffness degradation of stiffened composite panels in post-buckling compression-compression fatigue using guided waves. Composite Structures, 293, 115751. https://doi.org/10.1016/j.compstruct.2022.115751
5. Hong, M., Su, Z., Lu, Y., Sohn, H., & Qing, X. (2015, August). Locating fatigue damage using temporal signal features of nonlinear Lamb waves. Mechanical Systems and Signal Processing, 60–61, 182–197.
6. ASTM D7136/D7136M-15. Standard test method for measuring the damage resistance of a fiber-reinforced polymer matrix composite to a drop-weight impact event, 2020.