Title
Development of a Surrogate Model for Structural Health Monitoring of a UAV Wing Spar

ISBN
9783031041211

Authors
Razzini, Adrielly H
Kressel, Iddo
Ofir, Yoav
et al.

Publication Date
2022

DOI
10.1007/978-3-031-04122-8_12

Peer reviewed

Development of a Surrogate Model for Structural Health Monitoring of a UAV Wing Spar

Adrielly H. Razzini [1], Iddo Kressel[2], Yoav Ofir[2], Moshe Tur[3], Tal Yehoshua[3], Michael Todd[1]

[1] Department of Structural Engineering
University of California San Diego, 9500 Gilman Dr, La Jolla CA, USA

[2] Engineering Division, Israel Aerospace Industries (IAI), Ben Gurion International Airport, Israel

[3] School of Electrical Engineering, Tel-Aviv University, Tel-Aviv, Israel

ABSTRACT
A critical part to implementing a structural health monitoring system is being able to understand the structural response under different operational and environmental conditions. In this work, a detailed finite element model of an unmanned aerial vehicle's wings' spar was developed to serve as a synthetic data generator. A probabilistic understanding of the aerodynamic loads, and debonding damages at different locations and with different sizes were implemented to simulate observations of the spar's performance in service. The target measurements are uniaxial strain, measured in several paths throughout the spar. Given measured strain, the damage assessment problem is probabilistically formulated by defining local buckling from debonding as the observable damage, which is fundamentally characterized by load-dependent buckling eigenvalues. This FE physical model is highly computationally intensive, so a Gaussian process regressor and a multi-layer artificial neural network (MANN) were designed to serve as a "run time" surrogate model to learn the relationships between inputs (loads and damage conditions) and outputs (strain measurements and buckling eigenvalues). The results illustrate that the surrogate models presented are a reliable replacement to the computationally expensive inverse finite element model in damage identification.

Keywords: Structural Health Monitoring, Finite Element, Surrogate Model, Gaussian Process Regressors, Neural Networks

INTRODUCTION
Modern unmanned aerial vehicles (UAVs) have high performance demands and are often subjected to extreme loading and environmental conditions. They are typically constructed from composite materials due to high strength-to-weight ratios [1], but such materials might suffer internal damage without any obvious changes on the surface, only becoming evident in the proximity of failure. According to aviation requirements, any damage that would prevent the aircraft from carrying its ultimate service load must be detected [2]. In this work, the structure being monitored is the wing spar of a UAV, and the observable damage was defined as debonding of the spar's top flange from the shear clips and web. As the wings deflect upwards during flight and the top flange is compressed, this debonding can cause local buckling, which is critical to the structure. An FE model was developed to simulate hundreds of different combinations of damage size and location along the beam. Then, using this data for training, validation and testing, machine learning was used to create an inexpensive surrogate model to learn the relationships between inputs (loads and damage conditions) and outputs (strain measurements and buckling eigenvalues).

The FE model was developed using ABAQUS CAE. The spar is 5m long and is entirely made of carbon fiber reinforced polymer composites, with a sandwich panel web. To reduce computational costs, 3D linear shell elements were used instead of solid elements, and only a sub model of the first 1m of beam was analyzed in this work. The damage is fully characterized by the damage parameters $\boldsymbol{\theta} = \{\boldsymbol{\sigma}, \boldsymbol{x}\}$, where $\boldsymbol{\sigma}$ and $\boldsymbol{x}$ are independent random variables that refer to damage size and location, respectively. The debonding damage was introduced by removing a section of the bonding (tie constraints) between the top flange and the rest of the structure, as shown in Fig. 1 (a). Fig. 1 (b) shows a case where local buckling occurred as consequence of the debonding. The expected maximum service load was applied to the structure, and the analysis was divided into two independent steps – static, to measure uniaxial strain at several paths along the beam, and buckle, to provide buckling eigenvalues (λ). Prior probability density functions of the damage parameters $\boldsymbol{\theta}$ were used to create a comprehensive database of 2,500 different samples, that were simulated on ABAQUS, using a Python script to handle the model changes and data storage. The simulation is very computationally expensive, as one case takes up to 15 minutes to run.

