ON THE DEVELOPMENT OF THE STRUCTURAL DIGITAL TWIN OF AN UNMANNED AERIAL VEHICLE

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Abstract

Structural fatigue poses a significant concern for flight safety, particularly during the later stages of service. The Airframe Digital Twin plays a pivotal role in facilitating structural damage diagnosis and prognosis by establishing a multiphysics, multiscale, and probabilistic virtual model of an as-built system. This paper presents a comprehensive and integrated framework for constructing the digital twin of an Unmanned Aerial Vehicle, incorporating load tracking, multi-level structural analysis, and probabilistic diagnosis and prognosis. Flight tests of the UAV are utilized to validate the proposed method. Results demonstrate that the digital twin can effectively predict fatigue crack growth in real-time using flight parameters as input. Furthermore, with inspection data available, the digital twin model can be updated to provide a more accurate prediction of future damage evolution. These insights offer valuable guidance for optimizing aircraft fleet maintenance strategies, thereby enhancing safety and cost-effectiveness.

Keywords: Unmanned Aerial Vehicle, Digital Twin, Reduced-order Model, Load Transfer, Diagnosis and Prognosis

1. Introduction

The global challenge posed by the structural aging of aircraft fleets constitutes a critical issue, significantly impacting the readiness and availability of military aircraft [1] and compromising the safety of civil aviation worldwide [2]. Structural fatigue emerges as the predominant concern associated with aging, becoming increasingly severe as aircraft progress into their later service stages.

Over the past decades, the evolution of aircraft structural safety assurance has encompassed principles such as safe life, damage safety, and damage tolerance. Recently, the Individual Aircraft Tracking (IAT) program has been widely implemented across various aircraft types [3, 4]. Utilizing recorded flight data from installed data acquisition units [5], the IAT program aims to monitor potential fatigue damage growth and life consumption for each aircraft within a fleet. However, many IAT systems in engineering practice primarily focus on monitoring load data, such as aircraft overload, while often neglecting epistemic uncertainties. These uncertainties, including variations in geometric and material parameters, contribute to discrepancies in the damage states of aircraft.

To address this limitation, the U.S. Air Force has funded research on the airframe digital twin (ADT), an extension of IAT, also referred to as Probabilistic and Prognostic Individual Aircraft Tracking ($\mathrm{P^2IAT}$) in Spiral 1 of the project. ADT facilitates structural damage diagnosis and prognosis by establishing a multiphysics, multiscale, and probabilistic virtual model [6, 7] of an as-built system. This model integrates uncertainties from multiple sources to support proactive fleet maintenance [8]. The Royal Canadian Air Force has also adopted this framework [9].

For small aircraft, Willcox and her colleagues have developed a data-driven digital twin for the assessment of structural degradation in unmanned aerial vehicles (UAVs). They combined a library of component-based reduced-order models with Bayesian inference, enabling dynamic mission planning. This approach was demonstrated on an unmanned aircraft with a wingspan of approximately 3.6 meters [10, 11].

Despite these advancements, several challenges remain in developing a comprehensive airframe digital twin at the aircraft level. These include accurately tracking individual flight loads, obtaining local stress data that affects damage growth, predicting fatigue crack growth in real-time, and ensuring the digital twin's damage state remains consistent with the physical part under uncertainties [8, 12].

This paper presents a comprehensive and integrated framework for constructing the digital twin of a UAV by incorporating load tracking, multi-level structural analysis, and probabilistic diagnosis and prognosis. Building on the flight load tracking method introduced in [13], this study employs submodeling to dynamically track and transfer full-field loads to the structural details in real-time. Then, a novel reduced-order fatigue crack growth modeling method, leveraging principal component analysis and neural network fitting, is introduced. This method effectively addresses the crack growth issue within the boundary conditions of the submodel, providing a streamlined solution. Finally, utilizing the constructed reduced-order model, this study facilitates the probabilistic diagnosis and prognosis of fatigue crack growth in structural details based on the overall aerodynamic loading of the aircraft.

