Model-Assisted Damage Assessment in Composite Overwrapped Hydrogen Pressure Vessels Using Guided Waves

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ABSTRACT

Maintaining the structural integrity of composite overwrapped hydrogen pressure vessels (COPVs) is increasingly critical for safe hydrogen storage and transportation, given the unique challenges posed by composite materials. Accurate structural assessment is vital for effective Structural Health Monitoring (SHM), and guided ultrasonic waves (GUW) show significant potential for this application. This study presents a model-assisted approach to damage assessment using guided wave-based SHM (GW-SHM) on COPVs. By combining experimental data, numerical simulations, and machine learning techniques, we aim to enhance the reliability and accuracy of detection capabilities. Experiments were conducted on both intact vessels and those with artificial damage to generate baseline and damage-induced guided wave signals. Two simulation techniques were employed to support these measurements. Another key contribution of this work is the integration of model-based insights with data-driven approaches for damage assessment. The findings contribute to the advancement of GWSHM methodologies and support the safe, efficient deployment of COPVs in hydrogen storage applications.

INTRODUCTION

Hydrogen is emerging as a key alternative energy carrier, notably due to its high potential to facilitate decarbonization across multiple sectors. Efficient utilization of the hydrogen requires storage at high pressures, typically exceeding 700 bar, which poses significant safety challenges. Non-destructive evaluation (NDE) methods are suitable for regular inspections, but are not capable of continuous monitoring. Therefore, the SHM of COPVs is expected to reduce maintenance costs, extend the specified service life [1].

Several condition monitoring studies on COPVs particularly those acoustic-based SHM methods with various scenarios have emerged in recent years, [1–3]. However, explicit inclusion of environmental effects has not yet been addressed in GUW applications for COPVs. Such cases have previously been investigated for simpler geometries such as plate-like composite structures [4].

Addressing these challenges, we aimed to develop an advanced SHM system that leverages the GUW for reliable damage detection and assessment in COPVs including the environmental conditions to the assessment. Extreme operating conditions such as high internal pressures (up to 700 bar) and elevated temperature ranges with reversible

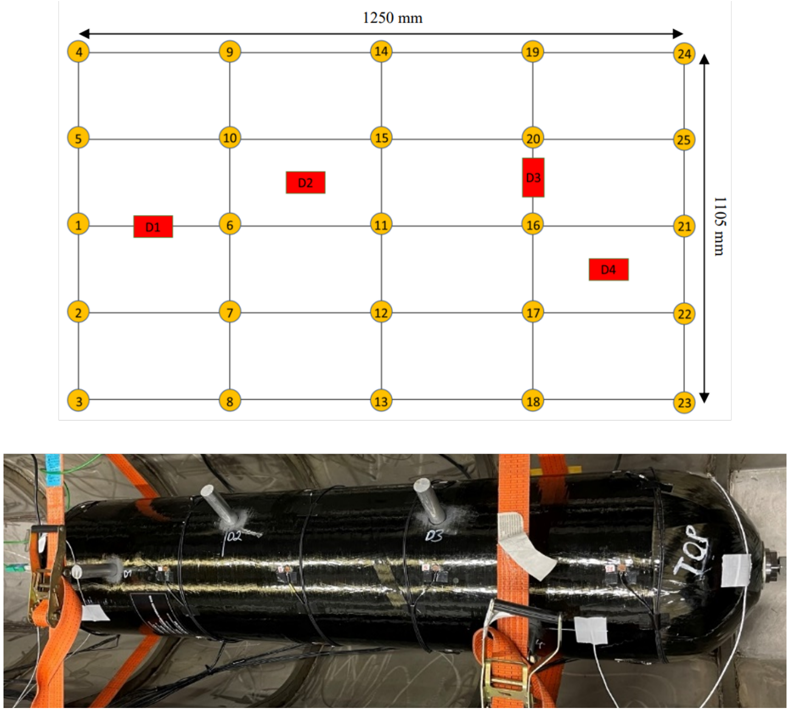

Figure 1. Overview of the sensor placement and reversible damage positions (D1-D4) on the unwrapped COPV without dome areas. COPV with four masses glued onto the surface as artificial damage on different positions (D1-D4)

and irreversible damage scenarios will be systematically introduced into controlled experimental setups. For further details, the reader is referred to [5].

