In-service Load Monitoring for an UAV Digital Twin

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Abstract. A load monitoring system plays an important role in recovering the actual load spectra of aeronautical structures, contributing to the online evolution of airframe digital twins. In scenarios where many aircrafts lack on-board strain sensors during the service phase, yet some strain data is available during the test flight phase, our innovative approach utilises deep learning-based flight-strain prediction and an inverse-direct approach for in-service load monitoring. Initially, a deep learning approach is employed during the test flight prior to service to establish a flight parameter-strain prediction model. This model, incorporating time series features of flight and strain data, exhibits superior predictive accuracy compared to traditional regression methods. Moving into the subsequent service phase, the flight parameter-strain prediction model seamlessly integrates with an inverse-direct load monitoring method. This integrated approach facilitates real-time monitoring of full-field load distribution, relying solely on flight parameters. Validation of the approach utilises flight test data from an unmanned aerial vehicle, revealing better performance compared with the strain-measurement-based method. Notably, our method's efficacy extends across diverse aircraft types, as it does not rely on on-board strain sensors during the service phase.

Keywords: load monitoring, digital twin, deep learning, inverse-direct, aircraft

Introduction

Aircrafts are subjected to continuous aerodynamic loads throughout flight, which causes structural deformation, and the structural fatigue damage may initiate and grow. The acquisition of the actual load history during operation, along with the distribution of structural deformation, is a critical step in tracking structural fatigue and evaluating the structural risk at critical locations through airframe digital twins [1,2]. Various methods for load data acquisition have emerged, including data-driven prediction, simulation-based prediction, and strain-based monitoring.

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The data-driven load prediction relies on the aircraft's flight parameters, capturing the pilot's control actions and external condition changes during flight. Strain sensors are typically installed on a limited number of test aircrafts during the flight test phase, when a surrogate model between flight parameters and measured strains is established based on the multiple linear regression or the artificial neural network [3]. In the subsequent service phase, real-time flight data from different aircrafts are utilized to predict loads at critical locations.

The simulation-based prediction involves leveraging data from a flight parameter recorder and employing surrogate models trained by full-order simulations including flight mechanics, computational fluid dynamics, and finite element structural analysis [4]. While offering detailed load distribution information, the accuracy of simulation-based methods depends on model fidelity, posing challenges in ensuring predicted results' credibility.

The strain-based load monitoring methods involve strategically placing sensors on the structure to directly measure strains and obtain load information at critical locations. Then methods including the inverse Finite Element Method (iFEM) [5] and calibration matrix methods [6,7] are adopted to obtain the full-field information. While strain-based methods offer high resolution, sensor installation and maintenance during the service phase can be challenging.

Given the complexity of equipping strain sensors during the service phase compared to the flight test phase, this study proposes a novel strain sensor-free in-service load tracking approach. Combining deep learning-based prediction with inverse-direct monitoring, the approach is validated using realistic flight test data from an Unmanned Aerial Vehicle (UAV). The innovations within the framework include: (1) the application of a deep learning method capable of accommodating time series dependencies to construct a surrogate model, thereby enhancing the accuracy of strain predictions at specific locations; (2) the incorporation of the flight parameter-strain prediction model with an improved inverse-direct load monitoring model, facilitating the tracking of deformation distribution across the field based on predicted strains. Results demonstrate comparable outcomes to strain-based load monitoring, suggesting potential applications in aircraft service phases.

The remainder of this paper is organised as follows: Section 1 describes the proposed in-service load tracking approach. Section 2 outlines the UAV configuration, available data, and model. Results and discussions are presented in Section 3, followed by concluding remarks in Section 4.

1. Methodology

In this section, a novel in-service flight load tracking framework is proposed, which is rooted in the existing individual aircraft tracking concept, with the primary objective of addressing the previously mentioned challenges.

