

Application of deep learning for structural health monitoring of a composite overwrapped pressure vessel undergoing cyclic loading

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Abstract. Structural health monitoring (SHM) using ultrasonic-guided waves (UGWs) enables continuous monitoring of components with complex geometries and provides extensive information about their structural integrity and their overall condition. Composite overwrapped pressure vessels (COPVs) used for storing hydrogen gases at very high pressures are an example of a critical infrastructure that could benefit significantly from SHM. This can be used to increase the periodic inspection intervals, ensure safe operating conditions by early detection of anomalies, and ultimately estimate the remaining lifetime of COPVs. Therefore, in the digital quality infrastructure initiative (QI-Digital) in Germany, an SHM system is being developed for COPVs used in a hydrogen refueling station.

In this study, the results of a lifetime fatigue test on a Type IV COPV subjected to many thousands of load cycles under different temperatures and pressures are presented to demonstrate the strengths and challenges associated with such an SHM system. During the cyclic testing up to the final material failure of the COPV, a sensor network of fifteen surface-mounted piezoelectric (PZT) wafers was used to collect the UGW data. However, the pressure variations, the aging process of the COPV, the environmental parameters, and possible damages simultaneously have an impact on the recorded signals. This issue and the lack of labeled data make signal processing and analysis even more demanding. Thus, in this study, semi-supervised, and unsupervised deep learning approaches are utilized to separate the influence of different variables on the UGW data with the final aim of detecting and localizing the damage before critical failure.

Keywords: Structural health monitoring, Deep learning, Ultrasonic-guided waves, Anomaly detection, Damage localization



1. Introduction

Composite overwrapped pressure vessels (COPVs) are increasingly used for storing hydrogen gases at very high pressure levels due to their strength and lightweight design. Current safety guidelines require periodic inspections at predefined time intervals to ensure safe operational conditions [1]. More importantly, these guidelines have a predefined useful lifespan for such pressure vessels. However, for both the visual inspections and determination of remaining useful life, the loading history of these COPVs is not considered. This can lead to a scenario where damages are not detected by visual inspection or a scenario where a fully intact pressure vessel is replaced since its predefined useful lifetime has arrived. Both scenarios lead to downtime of facilities, increased operational costs, and wasting of resources.

Structural health monitoring (SHM) systems could be used to alleviate these issues through continuous monitoring where data about the structural integrity of the monitored structure are gathered with the loading history. These data can be used for early detection of anomalies, potential damages, and for predicting the remaining useful lifetime. Ultrasonic-guided waves (UGWs) are especially well-suited for such tasks given their ability to travel long distances in complex geometries with minimal energy loss. More importantly, they have the ability to interact even with very small damages such as cracks, delamination, or impact damage. However, analyzing the collected UGW data and extracting the important features that are correlated with actual damages is still a very complex and challenging step. Especially due to the impact of the environmental factors on the UGW data. This becomes even more difficult if assessing the condition of the COPV has to be automated [2, 3].

Deep learning models can be used to remedy some of these issues since they have emerged as a powerful tool for analyzing large and complex data [3, 4]. In this work, a sensor network of fifteen surface-mounted piezoelectric (PZT) wafers is used to collect data during the cyclic loading of a Type IV COPV resulting in 105 unique time series data corresponding to 105 sensor-actuator combinations. However, the gathered data during the cyclic loading of the COPV are not labeled. Therefore, unsupervised or semi-supervised methods are required to analyze the data [5, 6]. The time series data are analyzed using the TimesNet model [7] in an unsupervised setting where the first dataset is used for model training and the rest of the data for calculating the anomaly scores. Finally, the anomaly scores are used within the reconstruction algorithm for probabilistic inspection of damage (RAPID) to localize the observed anomalies [8].