2. The Unmanned Aerial Vehicle

In this study, a small UAV, as depicted in [14, 15, 16] and shown in Fig. 1, serves as an exemplary subject for research in structural digital twin development. This UAV exhibits complicated structural configurations and loading conditions, introducing considerable uncertainty into both test data and simulation models. Moreover, the UAV shares significant similarities with large military and civil aircraft, albeit with lower complexity. This makes it an optimal platform for testing the applicability of methods on authentic structures and facilitates the generalization to larger aircraft.

(a) Launching (b) In flight

Figure 1 – The Unmanned Aerial Vehicle

The UAV's flight test lasted approximately 15 minutes. For the purposes of this investigation, only the dynamic forces during flight maneuvers were considered. Table 1 presents the 13 flight parameters documented during the flight test. FBG strain data collected during the flight test was utilized in this study. A total of 26 strain sensors were installed on the UAV, as illustrated in Fig. 2. Among these, 20 strain sensors were used to construct the load tracking model, while 6 FBG strain sensors were employed to test the prediction performance of the corresponding models.

3. Flight Load Tracking

In this study, the flight load tracking method introduced in [13] is adopted, offering a significant advantage by enabling full-field deformation prediction of the aircraft structure during the service phase using only flight parameters, thus eliminating the need for additional sensors. This is achieved by leveraging strain data collected during the flight test phase as the database. The fundamental flow of the proposed framework in this paper is illustrated in Fig. 3 and comprises two phases.

Table 1 – Recorded Flight Parameters

Parameter	**Meaning**	**Unit**	**Frequency**
GyrX, GyrY, GyrZ	X, Y, Z-axis angular velocity	deg/s	50 Hz
AccX, AccY, AccZ	X, Y, Z-axis linear acceleration	m/s^2	50 Hz
IAS	Indicated Airspeed	m/s	10 Hz
AOA	Angle of Attack	deg	10 Hz
SSA	Sideslip Angle	deg	10 Hz
PRESSURE	Atmospheric Pressure	MPa	10 Hz
Alt	Altitude	m	10 Hz
δ_l	Left Aileron Deflection	rad	10 Hz
δ_r	Right Aileron Deflection	rad	10 Hz