In this paper, we present a segment focusing specifically on how model-assisted studies were investigated and applied on the GWSHM for COPVs. For validation purposes initial experiments were conducted on COPVs instrumented with a network of 25 piezoelectric sensors arranged strategically in five circumferential rings, each containing five sensors as illustrated in Figure 1. The pressure vessel had a polyamide liner inside overwrapped with carbon-fibre reinforced polymer composite resulting 23 mm thickness. The cylinder's length was 1670 mm, and its outer diameter 352 mm. Artificial reversible damages were introduced at multiple positions on the vessels' surface using small metallic blocks to simulate realistic damage scenarios under baseline conditions without internal pressurization or significant temperature variations.

MODEL-ASSISTED APPROACHES IN GUIDED-WAVE BASED SHM SYSTEMS

The studies of numerical modeling in GWSHM systems have gained significant remark in recent years. Given the considerable complexity of the physical phenomena and technical principles involved, reliable assessment and effective design of GWSHM systems can strongly benefit from model-assisted approaches during design phase (e.g sensor placement algorithms) and further analysis (e.g Model-Assisted Probability of Detection (MAPOD)) [6, 7].

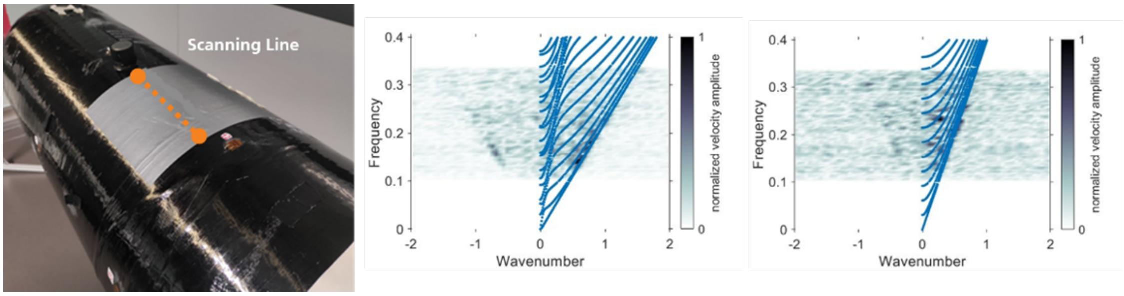

Figure 2. Test specimen for the conducted Laser Doppler Vibrometer Test (Right). Fitted dispersion curves (Left)

Different modeling approaches may be adopted at different stages of the validation and design processes, tailored specifically to their intended purposes. In this study, a semi-analytical Scaled Boundary Finite Element Method (SBFEM) was employed to accurately determine material properties via inverse modeling based on experimental wavefield measurements [8]. These refined material properties enabled more precise subsequent numerical simulations based on the Elastodynamic Finite Integration Technique (EFIT) to analyze and validate the model behavior systematically [9]. Simulations provided valuable preliminary insights into how GUW interact with structural features and defects. Moreover, synthetically generated datasets are introduced to the basic machine learning algorithm to examine the feasibility of this solution.

MATERIAL PROPERTIES EVALUATION

Given the structural complexity and anisotropic nature of COPVs, conventional material characterization approaches are often insufficient or yield uncertain results. To overcome these limitations, two complementary methods were utilized: an evaluation through inverse modeling based on wavefield measurements and subsequent validation using the open-source analytical tool.

Initially, experimental wavefield measurements were conducted to determine the elastic constant of the fiber-reinforced vessel. A three-dimensional Laser Doppler Vibrometer (LDV) captured displacement fields in various directions across the vessel surface. The measured data were subsequently transformed into the frequency-wavenumber domain via two-dimensional Fast Fourier Transform (2D FFT).

The theoretical dispersion curves required for material characterization were then generated using the Scaled Boundary Finite Element Method (SBFEM) based on an assumption of transverse isotropy. This semi-analytical method allows for accurate calculation of dispersion curves, mode shapes, and guided wave propagation characteristics [10]. An optimization algorithm was subsequently employed, iteratively adjusting the elastic stiffness constants to minimize the deviation between measured and simulated dispersion curves. Figure 2 illustrates the experimental setup and the associated dispersion curve analysis. For further methodological details, readers are referred to [11]. The resulting stiffness matrix was compared and validated against analytical results computed using the Dispersion Calculator [12]. Next step involves simulating guided wave propagation for various damage scenarios.