2. Methodology

2.1 Experimental Setup

The Type IV COPV was instrumented with fifteen DuraAct patch transducers (P-876K025) from PI Ceramics (Lederhose, Germany) forming three rings, two of them close to dome areas and one in the middle as shown in Fig. 1. The PZTs in each ring have a spacing of about 144 mm and the distance between the rings is kept at 610 mm. The PZTs were bonded to the surface of the COPV using a thin layer of two-component epoxy adhesive. The UGW measurements were carried out using a VantageTM 64 LF system from Verasonics (Kirkland, USA). The excitation signals consisted of 130 kHz and 220 kHz 5-cycle Hanning windowed sine waves. During the data acquisition process, the VantageTM 64 LF system cycled through all PZTs and used each one of them as an actuator while the rest of the PZTs were used as sensors. This process resulted in 105 different actuator-sensor combinations. These measurements were carried out during a predefined pressure ramp and at specific pressure

levels shown in Fig. 2. Between each pressure ramp the COPV was cycled 1000 times from 20 to 700 bar. In total and up until the failure, 46 pressure ramps were completed during which the state of the COPV was monitored at the pressure levels shown in Fig. 2.

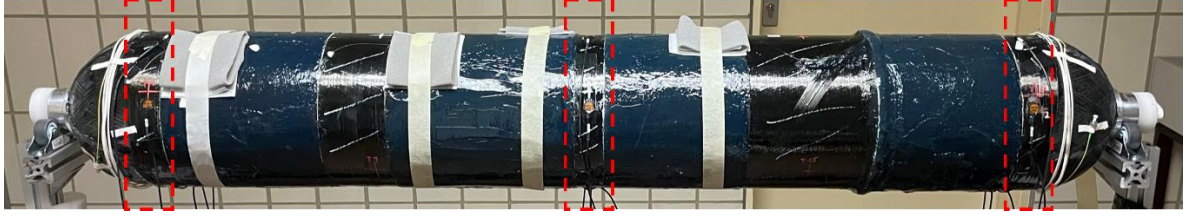


Fig. 1. The instrumented Type IV COPV. A total of fifteen PZT wafers are mounted on the COPV. Three rings of five sensors are formed (highlighted in red), two of them are close to the dome areas, and one is in the middle of the COPV.

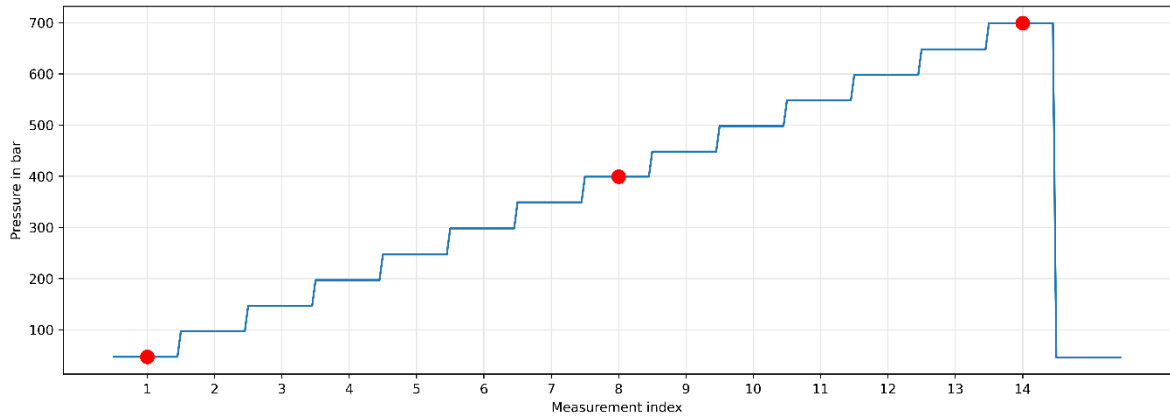


Fig. 2. Pressure ramp used for UGW measurements. Measurements were carried out at each step of this pressure ramp. The red circles mark the pressure levels used for the analysis in this work.

