

A Fleet Monitoring Concept for Modular Exchangeable Hydrogen Tank Units

Tobias Schalm¹, Tianxiang Huang², Linus Jacobsen³, Kai-Uwe Schröder¹

¹Institute of Structural Mechanics and Lightweight Design, RWTH Aachen University, Aachen, Germany, tobias.schalm@sla.rwth-aachen.de

²College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing, China, tianxiang.huang@nuaa.edu.cn

³German Aerospace Center (DLR), Institute of Lightweight Systems, Braunschweig, Germany, linus.jacobsen@dlr.de

Abstract This paper presents a fleet monitoring concept for modular, exchangeable hydrogen tank units used in distributed power supply systems. The proposed framework utilizes Bayesian inference based on physics-based damage modelling and is fine-tuned using in-service fleet data. For the first implementation of the Bayesian framework, fleet data is generated using detailed axisymmetric finite element models of composite pressure vessels, incorporating manufacturing uncertainties and simulated damage scenarios. A Gaussian process surrogate model is trained to efficiently approximate the mapping from damage parameters to characteristic strain deviations derived from surface strain measurements. Bayesian inference is then employed to estimate damage states, enabling probabilistic identification of damage location, size, and depth while accounting for multiple sources of uncertainty. The framework further allows the incorporation of real fleet data through both the likelihood and prior distributions, facilitating continuous model refinement. Results demonstrate the capability of the approach to handle ambiguity in damage identification and highlight the importance of integrating engineering knowledge into probabilistic monitoring.

Keywords: Structural Health Monitoring (SHM); Hydrogen Storage; Composite Pressure Vessels; Bayesian Inference; Damage Detection; Fleet Monitoring; Population-Based Structural Health Monitoring (PBSHM)

Introduction and scope

Modular generator sets (gensets) equipped with standardized hydrogen tank modules represent a promising technology for efficient temporary or backup hydrogen-based power supply, particularly in remote and off-grid locations. The modular and exchangeable design of the hydrogen tanks enables a rental-based business model, allowing users to rent filled tank modules instead of purchasing them. Once the hydrogen is consumed, the tank models are returned to the hydrogen supplier for refill and immediately exchanged for full hydrogen tanks. This approach alleviates upfront capital expenditure for hydrogen tanks and reduces on-site storage requirements. Centralized refilling at dedicated filling stations ensures consistent adherence to safety and quality standards, while also decoupling refueling time from the performance constraints of local hydrogen infrastructure. Within this novel business model, it is essential to guarantee the safety and reliability of each hydrogen tank provided to customers. Simultaneously, the regular return of tank modules to central refilling facilities creates favorable conditions for implementing efficient fleet monitoring and maintenance strategies. In this work, a Bayesian process framework for damage identification in a simulated population of modular,



exchangeable hydrogen tank units is presented. The proposed framework is grounded in a physics-based understanding of the system and incorporates engineering know-how. To enable population-based health monitoring, which is characterized by the transfer of information between similar structures within a population [1], the interfaces through which real fleet data can be integrated into the framework are explored. Consequently, this study constitutes a first step toward a comprehensive population-based health monitoring framework that bridges the gap between physics-based and data-driven health monitoring approaches for hydrogen tanks. For this first iteration of the framework, it is assumed that tanks fail in a so-called safe failure mode, where failure is governed by hoop layer fiber damage in the cylindrical tank section and the metallic bosses move inwards into the tank during the failure process [2]. Type IV hydrogen pressure vessels are generally designed to ensure this failure mode. Stiffness loss due to fiber damage leads to a redistribution of local load paths and therefore a shift in the local strain field. While optic fibers can be inserted in the laminate during the tank winding process for in-service strain data acquisition, this approach often leads to sensor damage with some authors reporting 47% of fibers failing during manufacturing and transport [3]. For this reason and to ensure maintainability, strain sensors shall be placed on the tank surface and the surface strain serves as a basis for damage identification. 2D axisymmetric finite element models are used to generate synthetic strain data for this study. It is assumed that the surface strain of the tank is known for the entire surface of the axisymmetric tank model. This can be achieved using OFDR fiber optic technology, digital image correlation during refuelling or strain field reconstruction from discrete measurement points using convolutional neural networks as outlined in a previous publication [4].

