Effects of multi-axial Loading on a GW-SHM System for a Composite Fuselage

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Abstract. A full-scale composite fuselage panel was instrumented with a Guided Wave-based Structural Health Monitoring (GW-SHM) system and subjected to multi-axial dynamic mechanical loading. Specifically, a hydraulic test rig applied a loading sequence resembling a full-scale fuselage test campaign. As a result, the dataset contains 17 load combinations derived from the basic load cases, which highlight the effects observed by the GW-SHM system under multi-axial loading conditions typical of fuselage structures. To account for the combined influences of environmental and operational conditions, multi-axial load and temperature, a data-driven approach based on Gaussian Processes is developed to distinguish these effects from those caused by damage.

Keywords: Guided Waves, Composite Structures, Aeronautic Structures, Environmental and Operational Conditions, Data-driven Damage Detection

1 Introduction

The introduction of composite materials in aeronautics has brought numerous advantages, along with unique damage and failure modes. The structural integrity is currently ensured by a damage-tolerant design and non-destructive inspections ([1]). Among other techniques, Guided Wave-based Structural Health Monitoring (GW-SHM) has gained interest as a cost and time effective alternative to traditional non-destructive techniques. One of the main challenges for GW-SHM is the influence of environmental and operational conditions on the damage identification capability.

Aircraft structures are subject to a wide range of variations in temperature, pressure, and other operational and environmental factors that affect the propagation of Guided Waves. This can compromise the effectiveness of GW-SHM systems, which often rely on limited baseline data to detect damage. Compensating for these changes remains an active area of research, with numerous techniques having been proposed ([2], [3]). However, applying these methods in real-world scenarios is frequently challenged by the complex geometry and structural behavior of monitored structures and the simultaneous presence of multiple environmental and operational factors.

Studying the influence of load is particularly important for applications where SHM systems must operate under varying conditions, including in-flight monitoring, on-ground inspections, and structural testing. In this context, the present work focuses on SHM systems designed for structural testing of full-scale composite components. Specifically, it investigates the use of a GW-SHM system to monitor damage in a full-scale composite aircraft fuselage subjected to multi-axial loading and uncontrolled temperature environment.

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2 Experimental Setup

A composite fuselage panel representative of the passenger door surrounding area of a wide-body aircraft, such as the Airbus A350, was selected for this study. The panel measures 4100 mm × 5700 mm and incorporates frames, stringers, windows, and the door surrounding structure ([4]). The fuselage panel was instrumented with a custom-designed guided wave SHM (GW-SHM) system. Key features include a robust transducer network, reliable transducer connections, and a modular architecture ([5]). This design ensures sensor reliability and practical applicability in an industrial setting.

Representative flight loads were applied using the test rig described in [6] and shown in Figure 1. Six actuators generate forces and moments along the three principal axes (x, y, z), enabling realistic simulation of operational conditions. The test rig can apply the basic load cases typical of a fuselage structure, as well as any combination of these, up to ultimate load. The basic load cases include vertical bending in both upward and downward directions (VBU and VBD), and lateral bending to the left and right (LBL and LBR).

A loading sequence, designed to resemble full-scale fuselage fatigue tests, produced a dataset containing 17 load combinations derived from the basic load cases. While this sequence does not capture the full complexity of in-flight load conditions, it provides sufficient variability to evaluate approaches addressing load influences. The experiment was conducted in a hangar under uncontrolled temperature conditions, resulting in a wide range of temperature variation throughout the testing campaign.