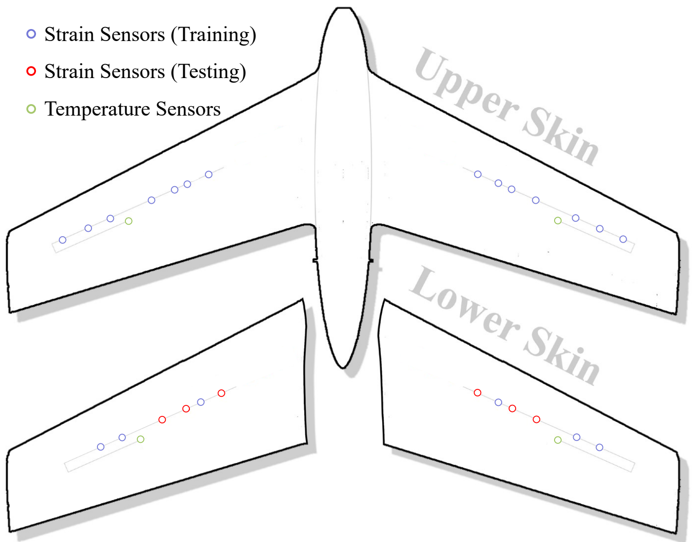


Figure 2 – Schematic Layout of FBG Sensors

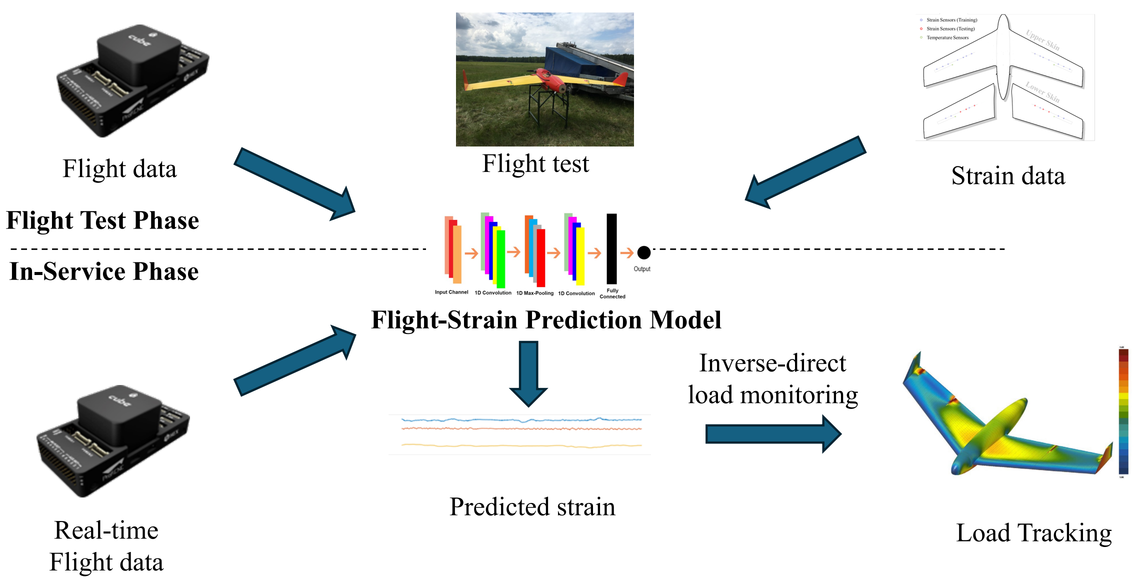


Figure 3 – In-Service Flight Load Tracking Combining the Flight Test Data and Inverse-Direct Load Monitoring

During the flight test phase, a designated set of strain sensors is installed on the aircraft, and flight parameters along with corresponding strain measurements are systematically collected. A local strain prediction model, designed to capture time series dependencies, is trained using a CNN-based deep learning approach. Concurrently, the inverse-direct load monitoring model is trained using a simulation database constructed through the batch simulation of full-order models.
In the service phase, real-time flight parameters of the aircraft are acquired and fed into the data-driven local strain prediction model to generate strain predictions at the respective sensor locations. Subsequently, these predicted strain values serve as inputs for the inverse-direct load monitoring model, which produces flight load tracking results at full-field and any specified position.

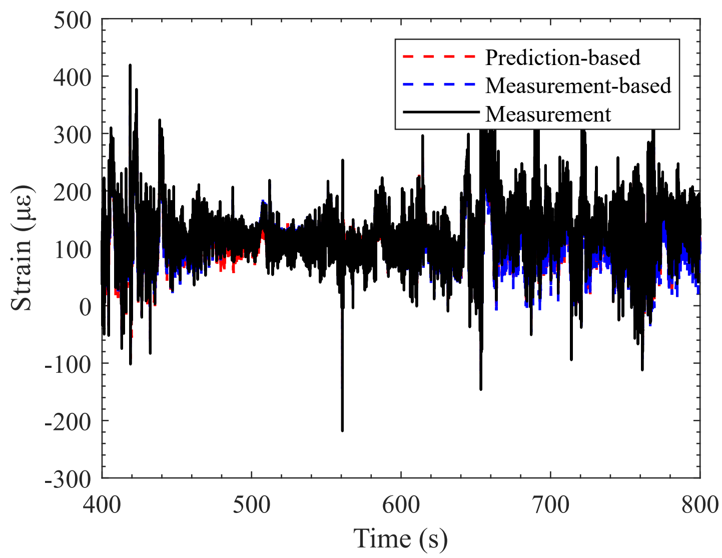


Figure 4 – In-service Load Tracking at the Sixth Test Sensor Location [13]

Fig. 4 depicts the results of the flight load tracking derived from the predictive strain using a convolutional neural network, coupled with an improved inverse-direct load monitoring method. It is evident that the load tracking method yields results comparable to the original strain-based load monitoring method, thus affirming the efficacy of the proposed approach.