1. Synthetic fleet data generation

1.1 Model description

The hydrogen tank fleet under consideration is interpreted as a population of nominally-identical homogenous structures. For the mechanical modelling of the pressure vessels, an axisymmetric model is generated through the python tool tankoh2 [5]. It makes use of the filament winding simulation provided by the python API of the commercial software μ Wind to generate the axisymmetric laminate geometry and mechanical properties. These are defined by nodes marking the contour of each layer, and sections between these nodes containing the local band angle, fiber volume content (FVC), and the fiber-aligned orthotropic mechanical properties. In this case, a layer refers to a homogenization of multiple overlapping $+\alpha$ and $-\alpha$ bands that are wound with one winding angle, which has the twice the band thickness in the cylindrical region. The local band angle α changes from the angle set in the cylinder towards 90° at the polar opening of each layer. Furthermore, the local mechanical properties are adjusted from the material mechanical properties by the fiber volume content for each section, using the rules of mixture [6]. For 700-bar pressure vessels, the mechanical influence of the wall thickness is not negligible. Shell-based FEM models cannot capture the radial stresses and the resulting through-thickness hoop stress gradient [7]. Therefore, starting from the results of the filament winding simulation, the methods within tankoh2 are used to generate axisymmetric solid FEM models for abaqus. For improved efficiency, reduced integration is utilized in this study (CAX4R and CAX3R elements). Each section as created by the winding simulation is mapped exactly to one FEM element. For each element, the fiber-aligned material properties need to be transformed into the coordinate system of the axisymmetric elements. Because layers consist of equal $+\alpha$ and $-\alpha$ fibers (known as a Balanced-Angle Ply or BAP), the fiber-aligned stiffness matrices C per layer can be homogenized into BAP stiffness matrices $\bar{C}$ in the element coordinate system, which remains orthotropic (allowing

it to be used in axisymmetric models), as the tension-shear and shear-shear coupling terms of the transformed positive and negative angled plies cancel out [8]. At the center of the cylinder, symmetry boundary conditions are applied. On the interior surface of the laminate, the interior pressure is applied. At the ends of the vessel, the axial pressure acting within the polar opening is added as a distributed load over the nodes that would be in contact with the metallic boss, which is not explicitly modelled. The plastic liner, although always present in Type-IV pressure vessels, is also not included, as due to its much lower stiffness than CFRP, its mechanical influence is considered negligible. Geometric non-linearity is considered.

1.2 Pressure Vessel Design

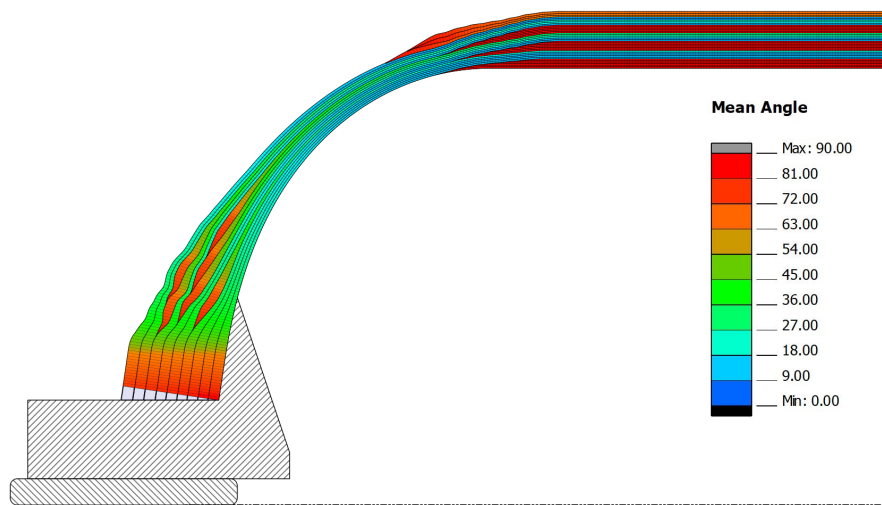


Fig. 1. Discretization and local winding angles of the pressure vessel.

The laminate for the investigated pressure vessel was generated using the optimization routines within tankoh2. It is built up layer-by-layer, with the optimal next winding angle chosen to minimize the maximum fiber failure index (fiber-direction stress divided by tensile strength) and bending, while also maintaining a contour without concavities or extremities that would hinder filament winding [5]. Hoop layers are clustered together and their ply drop locations are linearly distributed, and high-angle helical layers are sorted outwards. In an extension of the cited work, a multi-model approach is used for the optimization, employing the described solid-axisymmetric model as well as μ wind's internal axisymmetric shell model. For each new layer to be added, the solid model is calculated once and used as an element-wise correction to the shell model, which is evaluated within the angle optimization loop. Tables 1 and 2 show the parameters and material used for the pressure vessel design. The material data is taken from [9] and was previously used for a pressure vessel in [10]. Figure 1 shows the cross section of the generated laminate. The length of the element is set at 0.78125 mm, equal to 1/16 of a bandwidth.

