

Acquiring a Machine Learning Data Set for Structural Health Monitoring of Hydrogen Pressure Vessels at Operating Conditions using Guided Ultrasonic Waves

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Abstract. Hydrogen is an energy source of increasing importance. As hydrogen is very reactive to air and needs to be stored under high pressure, it is crucial to provide safe transportation and storage. Therefore, structural health monitoring, based on guided ultrasonic waves and machine learning methods, is used for Composite Overwrapped Pressure Vessels (COPVs) containing hydrogen.

To acquire data that allows robust detection of COPV defects, there are two main process parameters to consider. These are the pressurization of the vessel and the temperature conditions at the vessel. This paper will focus on the derivation of a design of experiment (DoE) from the needs of various validation scenarios (e.g. concerning pressure, temperature or excitation frequency).

We designed experiments with multiple reversible damages at different positions. A network of 25 transducers, structured as five rings with five sensors in one line, is installed on a vessel. Guided ultrasonic waves are used via the pitch-catch procedure, which means that the transducers act pairwise as transmitter and receiver in order to measure all transmitter-receiver combinations. This leads to 600 signal paths, recorded by a Verasonics Vantage 64 LF data acquisition system. Finally, the influences of temperature and pressure within the acquired data set will be visualized.

Keywords: Composite Overwrapped Pressure Vessel, Hydrogen, Guided Ultrasonic Waves, Data Acquisition, Pressurization, Machine Learning.



Introduction

In this paper, we explain the methodology to measure ultrasonic guided waves (GW) on a composite overwrapped hydrogen pressure vessel (COPV) used for the experiment. Previous work initially investigated these influences for simple geometries such as plate-like structures made of composites [2, 3]. Furthermore, a description of the experiment setup is provided. Following this, we explore the influence of temperature change between 28 and 32°C and pressure change between 100 and 700 bar on the acquired GWs. Finally, we inspect the capability of machine learning to classify the previously explored influence of pressure[5].

1. Methodology

1.1 Structure under Investigation

The structure under investigation was a fully composite type IV hydrogen high-pressure vessel (AH350-70-4) manufactured by NPROXX (Fig. 1). The pressure vessel had a polyamide liner inside overwrapped with carbon-fibre reinforced polymer composite. The cylinder's length was 1670 mm, and its outer diameter 352 mm. The pressure vessel is designed for pressures up to 700 bar.

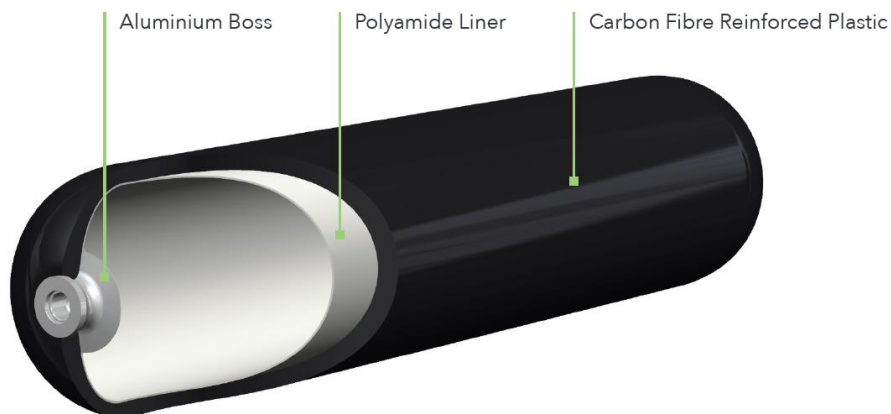


Fig. 1. Structure under investigation: Composite overwrapped pressure vessel (COPV) for storing hydrogen up to 700 bar [1].