4. Multi-level Load Transfer

In this section, to address the scale difference between the overall aerodynamic load and the local stress at the detail, the submodeling method is utilized, significantly enhancing efficiency in simulating fatigue damage at critical locations. The workflow of the submodeling approach is shown in Fig. 5.

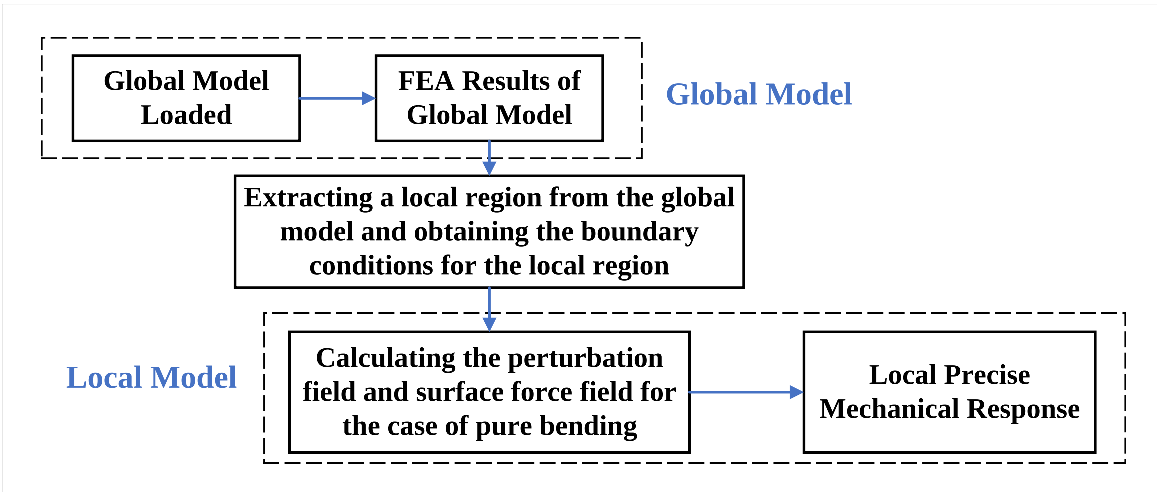


Figure 5 – Flow of the Submodeling for the Load Transfer

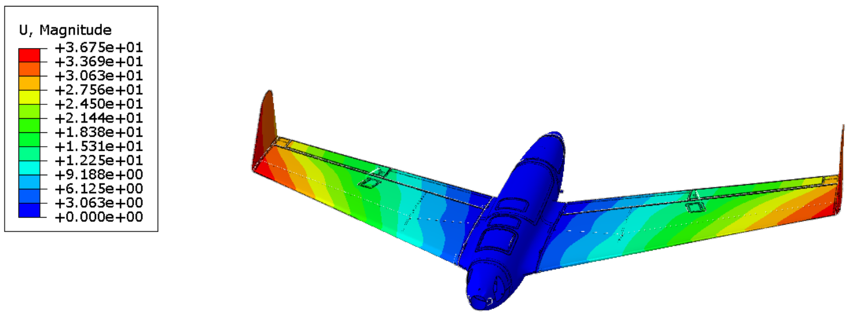
The UAV's selected fatigue-critical location is highlighted in Fig. 6. In the submodel, the overall mesh is intentionally sparse, with finer meshes concentrated at critical locations such as the area of interest for damage simulation.