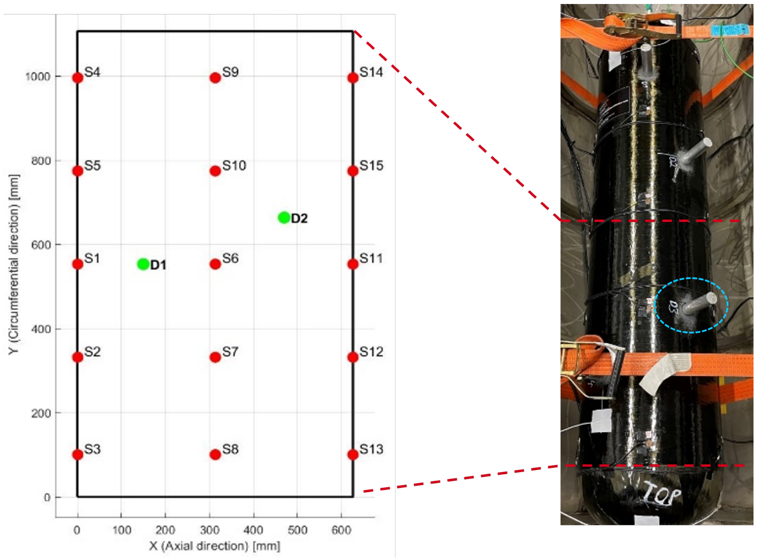

Figure 3. Created 2D model for simulation purposes and simulated damage positions (S: Sensor Positions, D: Damage Positions).

WAVEFIELD SIMULATIONS

The experimental setup is simulated using EFIT numerical model at the selected excitation frequencies. EFIT is a numerical scheme for simulating elastic wave propagation and is considered as a suitable tool for the design and optimization of GWSHM systems. It advances with integral form of the velocity–stress formulation on a staggered spatial and temporal grid similar to the velocity–stress finite difference method (VS-FDM). For further information, the reader is recommended to refer [6, 13].

Figure 3 illustrates the constructed simulation domain and corresponding segment of the vessel. To efficiently model the full wavefields across the domain, the Equivalent Single Layer (ESL) approach was utilized together with the homogenized material properties derived in the previous section [13]. In addition, due to the symmetric arrangement of the sensors, a two-dimensional representation of the half-unwrapped vessel is considered as an appropriate approximation.

The damage modeling approach was based on introducing local reductions in stiffness using coefficient κ and density within the simulation domain to represent defects, following established methodologies [6]. Using this model, a series of representative damage scenarios was simulated at the D1 and D2 positions, each evaluated separately at two excitation frequencies 100 kHz and 200 kHz. The simulation campaign's results were evaluated by comparing time responses and sensitivity maps, constructed using correlation-based Damage Indices (DIs), for each scenario. These indices were derived by quantifying the differences between baseline and damaged guided wave signals.

Figure 4 illustrates a comparison between simulated and experimental guided wave responses for two representative transducer paths: T01–T06 and T01–T11 at 100 kHz. The top row presents simulated total displacement signals under baseline and two damaged scenarios (D1 and D2), while the bottom row shows the corresponding experimental amplitude data. For both transducer paths, the waveforms exhibit clear changes in the presence of artificial damages. Notably, the arrival times in the simulation closely