1.3 Introducing Manufacturing Uncertainties

For this study, a selection of expected manufacturing uncertainties was introduced into the vessels. Table 3 shows the normal distributions of each considered uncertain property. Each property is independently randomized for each of the 35 layers in each realization. 200 realizations were created and calculated in Abaqus. The random distribution is realized using the Double precision SIMD oriented Fast Mersenne Twister algorithm of the open source python library *OpenTURNS* [11]. The standard deviations of the material properties were taken directly from Just [9]. For the fiber volume content, values were taken from a microscopic

Parameter	Value
Diameter	250 mm
Length	700 mm
Dome Shape	Isotensoïd
Polar Opening Radius	30 mm
Working Pressure	700 bar
Safety Factor	2.0
Additional Dome Safety Factor	1.15
Bandwidth	≈ 12.5 mm

Table 1. Pressure vessel geometry and service parameters.

X1t	E1	E2	E3	G12/G13	G23	ν_{12}/ν_{13}	ν_{23}	FVC
[MPa]	[MPa]	[MPa]	[MPa]	[MPa]	[MPa]			%
2089	129400	8050	8870	3910	2850	0.317	0.41	60.87

Table 2. Composite material properties of T700SC-12K / (LY556 + HY917 + DY070) [9].

analysis of filament-wound T700SC-12K rings [12]. In reality, FVC depends upon the compression of the layers during winding, and is generally higher on the inside than the outside of the laminate. In this work, it is simply randomized for each layer. Variation of the winding angle is taken from a probabilistic study by Yetgin [13]. It is implemented as variation to the winding angle in the cylinder, which also changes the polar opening of the layer according to geodesic winding, and thus, the material distribution within the dome. Finally, the locations of the ends of the hoop layers can vary with standard deviations taken from studies on layer overlaps taken from Rozo Lopez [14].

Parameter	Mean	Standard Deviation	Ref.
E1	129400 MPa	5400 MPa	[9]
E2	8050 MPa	440 MPa	[9]
E3	8870 MPa	200 MPa	[9]
G12/G13	3910 MPa	190 MPa	[9]
G23	2850 MPa	150 MPa	[9]
FVC	≈ 60 %	3.9 %	[12]
Helical Layer Angle	[as designed]	0.2°	[13]
Hoop Layer Ply Drop	[as designed]	1 mm	[14]

Table 3. Applied material and design parameter variation for manufacturing uncertainty modelling.

1.4 Damage modelling

Hoop layer fiber damage is modelled using a simplified damage model where the elastic modulus in fiber direction E_1 , as well as the shear moduli and poisson ratios with a fiber direction component G_{12} , G_{13} , ν_{12} , and ν_{13} are set to 10% of their initial value for damaged elements [15, 16].

2. Gaussian process surrogate model

The damage parameter space is defined by the axial damage location z , a discrete through-thickness depth d , which is restricted to hoop layers, and the damage size s . Latin Hypercube Sampling (LHS) is employed to efficiently generate a set of N training samples:

$$\theta_i = (z_i, d_i, s_i), \quad i = 1, \dots, N. \quad (1)$$

During model training, each sample θ_i is expanded across multiple tank realizations to account for manufacturing variability. These subsets of tank models are assigned using a balanced sampling scheme instead of random sampling to ensure uniform coverage of the available tank realizations. As a result, the same nominal damage configuration may appear multiple times in the training set with slightly different responses, reflecting the influence of unobserved manufacturing deviations. For each sampled parameter vector θ_i , an Abaqus finite element simulation is performed to compute the structural response in the damaged state. This simulation yields a surface strain field for the damaged configuration, which is compared to the undamaged configuration. Exemplary strain fields are provided in Figure 2 for the middle and outermost hoop layer of the layup.