(a) Location in the UAV

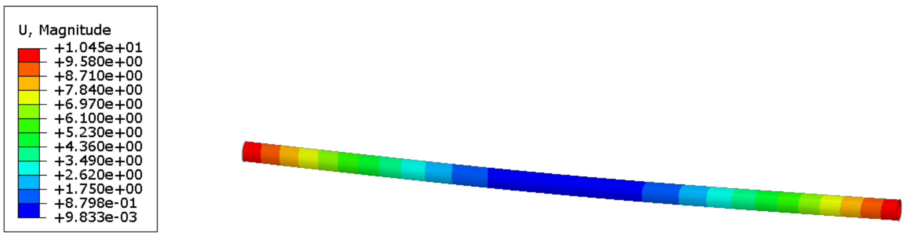
(b) Geometric shape

Figure 6 – Position and Geometry of the Connecting Aluminum Tube

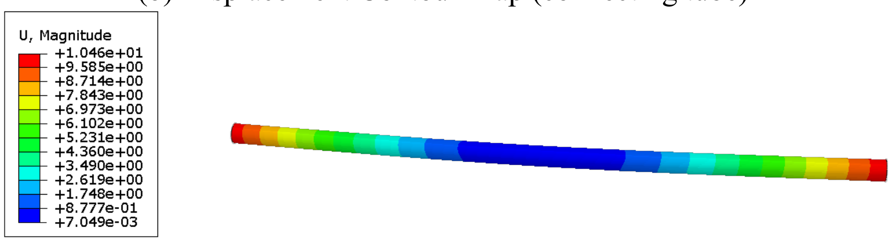
The validation of the aluminium tube sub-model was conducted in ABAQUS. The displacement cloud results are depicted in Fig. 7. It is evident that the displacement contour map of the submodel align closely with those of the global model. This alignment suggests an accurate transfer of displacement boundary conditions to the sub-model.



(a) Displacement Contour Map (Global Model)



(b) Displacement Contour Map (connecting tube)



(c) Displacement Contour Map (submodel of the connecting tube)

Figure 7 – Comparison of Displacement Contour Maps between the Connected Aluminium Tube Sub-model and the Original Model (ABAQUS Simulation)

5. Probabilistic Crack Growth

With the load at the local position acquired through load tracking and transfer, damage growth can be predicted. However, for digital twin applications, conducting full-order fracture mechanics simulations online is challenging. In this section, a novel reduced-order fatigue crack growth modeling method is introduced, leveraging principal component analysis and neural network fitting. This method effectively addresses the crack growth issue within the boundary conditions of the submodel, enabling real-time prediction of fatigue crack growth at critical locations under external aerodynamic loading. To elaborate, in conjunction with the employed principal component analysis method, the boundary conditions are reduced to derive a set of linearly independent loading cases. Subsequently, several reduced-order models (ROMs) of fracture mechanics are constructed for each loading case individually.