1.1 In-service Load Tracking Framework

Our proposed approach offers a significant advantage by enabling full-field deformation prediction of the aircraft structure during the service phase using only flight parameters, eliminating the need for additional sensors. This practical feature enhances the utility of existing models. Moreover, in contrast to fully simulation-based prediction, our approach integrates acceleration data into the results and circumvents errors introduced by aerodynamic simulation. 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. 1, and comprises two distinct phases.

1. Flight Test Phase

During this 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 based on the simulation database.

2. Service Phase

In the service phase, real-time flight parameters of the aircraft are acquired and inputted into the strain prediction model to generate local strain predictions at the corresponding sensor locations. Subsequently, these predicted strains are utilized as input for the inverse-direct load monitoring, yielding flight load tracking results at full-field and regions of interest.

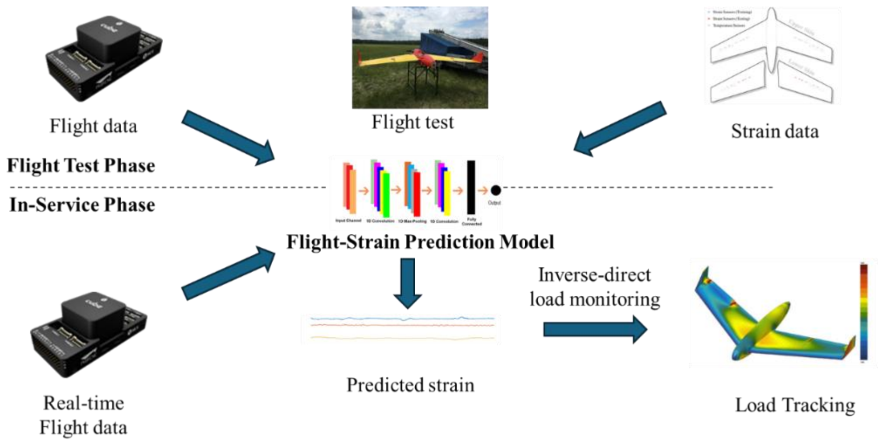

Fig. 1 In-service load monitoring

In the next two subsections, the two basic modules of the framework are introduced, respectively.

1.2 CNN-based local strain prediction

This subsection introduces the design of a local strain prediction model that integrates time-series dependency. This model leverages the One-Dimensional Convolutional Neural Network (1D-CNN) as foundational components. Training of the model is conducted using recorded flight parameters and strain data obtained from the UAV under examination.

As shown in Fig. 2, the CNN-based local strain prediction model encompasses key components, including an input layer, convolution modules, fully connected layers, and an output layer. By varying the number of convolution modules, diverse structures and parameter configurations for the CNN-based strain prediction model can be attained.

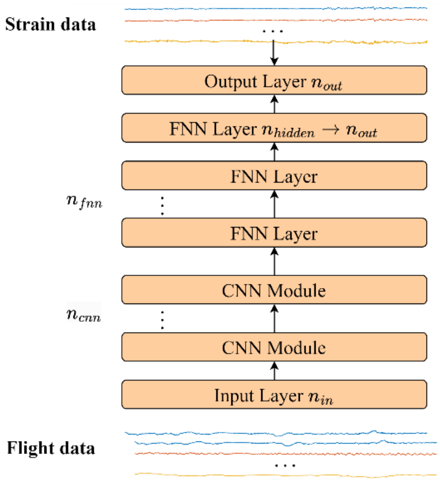

Fig. 2 Basic structure and component modules of load prediction neural networks

The network undergoes a training process utilising a dataset comprising paired flight parameter and strain measurement. During training, the mechanism involves iteratively adjusting the weights and biases of the network to minimise the disparity between predicted and actual strain values. The Mean Squared Error (MSE) loss function is employed to guide the network towards optimal parameter learning by measuring the square of the difference between predicted and true values. The training process utilises the Adam optimizer, which iteratively updates the network parameters to enhance the efficiency of the learning process.

1.3 Inverse-direct Load Monitoring

The inverse-direct method, based on reduced-order aerodynamic loads with linear regression, is delineated into two distinct processes: the inverse load estimation process and the direct deformation prediction process.