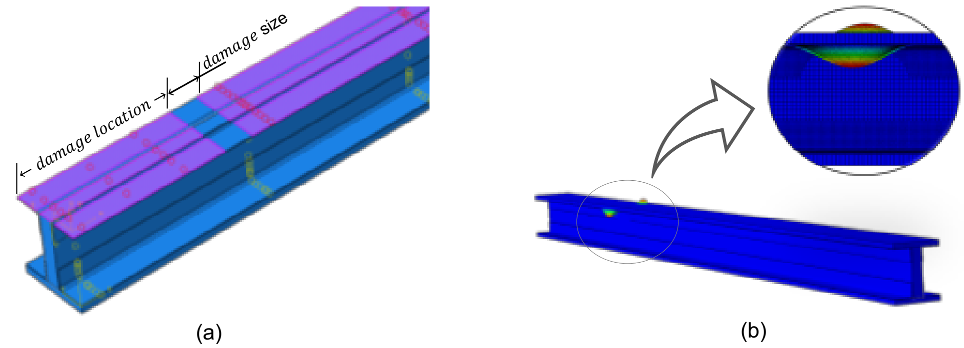

Fig. 1 Snapshots of the finite element model. **(a)** The top flange was suppressed from the view to display the debonding damage, introduced by removing the tie constraints. **(b)** Results of the buckling analysis, where local buckling occurred

STRAIN PREDICTION USING AN ARTIFICIAL NEURAL NETWORK

Bayesian inference can be used to produce a stochastic estimation of damage parameters, or even to choose an optimal sensor placement design considering Bayes risk. However, the likelihood $p(\boldsymbol{\varepsilon}|\boldsymbol{\theta})$ needs thousands of samples to be properly evaluated, where $\boldsymbol{\varepsilon}$ are the strain measurements. Running the FE model to do so is prohibitively time consuming, so a multi-layer neural network was created on MATLAB to act as a "run-time" surrogate model.

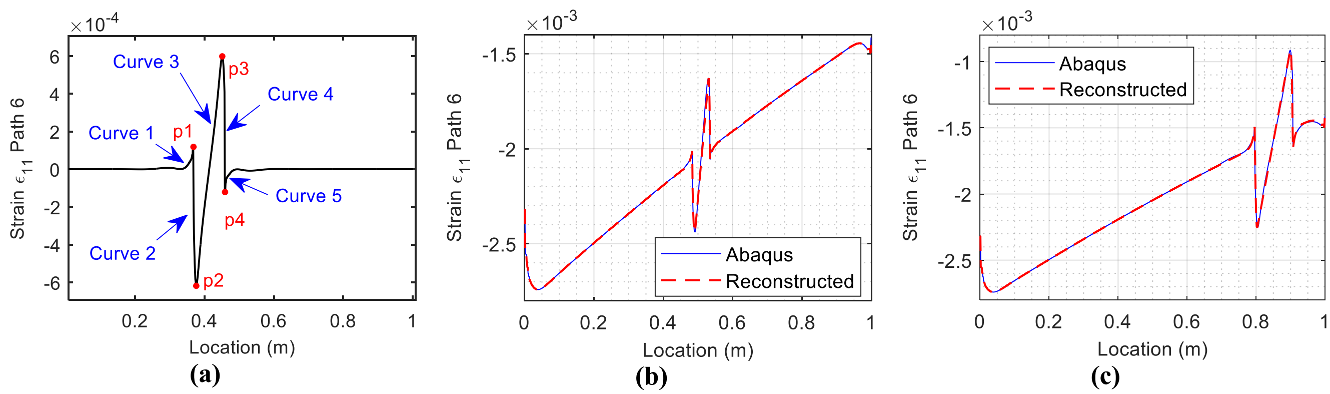

Fig. 2 (a) Strain measurement without baseline, divided into 5 curves that can be described by the coordinates of points p1-p4. **(b, c)** Strain measurement from Abaqus vs MANN reconstruction for different damage sizes and locations