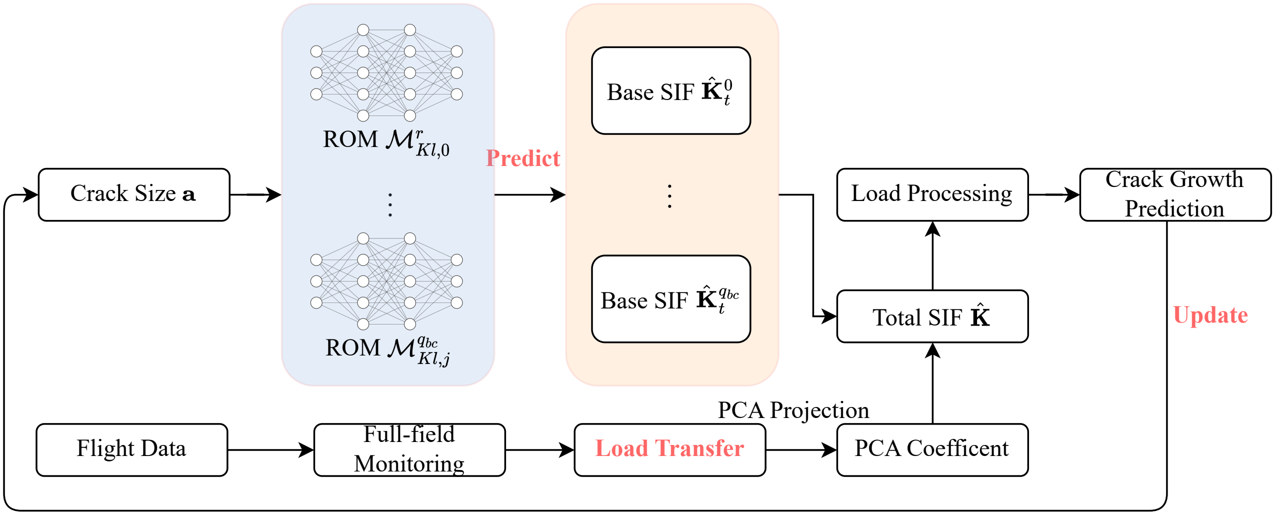


Figure 8 – Online Reduced-order Prediction under Submodel Boundary Condition Loading

In this study, we assume the presence of a crack on the lower side of the central cross-section of the aluminum tube, specifically a tensile crack (Type I crack). Given that the connected aluminum tube is a thin-walled cylindrical structure and the dimensions of the crack surface in the thickness direction are small compared to the other directions, the crack can be analyzed as a circular curve containing the leading edges of the left and right cracks. This crack grows tangentially along the wall of the tube under an external load. This crack grows tangentially along the wall of the tube under an external load. As depicted in Fig. 9, the left and right cracks are represented by the angular parameters θ_l and θ_r (in angular degrees), and the crack lengths are denoted, respectively:

$$\begin{aligned} a_l &= R_m \cdot \theta_l \\ a_r &= R_m \cdot \theta_r \end{aligned} \tag{1}$$

where a_l and a_r represent the left and right lengths of the crack, θ_l and θ_r are parametric representations of the left and right ends of the crack, respectively, and R_m is the average radius of the aluminium tube.

For the construction of the ROM, a batch simulation is performed on 64 samples generated from the sampling process. The simulation utilizes the Symmetric Galerkin Boundary Element Method (SGBEM) super element - Finite Element Method (FEM) coupled program [17]. The SGBEM-FEM fracture mechanics simulation program requires two input files: a finite element model and a crack surface model. A total of 384 fracture mechanics simulations are executed to determine the corresponding stress intensity factors. Six fracture mechanics simulation databases are generated, where the inputs for each sample are the two angular parameters characterizing the crack front. The outputs consist of the average stress intensity factors for the left and right fronts.

Table 2 provides the prediction errors for two crack samples not included in the crack database. The prediction error is within acceptable limits.

6. Diagnosis and Prognosis

Finally, leveraging the constructed digital twin model, a particle filter model is developed to facilitate the probabilistic diagnosis and prognosis of fatigue crack growth at structural details based on the

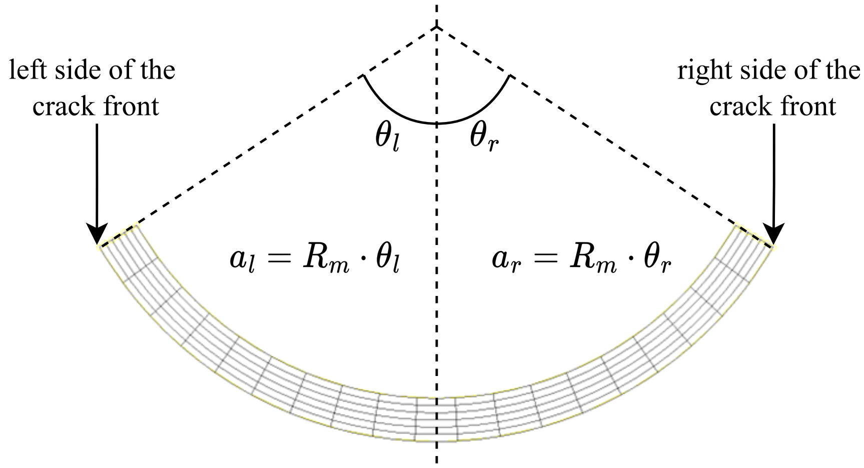


Figure 9 – Crack Definition and Crack Surface Modelling

Table 2 – Comparison of Prediction and Simulation of Stress Intensity Factors Outside Training Crack Samples