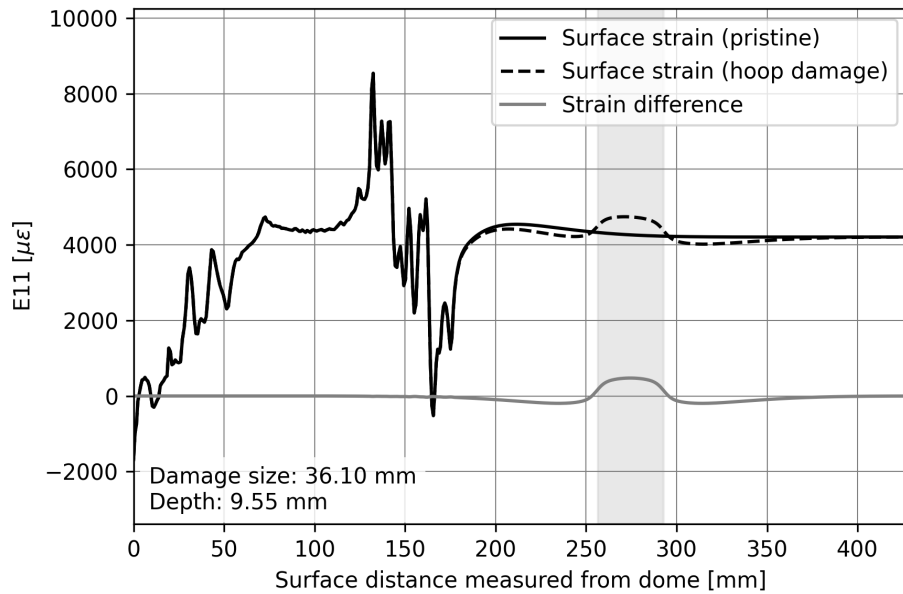


Fig. 2. Characteristic strain deviation for the inner hoop layer. The grey shaded area represents the location and size of the damage along the tank axis. E_{11} refers to the strain along the outer surface edge of the axisymmetric model.

The observed surface strain difference between the pristine and damaged states yields a strain deviation signal $\Delta\epsilon(z)$. As outlined in the introduction, it is assumed that the full strain deviation signal is known. From this signal, a set of strain deviation characteristics $\mathbf{y}$ is computed:

$$\mathbf{y} = [\text{fw}_{\text{hm}}, \text{slope}_{\text{hm}}, z_{\text{mid}}, \epsilon(z_{\text{mid}})], \quad (2)$$

where fw_{hm} denotes the full width at half maximum, slope_{hm} the average slope at half-maximum crossings, z_{mid} the midpoint location, and $\epsilon(z_{\text{mid}})$ the strain value at this position. A Gaussian Process (GP) surrogate model is trained to approximate the mapping between damage parameters θ_i and strain deviation characteristics $\mathbf{y}$ based on the finite element data. Thereby an individual surrogate model is trained for each strain deviation characteristic $\mathbf{y}$ for

improved interpretability of the results.

The surrogate models are constructed using a scaled radial basis function (RBF) kernel. The RBF kernel reflects the assumption that the strain deviation characteristics $\mathbf{y}$ vary smoothly with respect to the damage parameters $\boldsymbol{\theta}_i$. Manufacturing-related variability is not modelled by an additive white-noise kernel. Instead, it is incorporated through a heteroscedastic diagonal noise vector $\boldsymbol{\alpha}_j$ in the Gaussian process regression. For each output characteristic y_j , the entries of $\boldsymbol{\alpha}_j$ are estimated from the empirical variance of repeated simulations with the same nominal damage configuration but different manufacturing realizations. Since the output variables are standardized before training, the corresponding noise variances are also transformed to the standardized output space before fitting the Gaussian process models.

To improve the stability of the kernel hyperparameter optimization, each input and output variable is standardized using a z-score transformation. For the training data, 30 damages differing in width, local depth and location along the tank axis are introduced in each of the three hoop-layer (90°) clusters seen in Figure 1. Each of those 90 damage variations is then expanded over 20 tank variations with different manufacturing parameters. Training data is generated on half of the tank population featuring 200 tanks in total (see Section 1.3) with the other half used to generate validation data. After omitting damage parameters that lead to a surface strain deviation crossing the symmetry boundary, 1321 training samples remain.