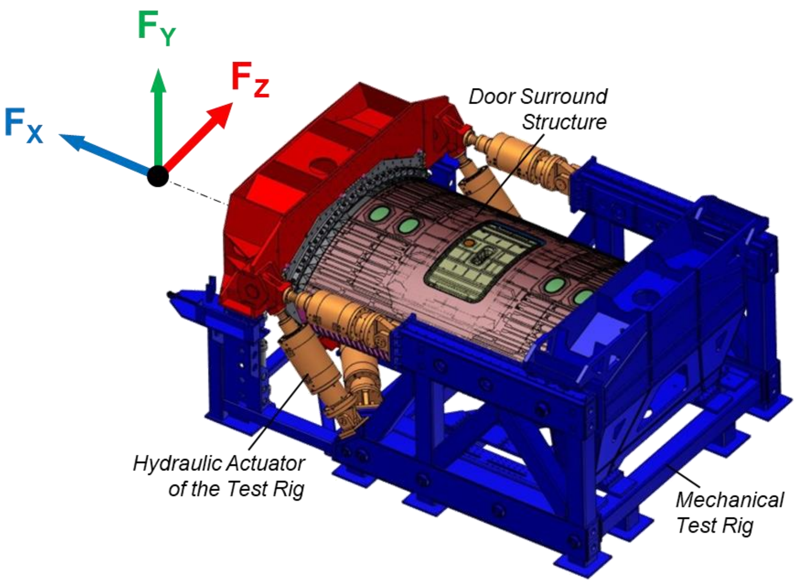


Figure 1: Composite fuselage panel mounted in the hydraulic test rig ([6])

The data acquisition infrastructure integrated multiple systems and uploaded its measurements to a central data management system. The panel was instrumented with 148 piezoelectric transducers and 31 temperature sensors, while a parallel system collected strain and test rig data. A time synchronization module aligned all data, enabling both online and post-processing analyses of data from multiple sources.

3 Methodology

This section presents Gaussian Process Regression (GPR) for damage detection using a GW-SHM system in the described application scenario. The approach is to develop a statistical model that captures the relationship between guided wave signals and environmental and operational conditions, enabling the separation of environmental and operational effects from damage effects. Gaussian Processes have been increasingly applied in SHM for tasks such as modeling time-series in vibration analysis [7], and quantifying damage with guided waves [8]. For a comprehensive overview of GPs in machine learning, see [9].

Here, GPR is employed for unsupervised damage detection using GW-SHM, mapping the input operational variables (temperature and load) to selected guided wave signal features. Previous work demonstrated the ability of GPR to detect damage in a single load case across a range of temperatures ([10],[11]). While effective, that approach is insufficient for multi-axial loading. The current study generalizes the model by expanding the input space from two dimensions (load level, temperature) to four: 3 elements of the 6-dimensional load vector, axial force F_x, bending moments M_y and M_z, and temperature T.

We employ GPR to map the input vector:

$$x = [F_x \; M_y \; M_z \; T\,]^{\mathsf{T}}$$

to a GW feature $y \in ToF$. In regression tasks, we often assume that the observed data y can be modeled as:

$$y = f(x) + \epsilon \qquad\qquad \epsilon \sim N(0, \sigma_n^2)$$

where x is the input (feature vector), $f(x)$ is the unknown underlying function we aim to learn, and ϵ is the noise term, assumed to be Gaussian noise with zero mean and variance σ_n^2.

GPR approaches the regression problem by placing a prior over the function $f(x)$, assuming that for any finite set of inputs, the corresponding function values follow a joint Gaussian distribution:

$$f(x) \sim GP(m(x), k(x, x'))$$

where $m(x)$ is the mean function and $k(x, x')$ is the covariance function.

The covariance function is defined by the choice of kernel, which specifies the set of possible functions the Gaussian process can represent. In this study, a combination of a linear kernel and a squared exponential kernel is selected. The covariance function is therefore defined as:

$$k(x, x') = \left(-\frac{\|x - x'\|^2}{2l^2}\right)$$

where $\|x - x'\|$ is the Euclidean distance between inputs, and l is the length-scale parameter controlling the smoothness.

Given a training dataset $D = \{(X, y)\}$, where $X = [x_1, \ldots, x_n]$ and $y = [y_1, \ldots, y_n]$, GPR computes the distribution over functions conditioned on the data. The process begins by calculating the covariance matrix K for all training points using the chosen kernel. Once the GPR model has been trained, classically in GPR, a new input x_* arrives and the predictive mean and variance at x_* is determined. To achieve this, a joint covariance matrix is computed for the new input x_*, representing the relationship between x_* and each training point. The joint distribution of the observed targets y and the function values at a new input x_* is:

$$[y \; f_* \,] \sim N(0, [K(X, X) + \sigma_n^2 I \; K(X, x_*) \; K(x_*, X) \; k(x_*, x_*)\,])$$

where $K(X, X)$ is the covariance matrix over training inputs, $K(X, x_*)$ is the covariance vector between training inputs and the test point, and $k(x_*, x_*)$ is the covariance at the test point. Finally, the noise present in the training dataset is represented by σ_n^2.