1.2 Experimental Setup

For assessing how varying pressure levels and temperatures impact the propagation of GWs in the COPV, and to evaluate their sensitivity to varying types and positions of artificial damage, a sensor network of piezoelectric wafers (PZT) was applied on the cylindrical surface of the pressure vessel (Fig. 2). The design of the sensor network consists of five rings with five PZTs each. The spacing between the PZTs around the circumference is about 221 mm and 312.5 mm is kept between the single rings for covering the total length of the COPV as shown in Fig. 3. 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. The total of twenty-five 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), a multi-channel ultrasonic data acquisition system.

The COPV filled with glycol as test medium was installed inside a hydraulic pressure test system (PN020) from Maximator GmbH (Nordhausen, Germany) as can be seen in Fig. 2. This test rig is capable of pressurising the COPV for different pressure levels while operating under different ambient temperatures. The data acquisition process was designed 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 600 different actuator-sensor combinations. This process was repeated for a set of different pressure levels, temperatures and excitation signals (Table 1). Besides the ambient and the temperature of the liquid, the temperature was also measured at four different locations on the surface of the pressure vessel.

To evaluate the sensitivity to potential damages on the COPV, different conditions of varying types and positions of artificial damages were considered during the data acquisition process as well (Table 1). The artificial damages are four identical cylindrical steel blocks (D1-D4). The blocks were glued onto the COPV's surface at various locations. The mass application leads to a local change of the acoustic impedance and thus to a change in propagation behaviour of the GWs. The positions of the simulated defects can be seen in Fig. 3 and 4. Before considering different damage scenarios, baseline measurements of the structure in a pristine state were recorded.

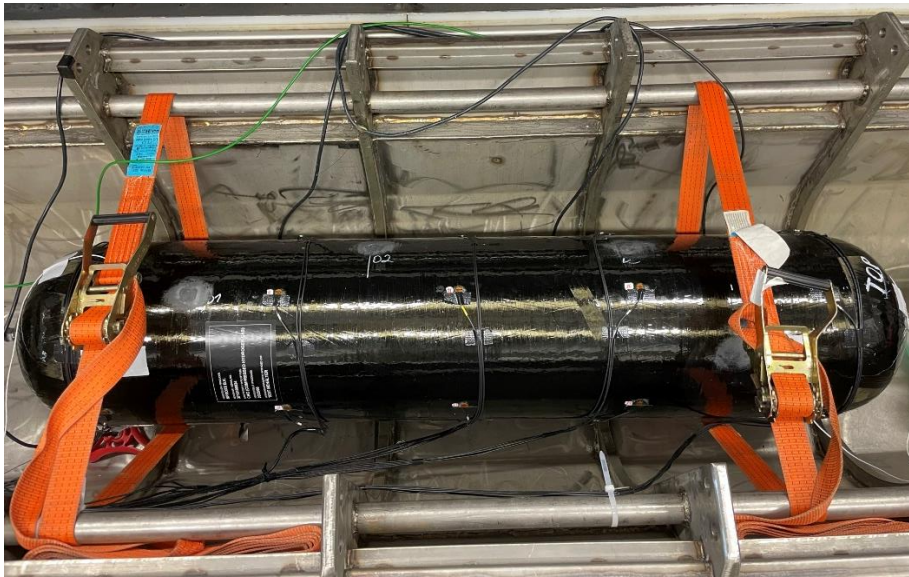


Fig. 2. Photograph of the experimental setup. The COPV is carried via tension belts inside the test rig (PN020). A sensor network of 25 PZTs forming five rings with five PZTs each is applied for damage localization with guided waves.

