



# A Machine Learning Based-Guided Wave Approach for Damage Detection and Assessment in Composite Overwrapped Pressure Vessels

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## Abstract

The applications of composite overwrapped pressure vessels (COPVs) in extreme conditions, such as storing hydrogen gases at very high pressure, impose new requirements related to the system's integrity and safety. The development of a structural health monitoring (SHM) system that allows for continuous monitoring of the COPVs provides rich information about the structural integrity of the component. Furthermore, the collected data can be used for different purposes such as increasing the periodic inspection intervals, providing a remaining lifetime prognosis, and also ensuring optimal operating conditions. Ultimately this information can be complementary to the development of the envisioned digital twin of the monitored COPVs. Guided waves (GWs) are preferred to be used in continuous SHM given their ability to travel in complex structures for long distances. However, obtained GW signals are complex and require advanced processing techniques. Machine learning (ML) is increasingly utilized as the main part of the processing pipeline to automatically detect anomalies in the system's integrity. Hence, in this study, we are scrutinizing the potential of using ML to provide continuous monitoring of COPVs based on ultrasonic GW data. Data is collected from a network of sensors consisting of fifteen Piezoelectric (PZT) wafers that were surface mounted on the COPV. Two ML algorithms are used in the automated evaluation procedure (i) a long short-term memory (LSTM) autoencoder for anomaly detection (defects/impact), and (ii) a convolutional neural network (CNN) model for feature extraction and classification of the artificial damage sizes and locations. Additional data augmentation steps are introduced such as modification and addition of random noise to original signals to enhance the model's robustness to uncertainties. Overall, it was shown that the ML algorithms used were able to detect and classify the simulated damage with high accuracy.

**KEYWORDS:** Machine learning, Structural health monitoring, COPV, Guided waves, Damage localization



## 1. Introduction

Structural health monitoring (SHM) offers a new paradigm for dealing with challenges imposed by safety requirements for critical infrastructures and the ever-increasing demand for using light-weight structures in extreme conditions, such as using composite overwrapped pressure vessels (COPVs) for storing hydrogen gases at very high pressures. SHM enables the continuous monitoring of COPVs by gathering data from a sensor network installed on the surface of the structure. Such data can be used for detecting structural changes and damages early on and preventing potential catastrophic failures. Ultrasonic-guided waves are well suited for application in an SHM system given their ability to travel in complex structures over long distances and their sensitivity to different kinds of damage. However, the challenging task remains in analyzing the gathered data and extracting relevant features for the automatic assessment of the structure's integrity. [1, 2]

Machine learning (ML) has proven itself a very powerful tool to be used as the main part of data analysis and decision-making [2], enabled by the advances made in recent years through new model architectures [3] and hardware capabilities. The successful application of ML for the task of time-series classification [3] and more specifically, damage detection and localization has been shown for different types of specimens and structures [4, 5]. This study focuses on the application of several model architectures for detecting multiple damages on a Type IV COPV combined with additional data augmentation steps. Thus, a long short-term memory (LSTM) autoencoder and a convolutional neural network (CNN) model are utilized for the tasks of anomaly detection and damage localization. Different damage scenarios are simulated by gluing single or multiple varying weights on different parts of the COPV. A sensor network comprised of fifteen piezoelectric wafers (PZTs) is used to generate and record the guided wave signals. Further, data augmentation steps are introduced to increase the number of samples in the training dataset and to increase the robustness of the model against uncertainties.

## 2. Methodology

### 2.1 Experimental Setup

For monitoring and assessing the condition of the Type IV COPV, a sensor network of PZTs was applied on the cylindrical surface of the pressure vessel. The design of the sensor network consists of three rings with five PZTs each. The spacing between the PZTs around the circumference is about 144 mm and 610 mm is kept between the single rings for covering the total length of the COPV. DuraAct patch transducers (P-876K025) with a 10 mm circular ceramic embedded in a ductile polymer from PI Ceramics (Lederhose, Germany) were the PZTs used in the setup. A total of fifteen PZTs were bonded to the COPV's surface with a thin layer of two-component epoxy adhesive and then wired to a Vantage™ 64 LF system from Verasonics (Kirkland, USA). The data acquisition process acts in a way that one single PZT worked as an actuator while the rest worked as sensors and the role alternated until all the PZTs served as actuators. This results in an entire dataset of 105 different actuator-sensor combinations also referred to as channels. Based on previous experiments, the excitation frequency ( $f = 220$  kHz) seemed to be the most promising. Several types of variations were considered during the data acquisition

processes, which are shown in Figure 1. Before considering different damage scenarios, baseline measurements of the intact structure were recorded.