The predictive distribution for the output f_* at the new input x_* is Gaussian with:

$$\underline{f_*} \triangleq E[f_*] = K(x_*, X)[K(X, X) + \sigma_n^2 I]^{-1} y$$

$$var[f_*] = K(x_*, x_*) - K(x_*, X)[K(X, X) + \sigma_n^2 I]^{-1} K(X, x_*)$$

This provides both a mean prediction $E[f_*]$ and an uncertainty estimate $var[f_*]$.

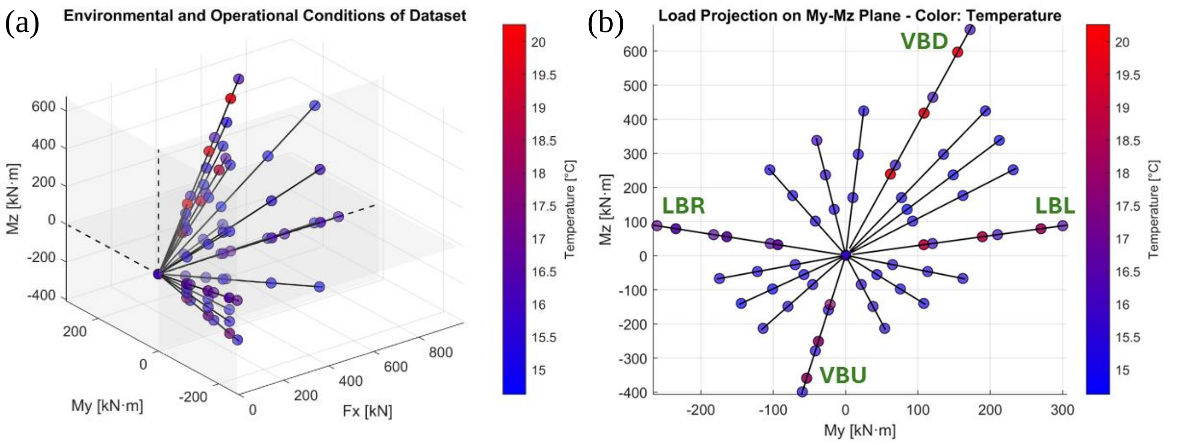
4 Results

This section presents a GW dataset acquired under multi-axial load conditions and varying temperatures on a fuselage panel. First, the influence of environmental and operational conditions on GW signal features is illustrated for selected paths. Next, the GPR model is trained on the described dataset, and its ability to differentiate between environmental and operational effect and damage is subsequently evaluated.

4.1 Environmental and Operational Conditions

The current GW dataset was acquired over three days, covering the four basic load cases, including lateral and vertical bending as well as axial tension in x-direction, along with several combinations of these cases. In total, 17 load combinations were applied at four load levels each. The experiment was conducted in an uncontrolled temperature environment, resulting in a range from 14.5°C to 20.3°C.

Figure 2 illustrates the distribution of the load and temperature conditions applied during the test campaign. Figure 2 (a) presents a three-dimensional view of the combined load space, showing how the applied forces and moments span the operational load envelope of the fuselage panel. Figures 2 (b) through (d) show two-dimensional projections of the load combinations on the My–Mz, Fx–My, and Fx–Mz planes, respectively. The temperature at each measurement point is indicated by the color scale, illustrating the variations introduced by the uncontrolled hangar environment. Linear regressions plotted for each load combination link together the different load levels belonging to a certain load combination, making it easier to identify the different load cases. Together, these visualizations give an overview of the environmental and operational conditions present in the test campaign, serving as a starting point for understanding how these factors affect the measured signals.