2.2 Deep Learning Model

The unsupervised anomaly detection task in this work has been carried out using a state-of-the-art model called TimesNet [7] implemented in [9]. In [7] it has been shown that, unlike many other task-specific models, TimesNet is well suited for different tasks, such as forecasting, classification, and anomaly detection. TimesNet uses a convolutional neural network (CNN) architecture. The main idea behind the TimesNet architecture is that many real-life time series exhibit multi-periodicity, such as daily, weekly, and yearly trends in a dataset, which interact with each other and can create complex patterns. To tackle this issue TimesNet reshapes the time series in a 2D space to capture intraperiod and interperiod-variations as shown in Fig. 3. TimesNet makes use of several TimesBlocks stacked on top of each other with residual connections. In each TimesBlock the time series are transformed into the frequency domain using fast Fourier transform (FFT). This is done to find the top-k important frequencies and their corresponding periods as visible in Fig. 3. This step enables the intraperiod and interperiod-variations to be represented as two different axes in a 2D space where variations in the time series are visible for both the adjacent points and adjacent periods. These 2D data are processed in the Inception Block which parses these data and extracts the most important features since the 2D kernels in the Inception Block enable the model to simultaneously aggregate the intraperiod and interperiod-variations. Afterward, the 2D representations are reshaped into 1D arrays and aggregated together using adaptive aggregation, which weights different periods based on their relative importance. For the unsupervised anomaly detection task, the time series data are split into consecutive overlapping segments. To achieve this, a sliding window is defined which is also a

hyperparameter of the model. The reconstruction error of the model for these time series segments is used as the anomaly criteria.

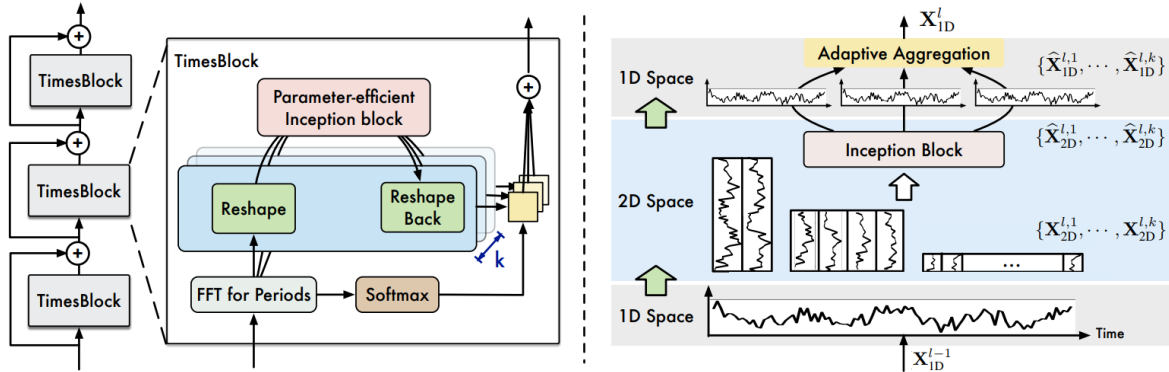


Fig. 3. Schematic overview of TimesNet architecture for capturing the intra and interperiod-variations [7].

2.3 Model Training and Evaluation

The collected experimental data lack any labels. The available information is that the COPV was intact at the beginning of the experiment and that the polymer liner failed after thousands of cycles after which the experiment was stopped. The position of the damage was located between sensors 1 and 5, and closer to sensor 1 as shown in Fig. 4. Thus, to detect possible anomalies before critical failure, an unsupervised deep learning method is chosen. In this setting, the TimesNet model is trained using the measurement datasets from the first measurement ramp shown in Fig. 2 since they belong to the pristine condition of the COPV. In order to reduce the training and evaluation time, only three pressure levels are chosen, namely 50, 400, and 700 bar. For each of these pressure levels, and each excitation frequency, a separate TimesNet model is trained. In total six models are trained on the dataset for the pristine condition of the COPV. The rest of the measurement data are used during the evaluation phase and for the calculation of the anomaly scores. During the evaluation phase, the datasets for the chosen pressure levels were selected from all measurement ramps and were used as input to the corresponding TimesNet model. The output of the model for each subsequent dataset was an array of anomaly scores corresponding to the 105 different paths or sensor combinations as shown in Fig. 6. The hyperparameters of the TimesNet model are as follows: learning rate = 0.0001, total training epochs = 40, sequence length = 200, batch size = 32, number of encoder layers = 8, dimensionality of the model = 128, dimensionality of the feedforward layer = 128, top-k frequencies = 5, and number of kernels for inception block = 6. The model was trained using an NVIDIA GeForce RTX 3090.