The construction process of the inverse-direct load monitoring model is graphically depicted in Fig. 3. Within the simulation database, we obtain key parameters such as the aerodynamic load distribution $\mathbf{L}^{\mathrm{sim}}$, the deformation field distribution $\mathbf{F}^{\mathrm{sim}}$, and the virtual sensing value $\boldsymbol{\varepsilon}_{\mathrm{FBG}}^{\mathrm{sim}}$ corresponding to each sample from strain sensors.

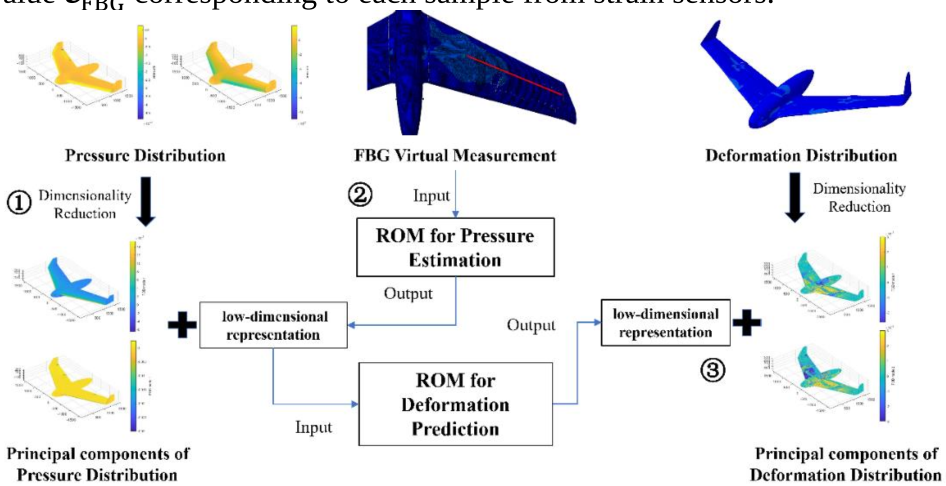

Fig. 3 Workflow of the inverse-direct model construction

The inverse load inversion process is examined first. The relationship between strain measurements $\boldsymbol{\varepsilon}_{\mathrm{FBG}}$ and flight aerodynamic loads $\mathbf{L}$ can be expressed as a linear relationship for most aircraft structures without a high aspect ratio:

$$\boldsymbol{\varepsilon}_{\mathrm{FBG}} = \mathbf{N}_{L\varepsilon}^{\mathrm{T}}\mathbf{L} \tag{1}$$

Then, a reduced-dimensional representation of the aerodynamic loads $\mathbf{L}_{\mathrm{rd}}$ is obtained using the principal component analysis (PCA):

$$\mathbf{L}_{\mathrm{rd}} = \mathbf{U}_{M\times q_L}^{\mathrm{T}}(\mathbf{L} - \bar{\mathbf{L}}) \tag{2}$$

where $\mathbf{U}_{M\times q_L}^{\mathrm{T}}$ is the linear transformation matrix from aerodynamic loads to strain sensor measurements, $\bar{\mathbf{L}}$ is the mean aerodynamic load in the dataset.

Then the mapping model for the low-dimensional representation of the aerodynamic loads $\mathbf{L}_{\mathrm{rd}}$ to the strain sensor measurements $\boldsymbol{\varepsilon}_{\mathrm{FBG}}$ is:

$$\boldsymbol{\varepsilon}_{\mathrm{FBG}} = (\mathbf{U}\mathbf{N}_{L\varepsilon})^{\mathrm{T}}\mathbf{L}_{\mathrm{rd}} + \mathbf{N}_{L\varepsilon}^{\mathrm{T}}\bar{\mathbf{L}} = \boldsymbol{\alpha}_{L\varepsilon}\mathbf{L}_{\mathrm{rd}} + \boldsymbol{\alpha}_{L\varepsilon,0} \tag{3}$$

where $\boldsymbol{\alpha}_{L\varepsilon} = \mathbf{N}_{L\varepsilon}^{\mathrm{T}}\mathbf{U}^{\mathrm{T}}$ is known as the calibration matrix, and $\boldsymbol{\alpha}_{L\varepsilon,0} = \mathbf{N}_{L\varepsilon}^{\mathrm{T}}\bar{\mathbf{L}}$ is a bias vector caused by the mean value of principal component analysis. Both $\boldsymbol{\alpha}_{L\varepsilon}$ and $\boldsymbol{\alpha}_{L\varepsilon,0}$ can be obtained from the simulation database through linear regression.