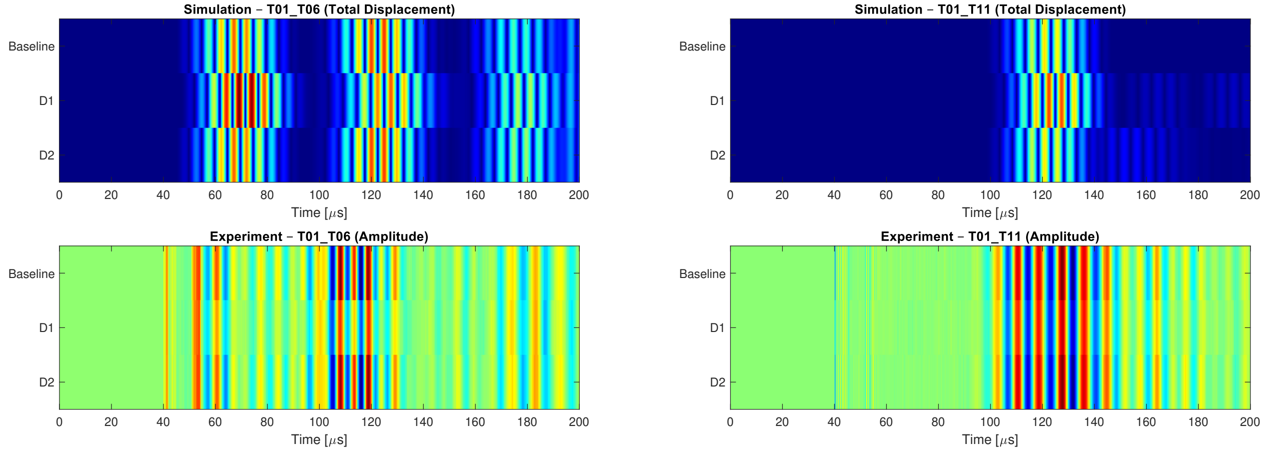

Figure 4. Comparison of simulated and experimental guided wave responses for two transducer pairs (T01–T06 and T01–T11). The upper panels show simulated total displacement signals for baseline and two damaged cases (D1, D2). The lower panels display corresponding experimental amplitude measurements for the same conditions.

match those observed in the experimental measurements. Figure 5 presents sensitivity maps comparing experimental and simulated guided wave measurements for two different damage scenarios, labeled D1 and D2 at 100 kHz excitation case. In each plot, the sensor network is visualized with connecting paths, where color intensity indicates the calculated response of each path to the respective damage condition, based on correlation-based Damage Index (DI). The results show that the sensor paths most affected by damage are those in proximity to the damaged area, with similar patterns evident in both experimental and simulated datasets.

The results demonstrated relatively good agreement with experimental findings confirming the feasibility of the modeling approach and its suitability for further analyses, such as MAPOD studies or synthetic dataset production for machine learning algorithms. Nevertheless, some discrepancies were observed, which can be attributed to inherent modeling assumptions and approximations.

MACHINE LEARNING MODEL BASED DAMAGE ASSESSMENT

Machine learning (ML) based models have been applied to investigate guided waves, and these models have improved the ability to detect and localize damages [14]. By augmenting experimental data with carefully designed synthetic signals, ML models can be trained to recognize a wider variety of damage cases and operational conditions [15].

In this work, synthetic signals corresponding to a range of damage scenarios were used to expand the diversity of the training datasets. The algorithm extracts the relevant signal region containing scattering and absorption effects caused by the presence of damage. This region is identified based on the calculated signal difference between the baseline and the damage-affected signals. The signals are then divided into equal segments and these segments are compared using the normalized root mean square deviation (NRMSD) metric, which is used to calculate the characteristic vectors [16].