2.4 Damage Localization

To localize the anomalies, a similar approach to RAPID is used [8]. In this approach, the location of the damage is determined by the anomaly scores from the deep learning model and the spatial distributions which are calculated using the positions of sensor pairs. In this work, an elliptical distribution function is assumed as the spatial damage probability distribution between two sensor pairs with these sensors being located at the foci. The scaling factor β controlling the elliptical size of this distribution is set to 1.05. The total damage probability distribution is calculated using all the anomaly scores and their corresponding spatial distributions. Only the cylindrical part of the pressure vessel is analyzed. The used sensor network and the damage localization results are shown in Fig. 7. The surface grid used for damage localization has a resolution of 1 mm.

3. Results and Discussion

The COPV was subjected to ~46000 load cycles between 20 and 700 bar at 65 °C before its failure. The failure occurred inside the COPV due to damage to the liner which led to penetration of the liquid through the carbon fiber-reinforced polymers (CFRP) during cycling until leakage detectors stopped the experiment. After the experiment, the COPV was cut for further analysis. The damage was located to be between sensors 1 and 5 and closer to sensor 1. The cut COPV dome section was also inspected by X-ray computed tomography (XCT), and the results are shown in Fig. 4. The XCT analysis revealed delaminations in the composite part of the COPV at the same location where the liner was damaged. In the next step, the collected data were analyzed. The signals from different paths and for different pressure levels and frequencies show similar behavior, where the signals slowly change from the beginning of the experiment up until the failure. These changes manifest themselves usually through an amplitude change and/or a frequency shift in the signals. This trend is mainly due to material aging caused by cyclic loading and shows that the UGWs are sensitive to material degradation and can be used to track the condition of the COPV. This behavior is shown for path 1-2 in Fig. 5 where all the 46 collected time series are compared against each other.