## 2.2 Data augmentation

Two different methods are utilized for anomaly detection and damage localization to identify damaged areas as shown in Figure 1. Anomaly detection is achieved by employing an LSTM autoencoder. For the damage localization, a CNN model is chosen. The experimental dataset consists of one undamaged case and nine different simulated damage scenarios conducted for two boundary conditions resulting in a total of twenty unique datasets for one frequency. The available experimental dataset isn't enough for model training and validation. Thus, further data augmentation steps are introduced to enhance the training procedure. First, half of the experimental datasets are chosen, including the undamaged case and cases 2, 4, 6, and 9 as shown in Figure 1. The remaining experimental datasets are excluded from the data augmentation and training steps. They are only used for testing purposes in the final stage. The damage cases 2, 4, 6, and 9 are all conducted with the 330 g weight placed on different locations. The difference between damage cases 2 and 6 is that for damage case 2, the areas A1 and A5 are active as opposed to area A1 for damage case 6, see Figure 1.

Second, synthetic datasets are generated by systematically changing the arrangement of the 105 channels, whereby each channel corresponds to a single actuator-sensor combination. For example, the signal recorded from the actuator-sensor combination S1 and S6 with the simulated damage in area A1 will become the recorded signal from the actuator-sensor combination S2 and S7 when the damage is located in area A2. In this way, it is possible to generate damage cases for all different areas. More specifically, this procedure is repeated for the experimental damage cases 2, 4, 6, and 9 so that all damage areas are included in the final training dataset. In total, the training dataset contains 42 different cases (21 for each boundary condition).

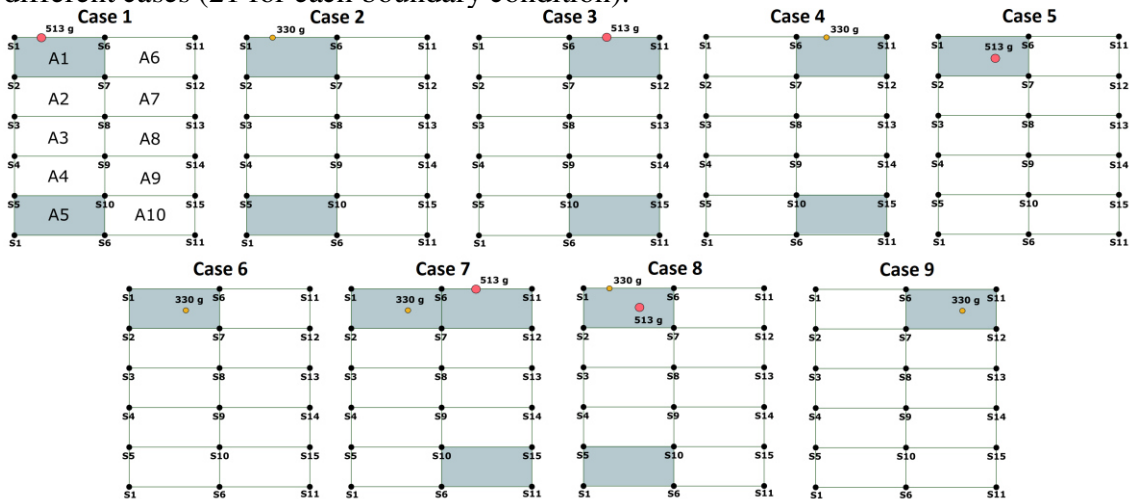
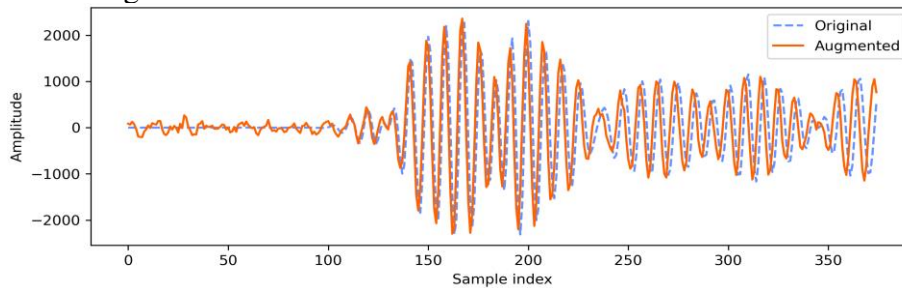