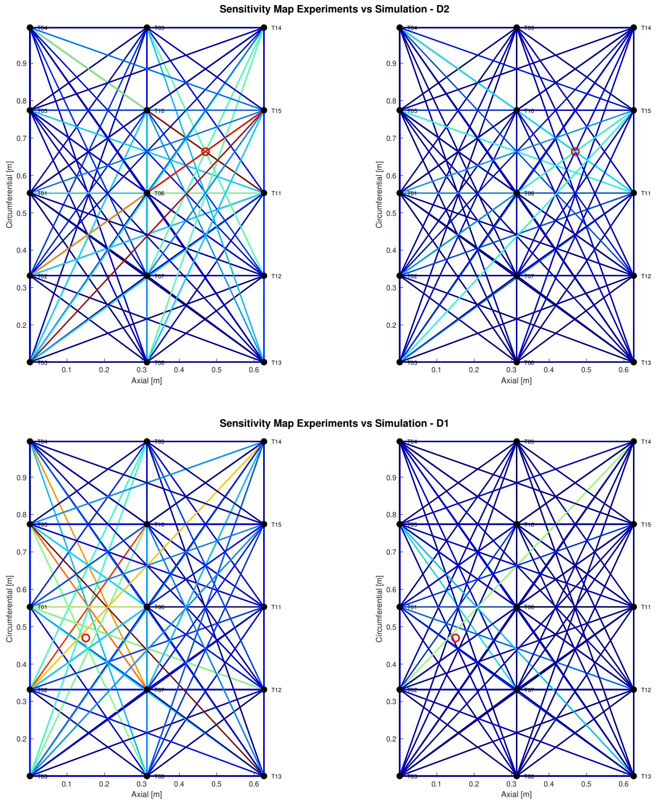

Figure 5. Comparison of sensitivity maps for experimental (left row) and simulated guided wave measurements (right row) under two damage scenarios (Top:D2 with $\kappa = 0.5$ and Bottom:D1 with $\kappa = 0.5$)

Model training uses the labels that quantify how a sensor pair is affected by damage, based on the ratio of direct and indirect signal path reflected by the damage before reaching the receiving transducer. Validation is performed using Leave-One-Group-Out Cross-Validation (LOGOCV), where each group corresponds to one of four distinct damage configurations. Finally, predictions are visualized using tomogram, enabling reconstruction of the predicted damage location. Figure 6 illustrates the predicted damage positions for each case. The average deviation between the predicted and actual damage positions is 16.55 mm.

CONCLUDING REMARKS

The findings presented in this study underscore the feasibility and critical importance of model-assisted strategies for structural health monitoring of composite overwrapped pressure vessels. By leveraging numerical modeling and simulation, it becomes possible to overcome traditional barriers related to experimental constraints and the inherent complexity of composite materials. These results provide a foundation for optimizing both the design and deployment of future SHM solutions, such as determining optimal sensor configurations or enabling accurate MAPOD assessments.

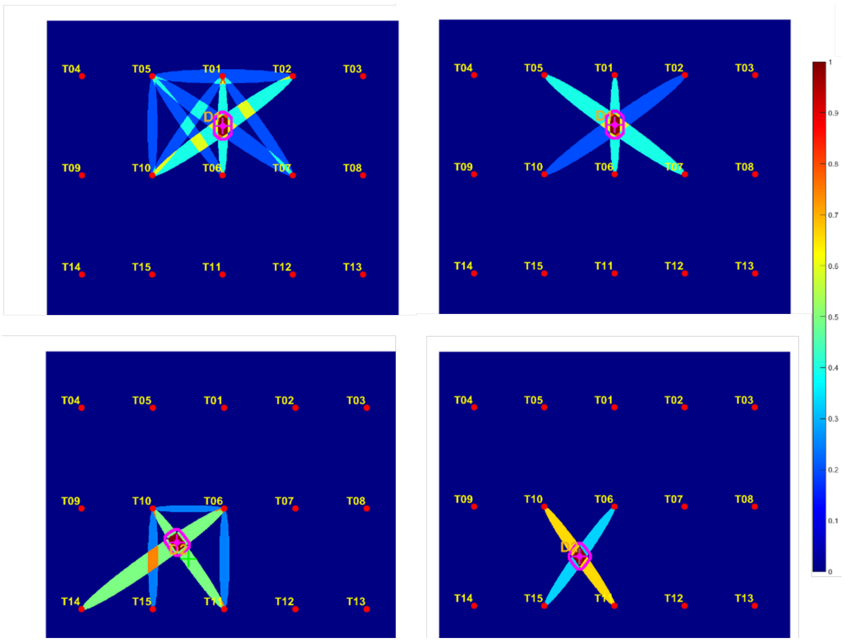

Figure 6. Visualization of the predictions made using ML model based on NRMSD for different local stiffness reduction coefficients : The tomograms at the top show damage D1 with $\kappa = 0.2$ (left) and $\kappa = 0.5$ (right), resulting in localization errors of 1.43 mm. The tomograms at the bottom show damage D2 with $\kappa = 0.2$ (left) and $\kappa = 0.5$ (right), resulting in localization errors of 61.99 mm and 1.37 mm, respectively.

Future work will continue to advance this integrated approach. Machine learning architectures and further optimization of synthetic data strategies will be explored, with the aim of maximizing system reliability under the diverse environmental and operational conditions characteristic of real-world hydrogen storage applications.

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