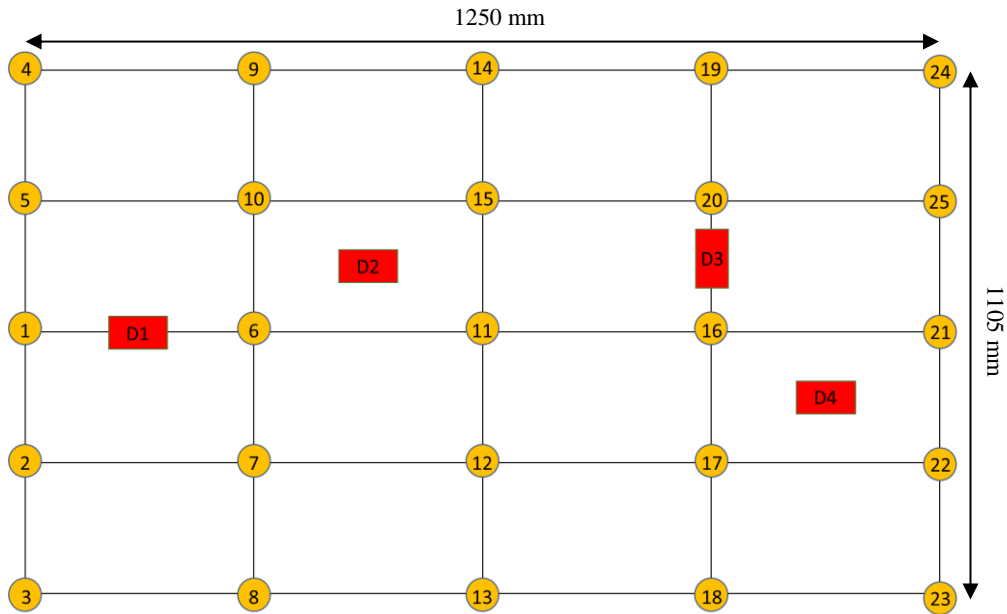


Fig. 3. Overview of the sensor placement and reversible damage positions (D1-D4) on the unwrapped COPV without dome areas.



Fig. 4. Photograph of damage case setup. COPV with four masses glued onto the surface as artificial damage on different positions (D1-D4). The fourth damage (D4) is covered by the tension belt.

Table 1. The measurements were conducted for following parameters and configurations.

Pressure:	20 bar (start pressure) Ramp from 50-700 bar in 50 bar steps
Temperature:	T1 = 28°C T2 = 30°C T3 = 32°C
Condition of COPV:	D0 = pristine D1-D4 = with artificial damages at four different positions.
Excitation signals:	Burst Chirp
Excitation frequencies (burst):	60-300 kHz in 20 kHz steps 5-cycle hann-windowed
Excitation frequency (chirp):	60-300 kHz Duration of 0.125 ms
Damage positions:	Four identical cylindrical blocks (see Fig. 3 & 4) glued at the same time and then removing one at the time

2. Investigating Temperature and Pressure Influence

As mentioned in the previous section, we studied the vessel under different conditions of inner pressure and temperature, from where we wanted to identify variations in acquired GW signals, due to either changes in temperature or inner pressure. Additional to this, under the previous defined conditions, reversible damage was strategically added in four different locations over the vessel's surface, this towards damage identification under various pressure and temperature conditions. For this matter, different types of GW signals were applied and measured all over the structure, we present in this section, the case where inner pressure and temperature will vary; for starters the inner pressure remain constant, while temperature fluctuate from 28°C to 32°C; the applied GW signal is a hann-windowed burst of 5 cycles at 60 kHz.

From the many channels over our transducer network, we started our study with transducer pairs 1Tx - 5Rx and 1Tx - 6Rx with a pristine structure under low pressure, namely 20 bar and three temperature steps. Fig. 5 present the signals recorded by sensors 5 and 6. These paths were selected since damage (D1) will be placed afterwards near and in the middle of this GW path. For both channels under this configuration, in (Fig. 5) only small differences were observed: a slight phase shift to the right and minor amplitude decrease for an increase in temperature.