Figure 1: Simulated damage cases are shown along with the corresponding active areas for the unwrapped middle section of the COPV with the sensor network of 15 PZTs forming three rings. Each experiment was conducted for two different boundary conditions (supported on four points and supported on the nozzles).

Third, the previously created datasets are augmented to increase the number of training samples. This step is necessary since even with the rearrangement of the channels and synthetically generating damage cases there aren't enough samples for splitting them into

training and validation datasets. Hence, more dataset samples are required, which are created by adding randomly generated noise to each of the 105 channels of the 42 samples from the previous step. The signal augmentation is conducted as follows. In the first step, the frequency response of each signal is determined. In the second step, specific parts of the frequency-amplitude curve are shifted to the left or right by a small value randomly chosen from a predefined range. After that, white noise is added to those parts of the frequency response. The signal is then converted back to the time domain. In the final step, white noise is added to the signal in the time domain. Figure 2 shows a typical original and augmented signal for one channel of a single dataset. This should help the reader to get a feeling for the impact of data augmentation on the experimental results. Each of the 42 samples of the synthetically generated dataset is augmented 10 times, which results in a total of 420 samples. These 420 samples are split into two 210 sample datasets used for model training and validation.

In summary, a total of 20 experiments were conducted for different cases and two boundary conditions (1 undamaged and 9 damaged cases for each boundary condition as shown in Figure 1). Each experimental dataset contains 105 different actuator-sensor readings referred to as channels. Afterward, a subset of experimental measurements was chosen (cases 2, 4, 6, and 9 together with the undamaged case) for the data augmentation and model training steps. In the data augmentation step, first, synthetic damage cases were generated by systematically changing the arrangement of the channels. And in the second step, new synthetic datasets were generated by augmenting the signals for all channels, see Figure 2. Thus, a total of 420 samples were available after the data augmentation step, which were split into two 210 sample datasets used for model training and validation. The remaining experimental datasets for cases 1, 3, 5, 7, and 8 were excluded from the data augmentation and model training steps and were only used for the final model testing.



**Figure 2: Comparison between the original and augmented signal for one channel of a dataset.**

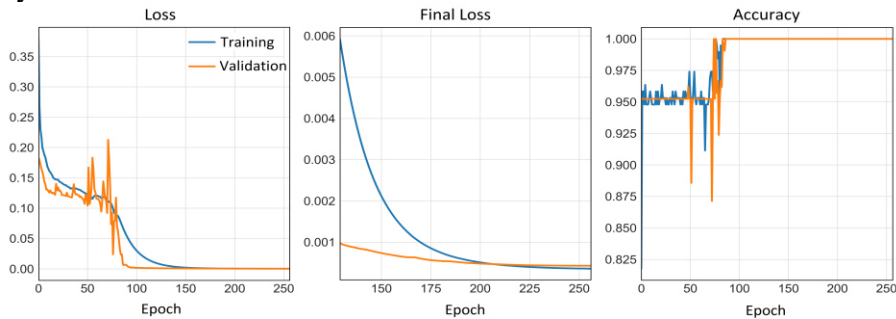
### **2.3 Model training**

The machine learning model chosen for anomaly detection is an LSTM autoencoder based on [6], which is modified for the application with time series and is implemented in tsai [7] as Time Series Sequencer. The Time Series Sequencer is used in a binary classification setting, where the undamaged case has the target class 0 and all other damaged cases have the target class 1. InceptionTime [8], implemented in tsai [7], is chosen for the multi-label classification task of damage localization. It is worth noting that in this context, the damage is successfully localized if the corresponding area (in this case areas A1 to A10, see Figure 1), where the damage is located, is correctly predicted. The target classes are specified with an array containing one or more values. For the undamaged case, the array only contains the value zero. And for the damaged cases, the

array contains the number designated to the active area. For example, the target array for damage case 2 contains the values 1 and 5, and for damage case 4, the values 6 and 10. The data are standardized using the mean and standard deviation before the model training. The models are trained using ADAM optimizer and the 1cycle policy introduced in [9] using a maximum learning rate of 0.001.