When performing strain measurements with Fibre Bragg Grating (FBG) sensors, Consequently, the effects of temperature must be thoroughly addressed when tracking flight loads. In this context, a strategy for temperature estimation and compensation is adopted [7]. Taking the measurement error due to thermal strain $\boldsymbol{\varepsilon}_{\Delta T}$ into account in the load monitoring model:

$$\boldsymbol{\varepsilon}_{\mathrm{FBG}} = \boldsymbol{\varepsilon}_{\mathrm{L}} + \boldsymbol{\varepsilon}_{\Delta T} = [\boldsymbol{\alpha}_{L\varepsilon} \quad \boldsymbol{\alpha}_{\Delta T}]\begin{bmatrix}\mathbf{L}_{\mathrm{rd}}\\ \Delta\mathbf{T}\end{bmatrix} + \boldsymbol{\alpha}_{\mathrm{L}\varepsilon,0} = \boldsymbol{\alpha}_{\mathrm{tot}}\mathbf{L}_{\mathrm{tot}} + \boldsymbol{\alpha}_{L\varepsilon,0} \tag{4}$$

where $\mathbf{L}_{\mathrm{tot}} = \begin{bmatrix}\mathbf{L}_{\mathrm{rd}}\\ \Delta\mathbf{T}\end{bmatrix}$ represents the augmentation vector for the load estimation, and $\boldsymbol{\alpha}_{\mathrm{tot}} = [\boldsymbol{\alpha}_{L\varepsilon} \quad \boldsymbol{\alpha}_{\Delta T}]$ is the augmentation corresponding to the calibration matrix.

During the flight, the reduced-dimensional model for predicting aerodynamic loads is:

$$\hat{\mathbf{L}}_{\mathrm{tot}} = (\boldsymbol{\alpha}_{\mathrm{tot}}^{\mathrm{T}}\boldsymbol{\alpha}_{\mathrm{tot}})^{-1}\boldsymbol{\alpha}_{\mathrm{tot}}^{\mathrm{T}}\left(\boldsymbol{\varepsilon}_{\mathrm{FBG}}^{\mathrm{meas}} - \boldsymbol{\alpha}_{L\varepsilon,0}\right) = \boldsymbol{\alpha}_{\mathrm{tot}}^{+}\left(\boldsymbol{\varepsilon}_{\mathrm{FBG}}^{\mathrm{meas}} - \boldsymbol{\alpha}_{L\varepsilon,0}\right)$$

Upon obtaining $\hat{\mathbf{L}}_{\mathrm{tot}}$ through the inversion of measured strains $\boldsymbol{\varepsilon}_{\mathrm{FBG}}^{\mathrm{meas}}$, simultaneous derivations of the aerodynamic load distribution $\hat{\mathbf{L}}_{\mathrm{rd}}$, and the temperature change $\Delta\hat{\mathbf{T}}$ can be achieved.

Then, the full-field deformation $\mathbf{F}$ of the aircraft can be determined through forward prediction. The mapping relationship between the low-dimensional representation of the aerodynamic loads $\mathbf{L}_{\mathrm{rd}}$ and the full-field deformation $\mathbf{F}$ is expressed as follows:

$$\mathbf{F} = \boldsymbol{\alpha}_{LF}\mathbf{L}_{\mathrm{rd}} + \boldsymbol{\alpha}_{LF,0} \tag{5}$$

where $\boldsymbol{\alpha}_{LF} = \mathbf{N}_{LF}^{\mathrm{T}}\mathbf{U}^{\mathrm{T}}$ represents the scaling factor between the reduced-dimensional load and the full-field deformation. The $\mathbf{N}_{LF}$ is the matrix of linear transformations from aerodynamic loads to strain sensor measurements, and $\boldsymbol{\alpha}_{LF,0}$ is the bias term.