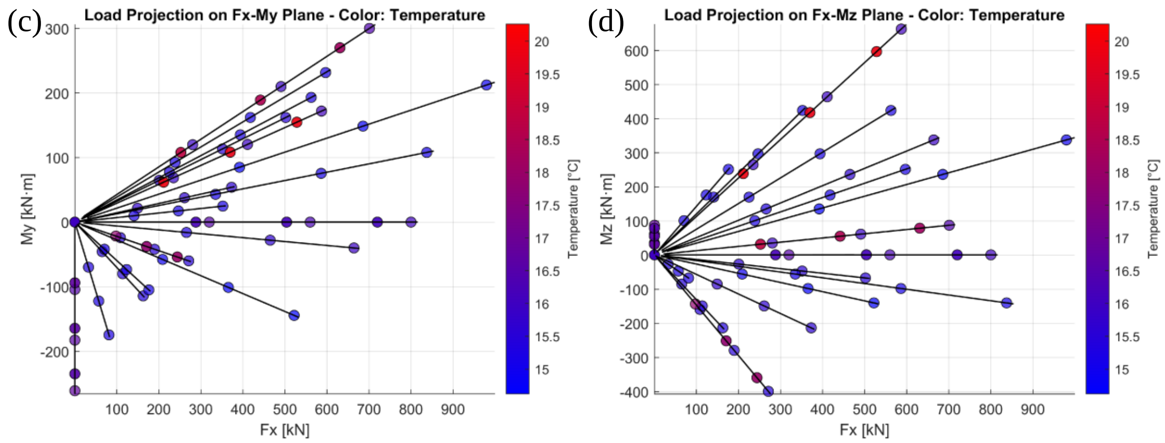


Figure 2: Load and temperature conditions during the GW measurement campaign.
(a) 3D view of applied loads; (b) Load projection on My–Mz plane;
(c) Load projection on Fx–My plane; (d) Load projection on Fx–Mz plane.

4.2 Guided Wave Propagation

The effects of the applied loads and temperature variations on the GW propagation are illustrated for two representative actuator-sensor paths located in a highly loaded area of the fuselage panel. The first path, from actuator 1 to sensor 3, is aligned with the x-direction, corresponding to the flight direction. The second path, from actuator 1 to sensor 5, is oriented perpendicular to the x-direction..