3. Bayesian damage state inference

Bayesian inference is performed to estimate the unknown damage parameters from observed damage characteristics $\mathbf{y}^{\text{obs}}$. Using Bayes' theorem, the posterior distribution is given by

$$p(\boldsymbol{\theta} \mid \mathbf{y}^{\text{obs}}) \propto p(\mathbf{y}^{\text{obs}} \mid \boldsymbol{\theta}) p(\boldsymbol{\theta}), \quad (3)$$

where $p(\boldsymbol{\theta})$ denotes the prior distribution and $p(\mathbf{y}^{\text{obs}} \mid \boldsymbol{\theta})$ the likelihood. Assuming independent Gaussian errors, the likelihood can be expressed as

$$p(\mathbf{y}^{\text{obs}} \mid \boldsymbol{\theta}) = \prod_{j=1}^4 \mathcal{N}(y_j^{\text{obs}} \mid \hat{y}_j(\boldsymbol{\theta}), \sigma_j^2), \quad (4)$$

where $\hat{y}_j(\boldsymbol{\theta})$ is the GP surrogate prediction. The variance σ_j^2 combines the measurement uncertainty with the predictive uncertainty returned by the GP surrogate. The latter reflects the uncertainty of the surrogate model after training with the heteroscedastic diagonal noise vector $\boldsymbol{\alpha}_j$, which represents manufacturing-induced output scatter estimated from repeated simulations of identical nominal damage configurations across different tank realizations.

The posterior is evaluated on a structured 3D grid over the damage parameter space, consisting of a continuous axial position z , a discrete set of admissible hoop layer indices (which implicitly define the depth d via the geometry), and a continuous damage size s ; each grid point corresponds to a physically consistent damage configuration $\boldsymbol{\theta}$. Damage estimates are obtained via the maximum a posteriori (MAP)

$$\boldsymbol{\theta}_{\text{MAP}} = \arg \max_{\boldsymbol{\theta}} p(\boldsymbol{\theta} \mid \mathbf{y}^{\text{obs}}). \quad (5)$$

An exemplary probability mass distribution and the corresponding MAP damage estimate is depicted in Figure 3 for a uniform prior. The depicted probability mass distribution reveals important insights into the investigated system: Firstly, the simulated variance may lead to a rather diffuse probability mass distribution (particularly for comparatively small and deep damages), which further underlines the necessity for a probabilistic evaluation. Sec-

only, contrary to initial intuition, a small and deep damage leads to a similar variation in surface strain as a bigger and shallower damage. This can be traced back to the observation that inner hoop layers carry more load than outer hoop layers (see also Figure 4).

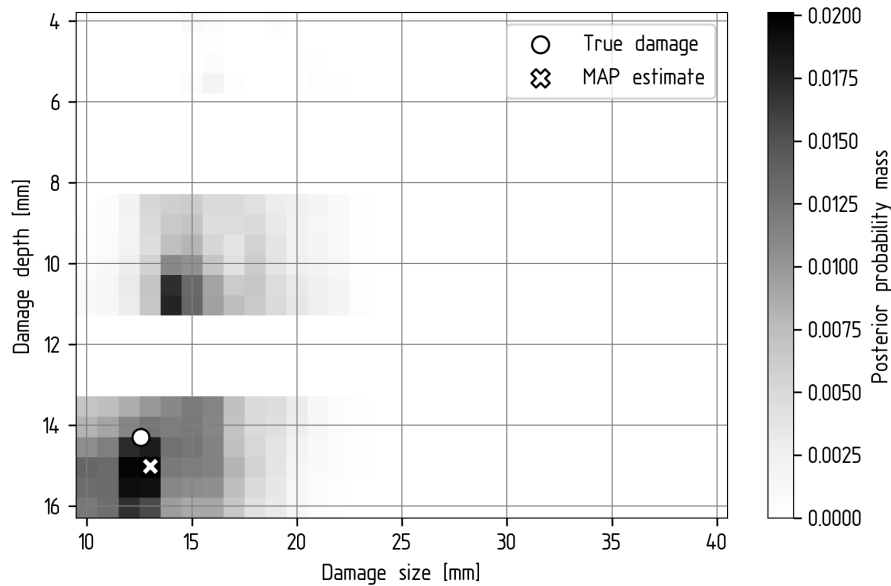


Fig. 3. Posterior probability mass distribution for a damage of size 12.6 mm and depth 14.3 mm and corresponding MAP damage estimate.