2. Application to an Unmanned Aerial Vehicle

2.1 UAV configuration and flight test

The flight test data employed in this study is derived from a UAV as shown in Fig. 4.

(a) Launching

(b) In flight

Fig. 4 The Unmanned Aerial Vehicle

The UAV's flight test lasted for approximately 15 minutes. For the purposes of this investigation, only the dynamic forces during flight manoeuvres were considered. Table 1 displays the 13 flight parameters documented during the flight test.

FBG strain data collected during the flight test was used in this study. A total of 26 strain sensors were installed on this UAV. Among them, 20 strain sensors were used to construct the load tracking model, while 6 FBG strain sensors were used to test the prediction performance of the corresponding models.

Table 1 Recorded Flight Parameters

Parameter	Meaning	Unit	Frequency
GyrX, GyrX, GyrZ	X, Y, Z-axis angular velocity	deg/s	50 Hz
AccX, AccY, AccZ	X, Y, Z-axis translational acceleration	m/s^2	50 Hz
IAS	Indicated Airspeed	m/s	10 Hz
AOA	Angle of Attack	deg	10 Hz
SSA	Angle of Sideslip	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

2.2 Simulation database generation

In this subsection, leveraging the aerodynamic and structural simulation models of the UAV, a corresponding simulation database is meticulously constructed for the training of the reduced-order simulation model. This constructive process is executed employing PANUKL aerodynamic simulation software and ABAQUS structural simulation software.

Table 2 Flight parameters utilised in the simulation database generation

Parameter	Meaning	Lower Limit	Upper Limit	Unit
V	Indicated Airspeed	0.01	100	m/s
α	Angle of Attack	-10	15	deg
β	Sideslip Angle	-15	15	deg
p	Roll Rate	-0.1	0.1	rad/s
q	Pitch Rate	-0.1	0.1	rad/s
r	Yaw Rate	-0.02	0.02	rad/s
δ_l	Left Aileron Deflection	-10	20	rad
δ_r	Right Aileron Deflection	-10	20	rad

Table 2 delineates the specific eight flight parameters employed in the simulation, along with their respective ranges. 2000 samples are generated utilising the Latin hypercube sampling method. The upper and lower limits are determined based on the range of measured flight data. Utilising the PANUKL software in conjunction with batch simulation scripts, the aerodynamic load distribution corresponding to 2000 samples was computed employs eight flight parameters as inputs. These samples adhere to a consistent form of face element division and an identical number of panels.

Following the acquisition of the aerodynamic load distribution for the 2000 samples, the loads are interpolated onto the outer surface of the finite element model in ABAQUS. Subsequently, structural simulation is executed through the batch simulations in ABAQUS. The load and deformation distribution data pertaining to the entire aircraft, specific components, or regions of interest is retrieved from the ABAQUS output database files. The virtual strain in correspondence of the location of the real FBG strain sensors are also extracted from the simulation database.

3. Performance verification

3.1 Performance comparison of the inverse-direct load monitoring

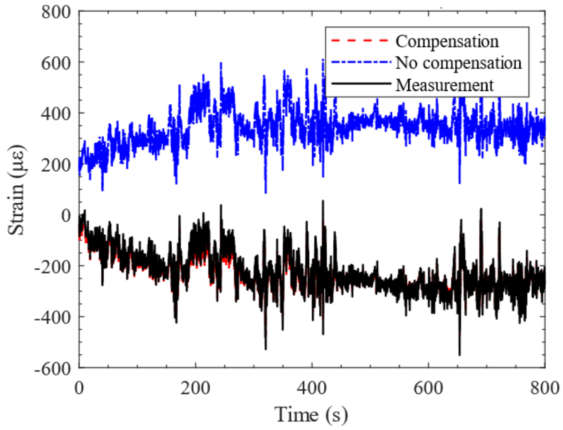

Fig. 5 Inversed strain at the sixth test sensor location

In Fig. 5, we visualise the predicted strains for the FBG sensors at the sixth test location. The strain predictions, incorporating a temperature compensation strategy, exhibit a close alignment with the measured results. Conversely, without temperature compensation, significant disparities emerge in the results.