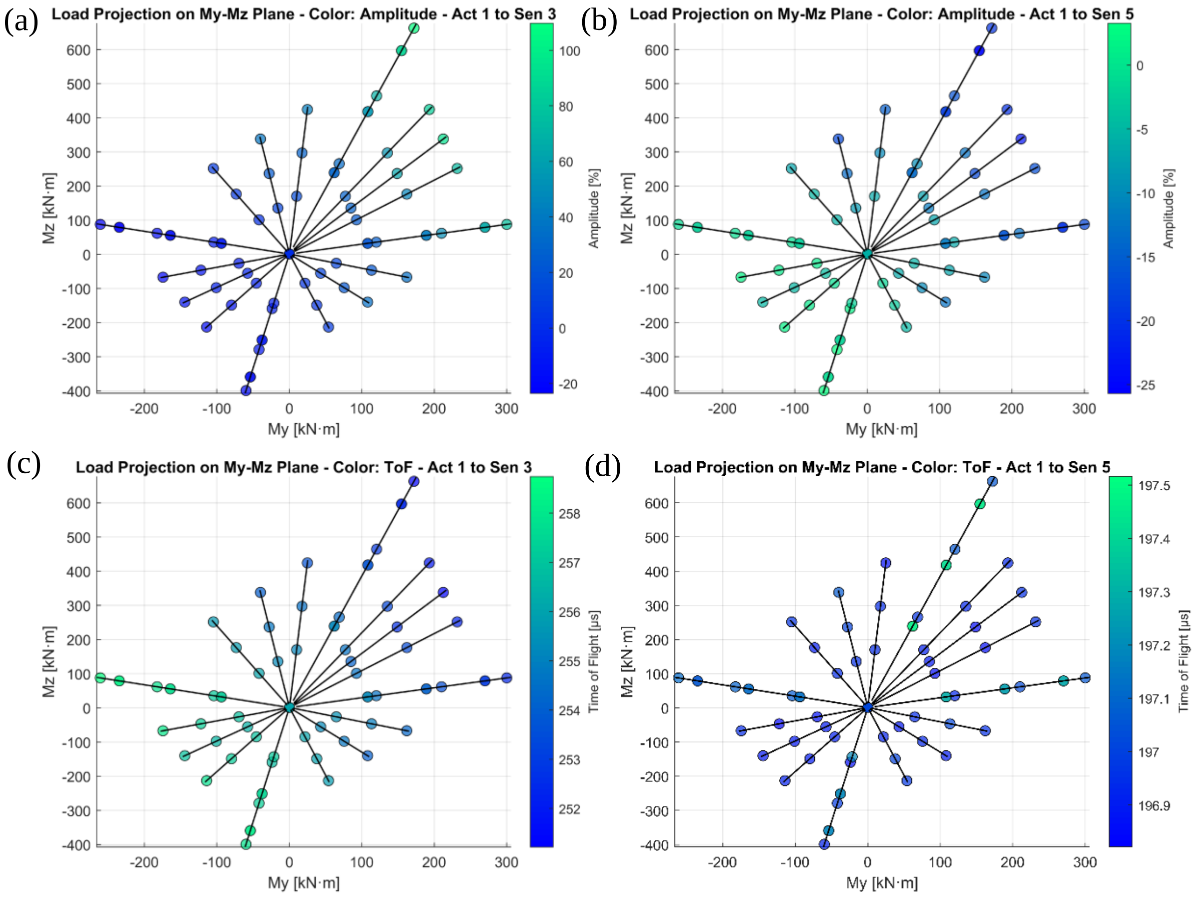


Figure 3: GW signal features under multi-axial loading.
(a) Amplitude path 1-3; (b) Amplitude path 1-5; (c) ToF path 1-3; (d) ToF path 1-5.

Figure 3 presents the extracted amplitude and time-of-flight (ToF) of the GW signals acquired at 70 kHz for the two selected paths, plotted on the My–Mz plane to illustrate the effects of different load combinations. Amplitude is expressed as the change relative to the unloaded state, while ToF is presented in absolute terms. For the path aligned with the x-direction (path 1-3), amplitude increases for positive values of My and Mz, whereas for the transverse path (path 1-5), amplitude increases for negative values of My and Mz. Time-of-flight exhibits the opposite trends: along path 1-3, ToF increases for negative My and Mz values, while along path 1-5, ToF increases for positive My and Mz values.

Simultaneously, temperature variations affect as well both amplitude and ToF. Along the transverse path, where the influence of applied loads is smaller, temperature effects dominate, particularly in the ToF measurements. In contrast, along the path aligned with the x-direction, load effects dominate signal variations, with temperature changes contributing secondarily.

The comparison of these two paths highlights the complex interaction between multi-axial loading and environmental conditions on guided wave propagation in composite engineering structures

4.3 Gaussian Process Regression

Using the dataset described in the previous section, a GPR model was trained to predict guided wave features as a function of axial force, bending moments, and temperature. The model includes four independent variables (Fx, My, Mz, T) and one dependent variable, in this case the ToF of the guided waves. Two partial views of the resulting four-dimensional model are presented in figure 4, showing how the model captures the combined effects of load and temperature on wave propagation.

The plotted results include the predictive mean, the 95% prediction intervals, and the experimental data points used for training. Points corresponding to the two-dimensional cuts shown in the plots are highlighted in black, while the remaining points are shown in gray scale, indicating their distance from the displayed cut. The linear component of the kernel captures the overall trend of the data across the load-temperature space, while the squared exponential kernel accounts for local deviations and provides a measure of predictive uncertainty. In regions with sufficient training data, the prediction intervals are narrow, reflecting high confidence in the model. Conversely, in regions with sparse or absent data, the intervals widen, indicating increased predictive uncertainty.