Sample	Boundary condition	SGEBM-FEM Simulation		ROM Prediction		RMSE
		Left side	Right side	Left side	Right side	
1	1	48.5268	49.8127	49.6398	49.3985	0.8398
	2	15.6753	16.0897	17.0698	16.0979	0.9861
2	1	70.4269	69.6156	69.5878	69.3872	0.6149
	2	22.7379	22.4722	22.3970	22.6503	0.2719

overall aerodynamic loading of the aircraft. More details about the particle filter can be found in [18, 19].

The complete state transfer equation can be formulated as:

$$\begin{bmatrix} a_k^l \\ a_k^r \\ \log C_k \\ n_k \end{bmatrix} = \begin{bmatrix} a_{k-1}^l + e^{\omega_k} \Delta a_k^l \\ a_{k-1}^r + e^{\omega_k} \Delta a_k^l \\ \log C_{k-1} + \omega_{\log C} \\ n_{k-1} + \omega_n \end{bmatrix} \tag{2}$$

where ω_k is the crack growth process noise, $\omega_{\log C}$ is the process noise of the parameter $\log C$, and ω_n is the process noise of the parameter n.

It is assumed that the total crack length (the sum of the crack lengths on the left and right sides) can be observed by visual inspection, so the observation process can be expressed as follows:

$$y_k = a_k^l + a_k^r + \varepsilon_a \tag{3}$$

where ε_a is the inspection noise.

A crack-growth specimen is assumed for analysis. Fig. 10 illustrates the results of crack diagnosis and prognosis for the hypothetical case. It can be observed that, with the update using inspection data, the prediction of crack growth has become more accurate.

Upon further examination of the model parameter updates in particle filtering, Fig. 11 reveals a trend of narrowing uncertainty parameter distributions with successive inspections. Therefore, it can be concluded that our digital twin can predict fatigue crack growth using flight parameters as input. When inspection data is available, the digital twin model can be updated to provide a more accurate prediction of future damage evolution. These insights can be further utilized to arrange the maintenance of the aircraft fleet, thereby better balancing safety and economy.

7. Conclusion

This study addresses the challenge of scale disparity between overall loading and detailed fatigue damage in aircraft structures through the development of a digital twin for a UAV. This comprehensive