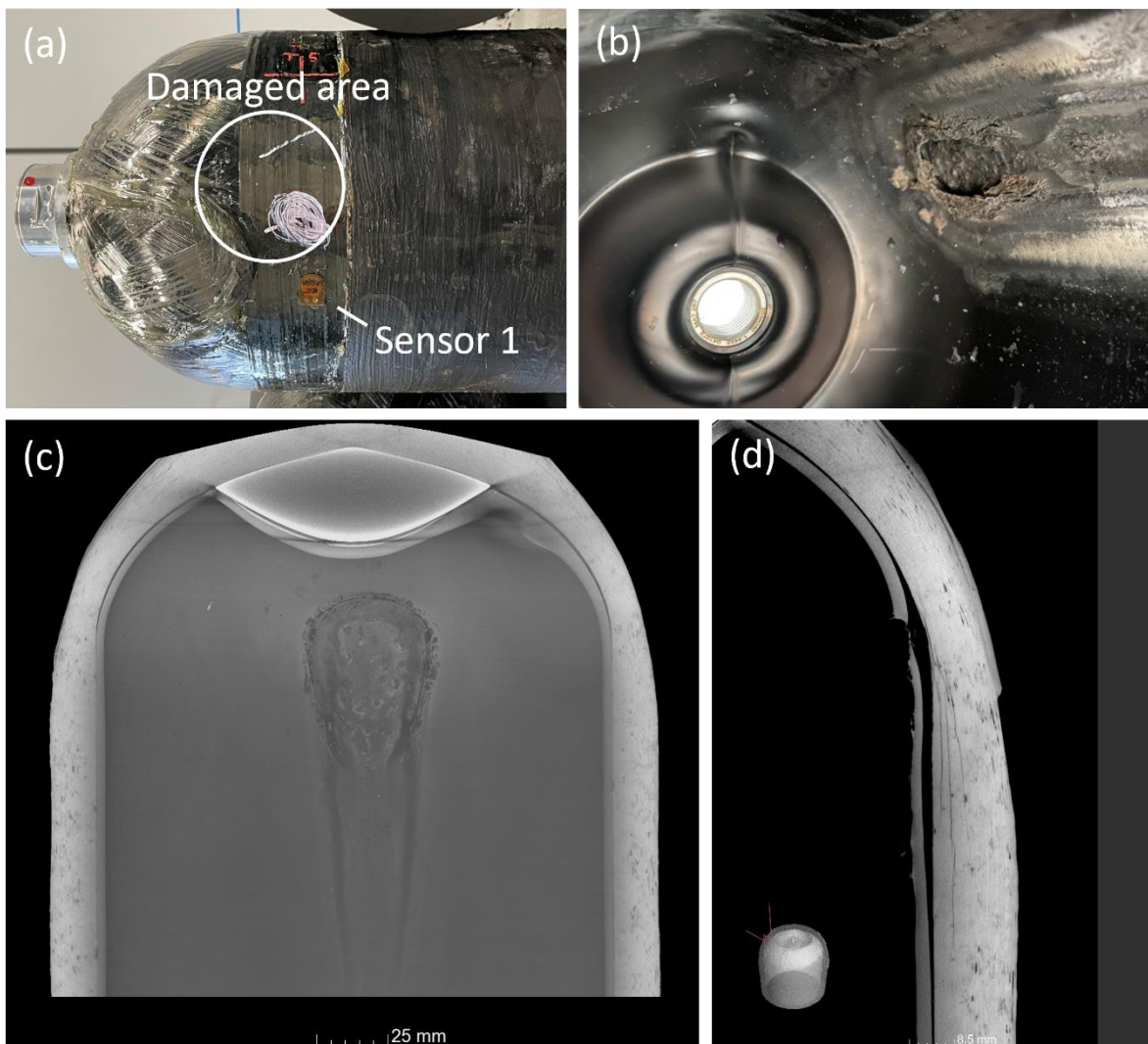


Fig. 4. (a) Photograph of outside of the COPV: the estimated location of the damaged liner is marked. (b) Photograph taken from the inside of the COPV showing the damaged liner. (c) Reconstruction of the XCT scan where the damaged liner is visible. (d) Virtual cut of the reconstruction of the XCT scan where the damaged liner and the damaged composite are visible.

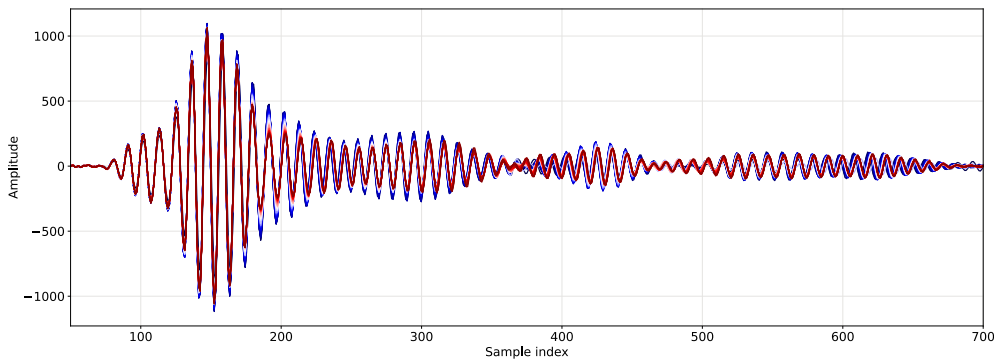


Fig. 5. Time series data collected during the experimental campaign for sensor path 1-2 and a pressure level of 50 bar and a frequency of 220 kHz. Each of the 46 time series shown in this image has a unique color and the changes in color from blue to red indicate the chronological order of the measurements from the very first to last measurements. This figure shows the continuous evolution of the recorded signals, mostly evident from the decrease of the amplitude due to the aging process occurring during cyclic loading of the COPV.

The collected data are analyzed using TimesNet to detect anomalies that could indicate critical failure. The anomaly scores are shown in Fig. 6 which are calculated from six different TimesNet models trained on data for different pressure levels and excitation frequencies. Most of the sensor paths exhibit similar behavior. They are either zero or gradually increasing which shows that there is a direct relation between degradation and output of the models. It must be pointed out that a higher anomaly score usually corresponds to a greater change in the time series data which in turn is likely caused by different types of damage. The different rate of degradation between sensor paths indicates possible critical areas of higher rates of degradation. It is also worth noting that not all sensor paths show a gradual increase in the anomaly score such as sensor paths 8-10 and 9-10, where there is a sudden increase in the anomaly score that remains nearly the same during the rest of the experimental campaign. There could be different reasons for this behavior such as actual damage to the COPV, problems with the sensor itself, or changes to its bonding characteristics to the COPV. In this case, the high anomaly scores for sensor paths leading to sensor 10 are most likely not caused by actual damage. However, since the pressure vessel was not available for further investigation and due to the absence of experimental evidence, actual damage cannot be ruled out. This issue shows challenges for SHM that could also arise in real-life scenarios where environmental factors impact the recorded signals and make it very difficult to separate the influence of damage from other influencing factors.