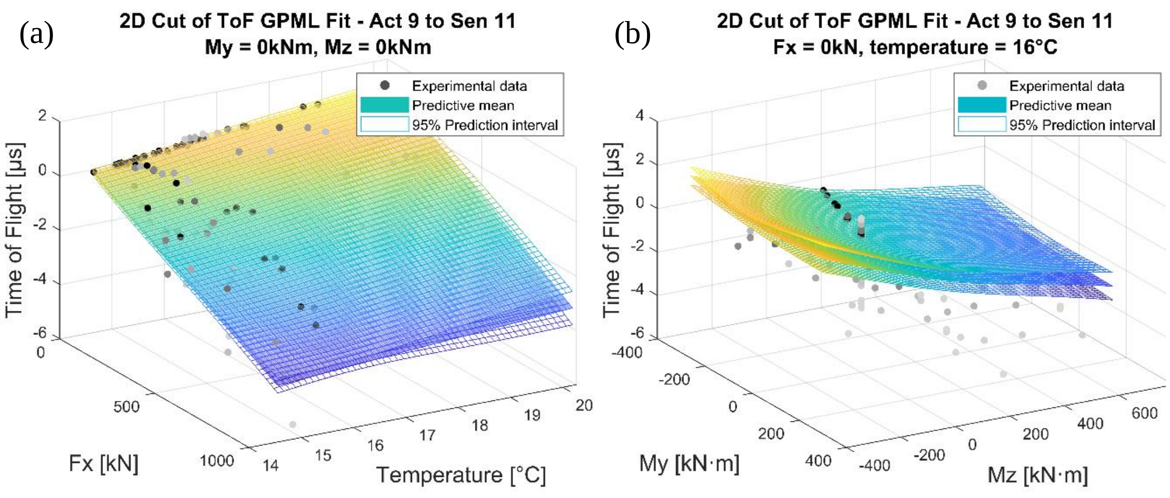


Figure 4: Partial views of the trained GPR model. (a) Fx–Temperature vs. ToF;(b) My–Mz vs. ToF

This four-dimensional GPR framework enables continuous prediction of guided wave responses across untested combinations of Fx, My, Mz, and temperature. By quantifying both the predicted response and its uncertainty, the model provides a robust, data-efficient tool for structural health monitoring under realistic environmental and operational conditions, supporting reliable damage detection in multi-axial loading scenarios.

4.4. Damage Detection

The trained GPR model was applied to a path where a barely visible impact damage (BVID) was introduced during the test campaign in figure 5. The measurements are plotted in chronological order, with each point corresponding to a different combination of load and temperature at the time of acquisition. The experimentally measured time-of-flight is shown alongside the GPR predictive mean and the 95% prediction intervals. Training data are represented as black points, while test data are colored according to the likelihood of belonging to the predicted mean and interval.

Initially, the structure is undamaged, and the model predicts the guided wave responses with high likelihood and narrow prediction intervals. When a barely visible impact damage is introduced but the temperature exceeds the range covered by the training data, the prediction intervals widen, and the damage detection becomes inconclusive. As the temperature returns to values within the training range, the prediction bounds narrow, and the presence of damage is clearly identified. This sequence demonstrates that the GPR approach can effectively accommodate both variations in environmental and operational conditions and the introduction of damage, while explicitly reflecting uncertainty in regions where training data are limited. The results further illustrate that the effects of the BVID may be subtle and can sometimes only be reliably detected when both load and temperature are considered.