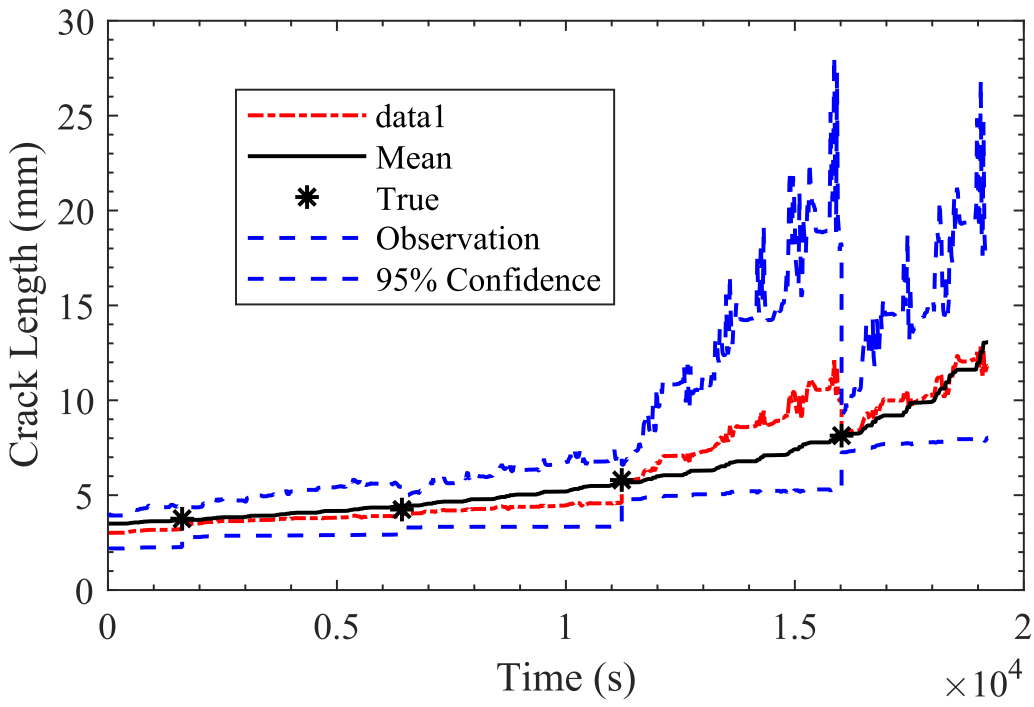


Figure 10 – Crack Diagnosis and Prognosis for the Hypothetical Case

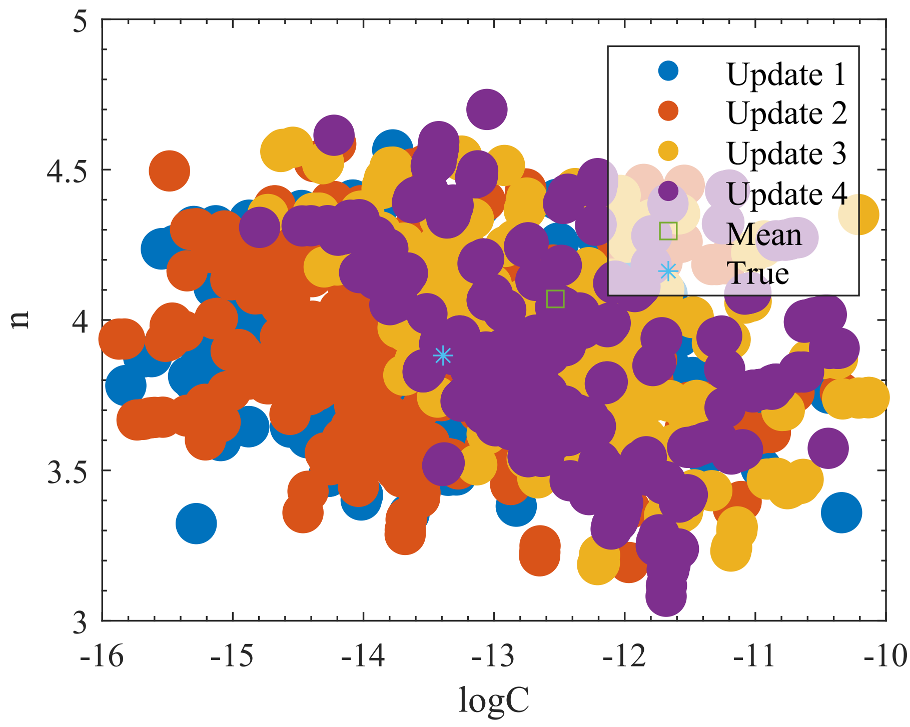


Figure 11 – Updating of Uncertain Parameters for the Hypothetical Case

approach integrates flight load tracking, multilevel load transfer, a novel reduced-order fracture simulation method, and probabilistic diagnosis and prognosis. The proposed methodology contributes to the advancement of digital twin models for unmanned aircraft, offering adaptability, continuous refinement, and potential extensions to more complex structures. Although the validation currently relies on hypothetical UAV damage data, future work involves validation with actual datasets to enhance feasibility. In future research, the aforementioned models will be amalgamated into a comprehensive simulation model utilizing Simulink, accompanied by the development of a visualization system.

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