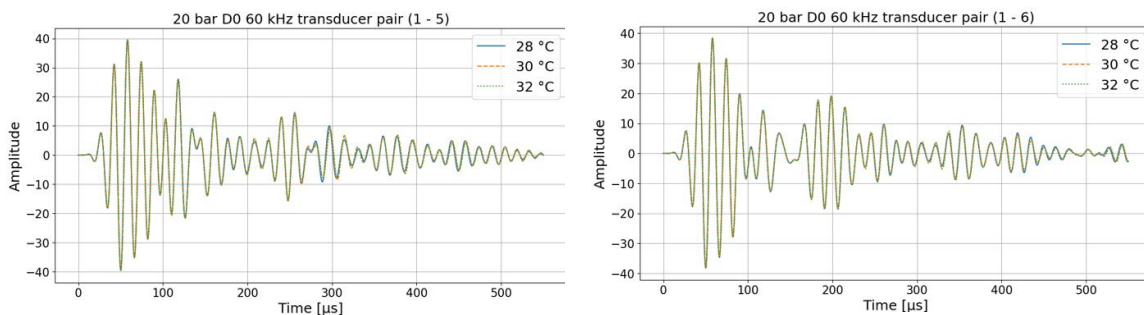


Fig. 5 Sensed signals for temperature variation at 20 bar and no damage D0.

Next, we performed the same experiment but kept stable the temperature at 28°C, while the pressure within the vessel increased from 20, to 50 bar and then in steps of 50 bar up to 700 bar. The results registered by sensors 5 and 6 are plotted in Fig. 6. For sake of clearness, we present only three pressure steps: for pair (1Tx - 5Rx) a noticeable amplitude reduction is shown when pressure rises from 20 bar to 350 bar, although by a continuous increase in pressure up to 700 bar there is no major amplitude variation.

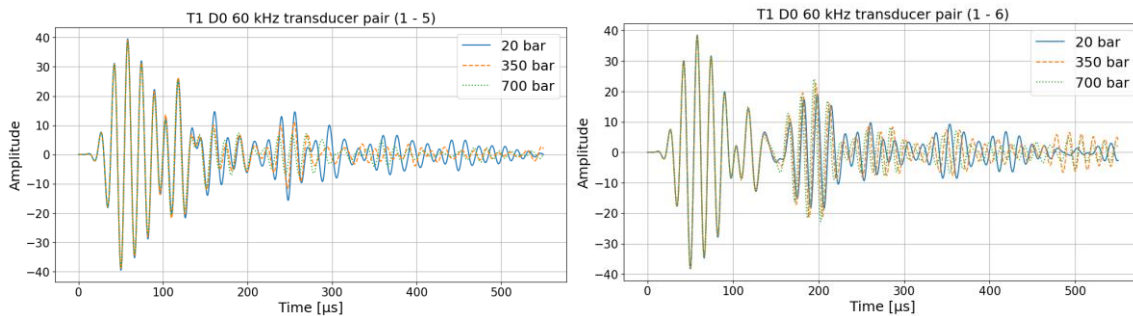


Fig. 6 Sensed signals for inner pressure variation at 20 bar, 350 bar & 700 bar at constant 28°C and no damage D0.

On the other hand, the signals referred to pair (1Tx - 6Rx) present a different behaviour, the amplitude of the signals increase with rising pressure, and although the major variation is displayed for a change in pressure from 100 bar to 350 bar, the increase in amplitude is easy to identify when pressure goes up to 700 bar with respect to 350 bar.

On both cases, we distinguish a phase shift of the signals to the left that grows larger for rising pressures. This phase shift is easier to recognized with the surface representation of Fig. 7, where more pressure steps are displayed, on the right side of Fig. 7, a slight angle leaning to the left can be recognized along with increasing pressure; this is especially perceptible for signals related to pair (1Tx - 6Rx) of Fig. 7 – right.