The localization of the anomalies is carried out using the RAPID algorithm and the results are shown in Fig. 7. The results are filtered using a threshold based on the maximum value obtained after applying the RAPID algorithm. These results highlight two regions with higher anomaly scores. One region is close to sensors 6, 9, and 10 which is likely caused by sensor 10 and not an actual damage as explained before. The second area with higher anomaly scores is located near sensors 1, 5, and 4. This is where the line damage is located together with the observed cracks in the composite part of the COPV as shown in Fig. 4. Although this approach looks very promising and can be used to localize the damage before critical failure, the main challenge remains the fact that thresholds are needed for automatic evaluation and decision-making process. And the current experimental results are not sufficient enough to determine these thresholds. Thus, further experimental work is needed to account for these issues and more importantly, to include the effect of sensor degradation and sensor failure to create robust SHM systems.

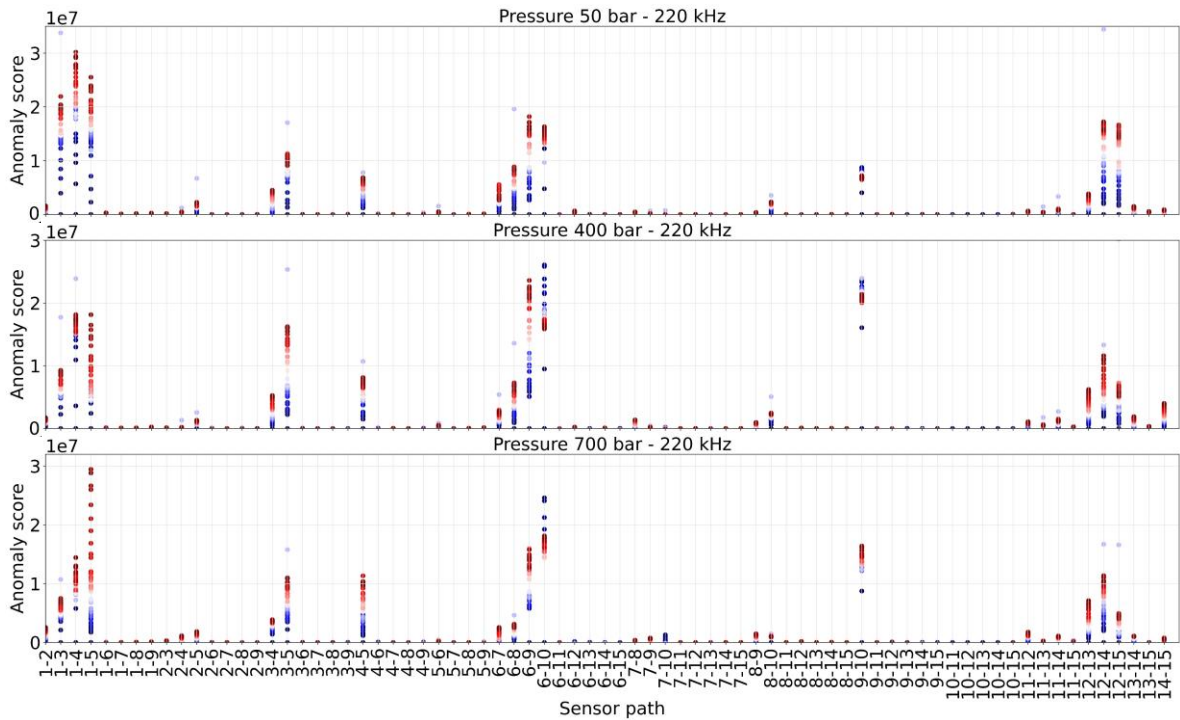


Fig. 6. Anomaly scores for all existing sensor combinations and all measurement data. The colors go from blue to red highlighting the chronological order of the measurements from the first to the last measurement ramp. These figures highlight three main areas with higher anomaly scores, which are more visible after applying the RAPID algorithm, see Fig. 7. The results for 130 kHz are very similar to those for 220 kHz but are not shown due to space limitations.