So far, a uniform prior distribution $p(\theta)$ was used for damage inference. The Bayesian prior represents a natural interface to incorporate engineering know-how and fleet data in the framework [17]. As demonstrated by an exemplary numerical simulation visualized in Figure 4, the circumferential strain within the hoop layers varies significantly, indicating non-uniform damage accumulation rates across the laminate thickness. This information can be directly translated into a depth-dependent prior probability $p(d)$, where hoop layers subjected to higher strain levels are assigned a higher probability of damage occurrence. The incorporation of engineering knowledge through the Bayesian prior distribution is particularly important given the relatively diffuse posterior probability mass observed for certain damage parameters when a uniform prior is assumed (see Figure 3).

4. Considering real population data in the proposed framework

For initial roll-out of the fleet monitoring system, the surface strain shall be interpreted at a specified pressure during the centralized refuelling process in order to ensure a stable environment for health monitoring. This also enables a more cost-effective implementation of fiber-optic sensing or digital image correlation for strain measurement as the data-acquisition systems are centralized. Tanks featuring abnormal strain under pressurization shall be subjected to a localised ultrasonic or thermography test. In combination, these tests yield the fleet data to be incorporated in the Bayesian framework. This fleet information can be incorporated at two distinct levels of the Bayesian framework: the likelihood model and the prior distribution. When transitioning to real fleet data, model mismatch will arise between the finite element model (and therefore the GP surrogate) and the actual tank behaviour. Further knowledge on physical model mismatch and the actual variability can improve the FE Model and the GP surrogate model which leads to an improved likelihood formulation in the Bayesian process. Furthermore, some characteristics of the in-service environment that were

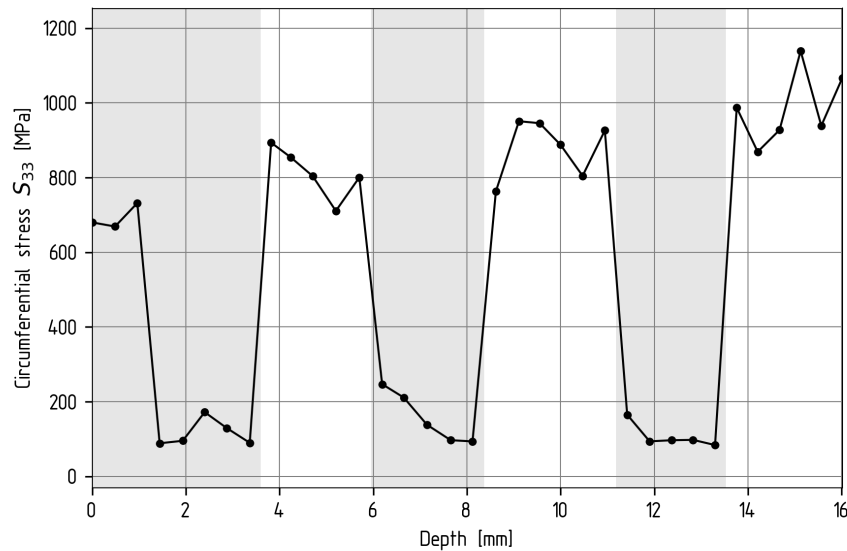


Fig. 4. Exemplary circumferential stress distribution within the cylindrical tank section. Non-hoop layers are shaded grey. The circumferential stress within the hoop layers ranges between 711 and 1139 MPa.

previously unaccounted for may influence the probability of specific damage parameter combinations. This effect can be accounted for in the Bayesian prior, potentially reducing the search space and improving identifiability of different damage modes.

5. Conclusion and future research

In this paper, a fleet monitoring concept for modularly exchangeable hydrogen tanks was presented, which is grounded in physics-based system modelling and engineering knowledge to capture the form of the population. The interfaces, via which fleet data can be incorporated in the framework, are explored. As such, this study represents the first step toward bridging the gap between physics-based and data-driven health monitoring approaches for hydrogen tanks in distributed power supply systems. In contrast to an additive white-noise kernel, the present implementation employs a heteroscedastic diagonal noise vector in the Gaussian process surrogate model. This allows output scatter caused by manufacturing variability to be represented separately for each strain deviation characteristic and each nominal damage configuration. Future work should investigate the calibration of this noise model using real fleet data and assess whether additional sources of model discrepancy need to be represented explicitly. Secondly, further damage labels such as no damage, matrix degradation and delamination shall be considered in the framework. This step requires the identification of a more general set of strain deviation characteristics y . Lastly, an uncertainty based fatigue and degradation model shall be implemented for the hydrogen tanks to generate synthetic fleet data that can be compared against the data from the simplified model presented in this study and serve as a source for fleet data to incorporate in the Bayesian framework.

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