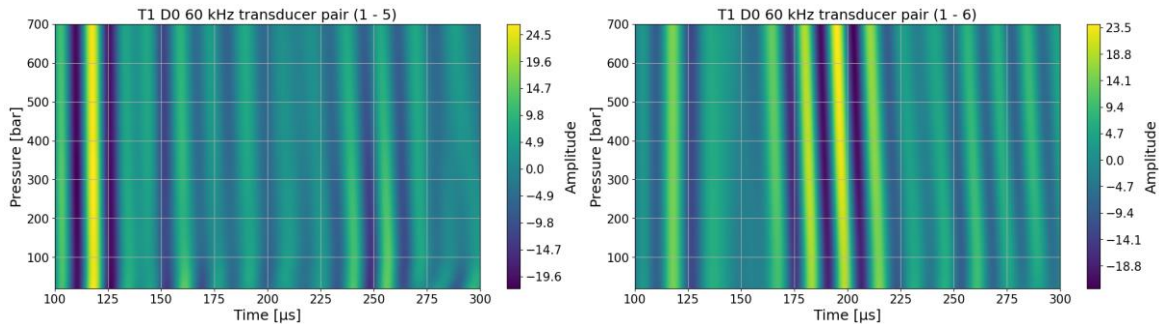


Fig. 7 Surface plot for inner pressure variation from 100 to 700 bar at constant 28°C and no damage condition D0.

After following the experience, we may determine that our method using GWs to identify temperature variations of a vessel structure still requires further refinement before we could determine it does provide reliable information about temperature variation. The small changes shown by the signals in the temperature variation experiment could be due to the small temperature variation-range used (a variation of only 4°C). On the other hand, the approach used to sense variations in the inner pressure via GWs seem quite promising from our results, and given that the changes are higher for channel 6 in the longitudinal direction as for channel 5 in the radial direction, we may also say that they are path-dependent, this could also be related with the positions of the sensors, since we expect a greater deformation of the surface of the vessel while we approach the centre of the structure.

3. Pressure and Damage Clustering

In this chapter, we explored the feasibility of utilizing machine learning to cluster the influence of pressure on GW behavior in COPVs. In particular, the complex structure of the pressure vessel poses a challenge compared to less complex geometries that have already been analysed using machine learning [3,6]. In an initial experiment, we focused on a single sensor pair, from pitch sensor 3 to catch sensor 24, at a fixed frequency of 120 kHz. Pressure varied between 100 and 700 bar in 50 bar increments, aiming to minimize variations caused by factors like sensor position. Temperature change within the narrow range of 28 to 32°C was disregarded, as shown in Chapter 2 to have minimal impact on signal behavior.

Initially, we employed time-frequency feature extraction with a segmentation parameter of 20 (TimeFrequencyExtractor(1,20) [4,8]) on 270 time series. Subsequently, we applied standardized Principal Component Analysis (PCA). The left plot in Fig. 8 illustrates the pressure changes, with two discernible clusters attributed to the presence of glued artificial damages. The pressure change is depicted by the coloring from bottom/low to upper/high.

The right plot in Fig. 8 provides a PCA resolution regarding the extent of damages. The right cluster comprises measurements with one, two, and no damages, while the left cluster contains measurements with three and four damages. Hence, we assume that the amount of available damage leads to the present clustering [7].