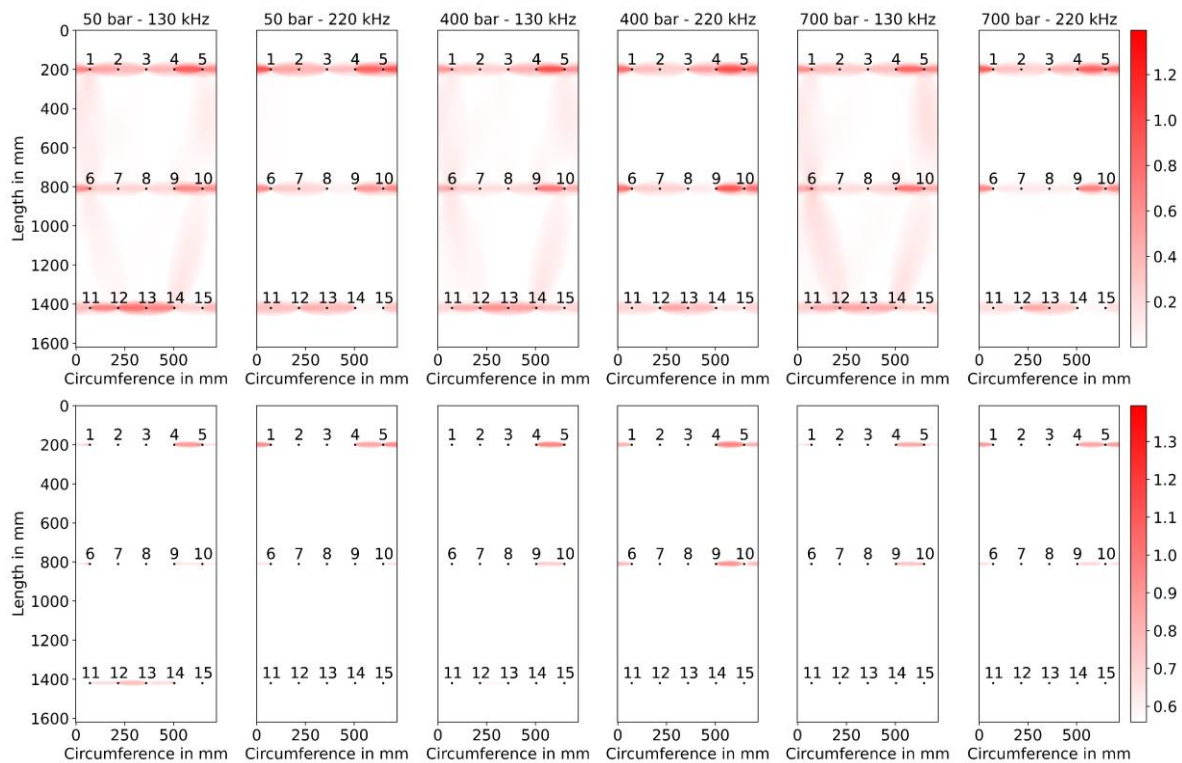


Fig. 7. Localization results using the RAPID algorithm. The figures in the upper row show the results obtained for all possible sensor combinations. And the results on the lower row show the same results but for a limited anomaly range where the upper limit is the same and the lower limit is set to 40% of the maximum anomaly value. These results clearly show that the area around sensors 1, 4, and 5 together with the area around sensors 6, 9, and 10 show the highest anomaly scores.

4. Conclusion

In this study, a sensor network of fifteen PZTs was used to monitor a COPV under cyclic loading and it was shown the UGWs are well-suited for continuous monitoring of COPVs since they are sensitive to material degradation and localized damages. Furthermore, it was shown that state-of-the-art unsupervised anomaly detection models such as TimesNet are capable of calculating anomaly scores that are correlated with material degradation and damage which eliminates the need for hand-crafted and task-specific signal processing pipelines that are otherwise required to extract such features or damage indices to assess the structural integrity of the COPV. Moreover, it was shown that these anomaly scores can be used with the RAPID algorithm to localize these anomalies to improve the inspection process. However, it was also shown that challenges remain such as the determination of a threshold value for automatic evaluation of anomalies, accounting for environmental variables, and sensor degradation and failure.

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