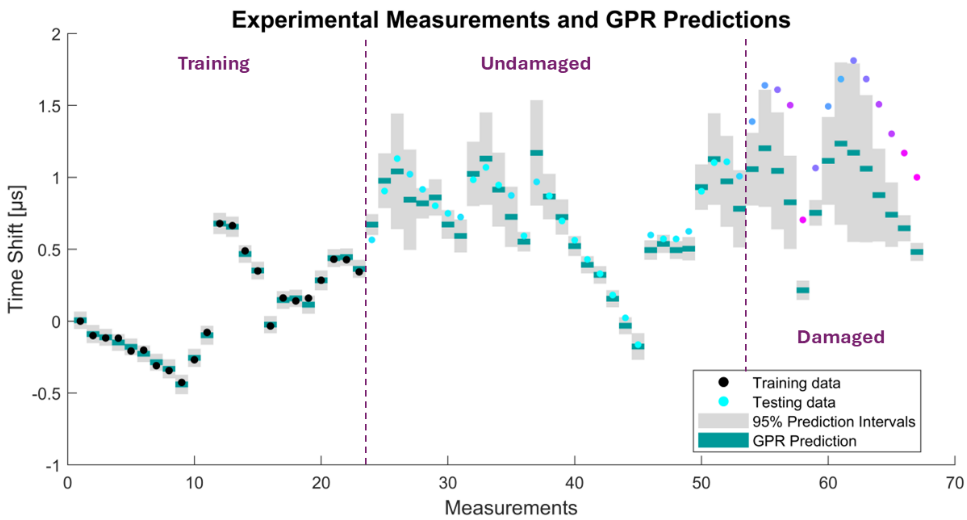


Figure 5: Damage detection using the trained GPR model under changing load and temperature

5 Summary and Outlook

A GW-SHM system was installed on a representative composite fuselage structure, and a full-scale test involving multi-axial mechanical loading produced a comprehensive dataset for the application of GW-SHM in realistic operational scenarios.

The study demonstrates that GPR can robustly model guided wave propagation under multi-axial loading and variable temperature conditions in full-scale composite aircraft structures. The GPR framework predicts time-of-flight while providing a quantitative measure of uncertainty, enabling sensitive damage detection. These results highlight the potential of data-driven approaches to enable GW-SHM in full-scale structure tests, offering reliable damage detection across operational load envelopes.

Future work will focus on extending the GPR framework to multi-dimensional outputs, incorporating additional guided wave signal features to enhance robustness in damage detection. Further challenges include addressing long-term damage detection, such as monitoring slowly growing damage, and strategies for detecting and correcting potential model degradation over time.

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7 References

[1] European Union Aviation Safety Agency. (2018). Easy Access Rules for Large Aeroplanes (CS-25) (Initial issue)

[2] Schackmann, O., Marquez Reyes, O., Memmolo, V., Lozano, D., Prager, J., Moll, J., & Kraemer, P. (2025) Machine Learning Strategies with Ensemble Voting for Ultrasonic Damage Detection in Composite Structures Under Varying Temperature or Load Conditions. Structural Health Monitoring.

[3] Le Bourdais, F., Mesnil, O., & d'Almeida, O. (2019). Machine-Learning Based Temperature Compensation for Guided Wave Imaging in Structural Health Monitoring. 11th International Symposium on NDT in Aerospace

[4] Kruse, F., Kühn, M., Krombholz, C., Ucan, H., & Torstrick, S. (2015). Production of a Full-Scale Demonstrator-Structure within the FP7 Project "Maaximus." 5th International Workshop on Aerostructures.

[5] Schmidt, D., Moix-Bonet, M., Petersen, J., & Wierach, P. (2024). SHM system architecture based on ultrasonic guided waves for aircraft application scenarios. In Proceedings of the 11th European Workshop on SHM.

[6] Sachse, M., Götze, M., Nebel, S., Berssin, S., & Göpel, C. (2020). Testing approach for over wing doors using curved fuselage panel testing technology. Lecture Notes in Mechanical Engineering, 831–837.

[7] Avendaño-Valencia, L. D., Chatzi, E. N., & Tcherniak, D. (2020). Gaussian process models for mitigation of operational variability in the structural health monitoring of wind turbines. Mechanical Systems and Signal Processing, 142, 106686.

[8] Amer, A., & Kopsaftopoulos, F. (2023). Gaussian process regression for active sensing probabilistic structural health monitoring: experimental assessment across multiple damage and loading scenarios. Structural Health Monitoring, 22(2), 1105-1139.

[9] Rasmussen C.E., Williams C.B. (2006) Gaussian processes for machine learning. MIT Press.

[10] Moix-Bonet, M., Schmidt, D., Eckstein, B., & Wierach, P. (2024). A Composite Fuselage under Mechanical Load: a case study for Guided Wave-based SHM. 11th European Workshop on SHM.

[11] Moix-Bonet M, Schmidt D, Eckstein B, Wierach P. (2025). Damage Detection in Composite Aircraft Fuselages Under Load and Temperature Using Gaussian Processes for GW-SHM. 15th International Workshop on SHM.