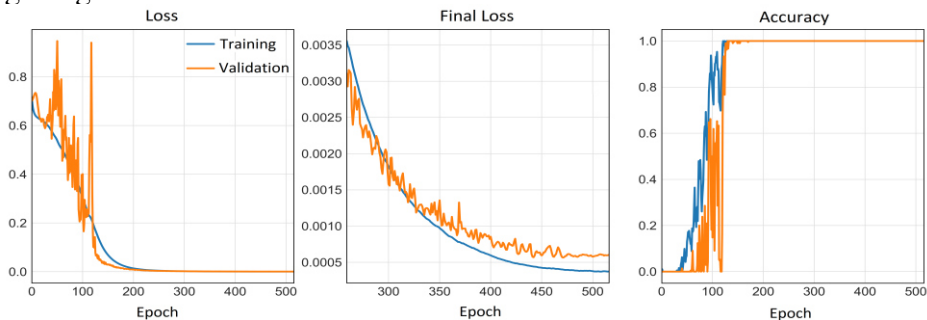
### 3. Results

The performance of the LSTM autoencoder is shown in Figure 3. The accuracy reaches 100% after 100 epochs. After the training is completed, the experimental test dataset containing the damage cases 1, 3, 5, 7, and 8, is used to test the model's accuracy and robustness. The model correctly classified all damage cases with 100% accuracy. It is worth noting that these damage cases were not included in the training dataset, which shows that the model has learned the correct features and is suited for use in the setting of anomaly detection.



**Figure 3: Loss and accuracy of the Time Series Sequencer during the training.**

In Figure 4, the loss and accuracy history during the training are shown for the InceptionTime model, where it reaches 100% accuracy after about 150 epochs. Similar to the anomaly detection case, the model's accuracy and robustness are tested against the experimental dataset excluded during the training. The model was able to predict the correct labels for the damage cases 1, 3, 5, and 8, which shows that changing the weight or having multiple weights in one single area does not pose an issue for the model. However, the model was not able to predict all labels for damage case 7. Labels 6 and 7 were correctly predicted, which belong to the 513 g weight placed between A6 and A10, see Figure 1. However, label 1 was missing, which shows that the model did not detect the 330 g weight located in area A1.



**Figure 4: Loss and accuracy of the InceptionTime model during the training.**

This could be explained by the fact that in the training dataset, the target classes had either 0, 1, or 2 active labels. However, in damage case 7, the number of active labels is 3. Nonetheless, this example shows the limitation of the model and also the need for robust

training data, where all relevant damage scenarios are included. It is acknowledged that more experimental datasets are required to thoroughly analyze the performance of the models and check for issues such as overfitting and lack of generalization.

## 4. Conclusions

In this study, it was shown that data augmentation can be utilized as a powerful tool for creating rich datasets needed for model training and validation. Furthermore, an LSTM autoencoder was used for the task of anomaly detection in a binary classification setting, where it performed with 100% accuracy in separating damaged and undamaged cases. Moreover, a CNN model was utilized for the task of multi-label classification to predict damage areas on the pressure vessel, where it reached 100% accuracy on the training and validation dataset. However, the model didn't reach 100% accuracy on the excluded test data due to insufficient damage cases in the training dataset. In summary, while it was shown that Machine Learning is a promising tool for the tasks of anomaly detection and damage localization and that the models performed with high accuracy on the existing dataset, more experimental analysis is required to check for issues such as overfitting and to ensure that the models perform well in other scenarios and also in cases where real and not simulated damages are present.

## Acknowledgments

This work has received funding from the German Ministry of Economic Affairs and Climate Actions within the QI-Digital initiative.

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