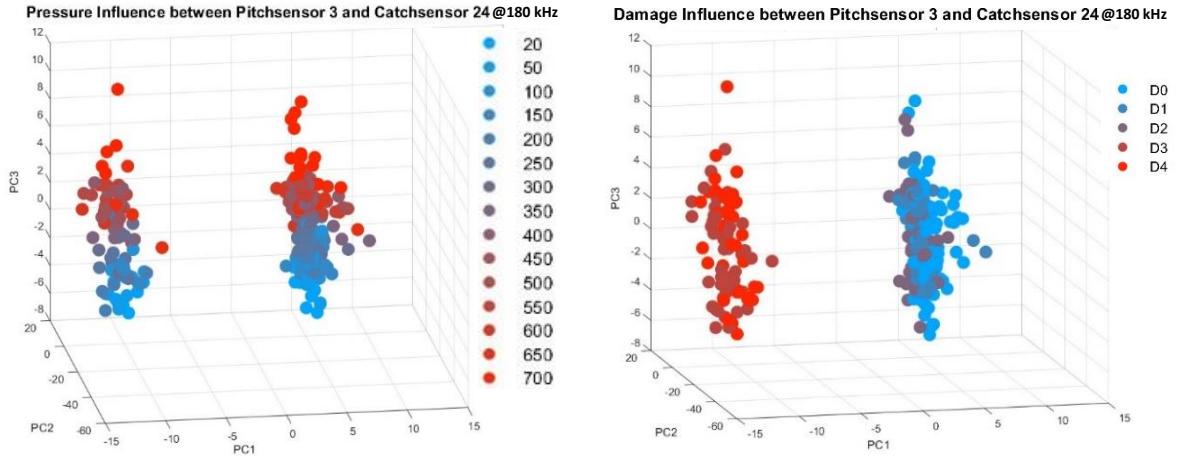


Fig. 8 PCA plots showing the influence of the pressure (left) and the quantity of damages (right).

In the second experiment, we explored a method to detect and visualize the influence of pressure on GWs, irrespective of the position of the pitch-catch sensors. To achieve this, we trimmed the first 2000 samples of the measured signals. As shown in Fig. 7 the phase shift induced by pressure changes typically occurs in the middle or at the end of the 7552-sample-long signal [9]. To extract features, we opted for the Best Fourier Coefficient (BFC) feature extractor [4,10], which emphasizes signal phase. Fig. 9 illustrates the standardized PCA applied to around 20,000 signal series, with coloration indicating variations resulting from increased pressure.

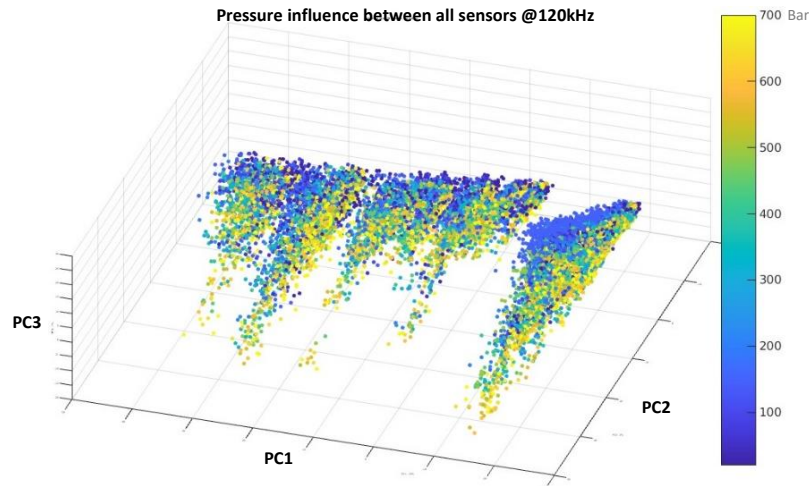


Fig. 9 Plot of the PCA over the BFC features showing the pressure influence.

4. Conclusion

The paper focuses on analyzing a fully composite hydrogen high-pressure vessel, capable of withstanding pressures up to 700 bar. To investigate the impact of varying pressure levels and temperatures on GW propagation, the vessel's surface was equipped with a sensor network comprising PZTs, where the sensors are connected to the data acquisition system. Furthermore, artificial reversible damages were introduced by affixing cylindrical steel blocks to various locations on the vessel's surface. These damages were designed to alter propagation behavior of GWs.

The study investigates the vessel's response under varying inner pressure and temperature conditions to identify changes in GW signals. Different GW signals are applied and measured across the structure. Varying the pressure demonstrated the most significant impact on the signal, particularly evident in the phase shift. This effect was visualized through individual time series and further analyzed using machine learning techniques.

Acknowledgments

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