3.2 Performance comparison of data-driven strain prediction

The prediction results for the test samples in the second half of the flight test are presented in Fig. 6. The 1D-CNN in Fig. 6(a) excellently captures the high-frequency variation of strain, yielding prediction results closely aligned with measured values. Conversely, the fully-connected neural network (FNN) in Fig. 6(b) produces smoother results with deviations.

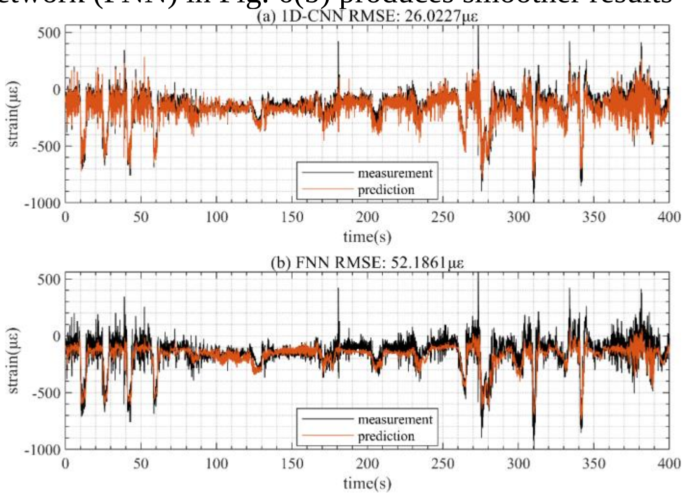

Fig. 6 Comparison of strain prediction results

3.3 Performance of the in-service load tracking

Fig. 7 depicts the outcomes of flight load tracking derived from the predictive strain utilising a convolutional neural network, coupled with the improved inverse-direct load monitoring method. As the convolutional neural network model was trained using data from the first half of the flight test, only results from the latter portion are presented herein. It is evident that the fusion of deep learning and load inversion, as employed in this section, yields result comparable to the original strain-based load monitoring method, thus affirming the efficacy of the proposed approach.

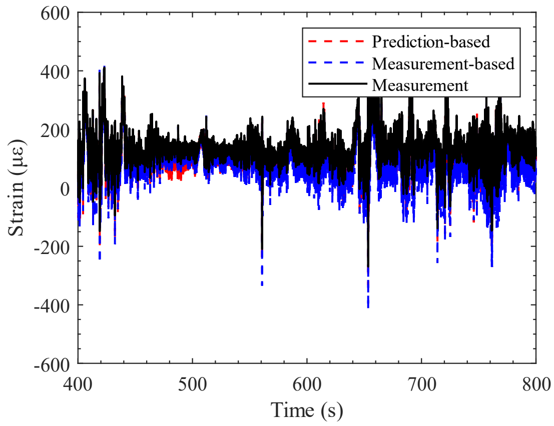

Fig. 7 In-service load tracking result at the sixth test sensor location

4. Conclusions

In this study, a novel flight load tracking framework tailored to the airframe digital twin's flight load acquisition requirements is proposed. The framework integrates available flight and strain data from UAVs with aerodynamic and structural simulation models. The data-driven load prediction model is combined with the inverse-direct method to achieve full-field load tracking during the service phase. This approach's advantage lies in its ability to be trained based on flight and strain data during the test flight phase, enabling the prediction of full-field load during the service phase without the need for additional strain sensors. Further validation through multiple sets of flight tests and across multiple aircraft of the same type is required.

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