To do so, strain measurements were collected from a path below the top flange, and the baseline signal was removed from them. Then, they were divided in 5 curves, as shown in Fig. 2 (a), and general equations that fully describe the strain signature based on the coordinates (x,y) of points p1 to p4 were found. These 8 coordinates are the target outputs from the regression MANN, and the two input features are damage size and location. Unlike normal regression where a single output value is predicted for each sample, multi-output regression requires specialized machine learning algorithms, such as deep neural networks, that support outputting multiple variables for each prediction. An advantage of these multi-output approaches is that they might produce simpler models with improved computational efficiency [3]. The number of hidden layers was defined first in a simple optimization. Then, a Bayesian optimization was performed to define the values of six hyperparameters of the NN.

Samples of strain reconstruction using the 8 coordinates predicted by the trained NN are shown in Fig. 2 (b) and (c), and the results produced an average RMSE of 0.0067 for the testing data set. Evaluating a single sample takes around 10^{-3} seconds.

THE GAUSSIAN PROCESS REGRESSOR

Given that $failure\ load = \lambda \times applied\ load$, the buckling eigenvalues can estimate the percentage of the applied loads the structure can withstand before the structure fails (i.e., local buckling occurs). This eigenvalue can be obtained using the FE model, but its high computational time makes it not suitable for real-time applications. Thus, a GPR was built as a surrogate model to learn the relationship between $\boldsymbol{\theta}$ and λ. When compared to traditional NN models that only provide point estimates, the GPR models also provide standard deviations of the predictions, that can be used to infer their expected accuracy [4]. A squared exponential kernel was used, and the 2,500 samples were randomly divided in a 70/30 train/test split. The predictions using the GPR model yielded a RMSE=0.00281, and the results for the testing data set are shown in Fig. 3.

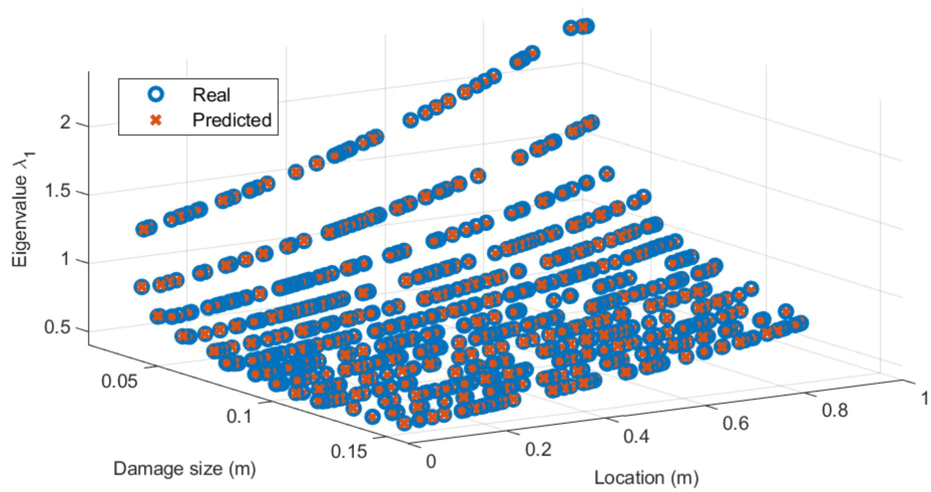

Fig. 3 Buckling eigenvalues obtained using ABAQUS (blue) vs. predicted using the GPR model (orange).

CONCLUSION

This work presented a high-fidelity finite element model of an UAV wing's spar and introduced occasions in which using a surrogate model might be necessary. The results illustrate that the surrogate models presented had small RMSEs and are a reliable replacement to the computationally expensive inverse finite element model in damage identification. This approach directly supports modern model-assisted probability of detection approaches.

ACKNOWLEDGEMENTS

This work is sponsored by the Israel Ministry of Defense under contract award #PO 4441026546.

REFERENCES

[1] Grodzki, W. and Łukaszewicz, A., "Design and manufacture of umanned aerial vehicles (uav) wing structure using composite materials: Planung und bau einer flügelstruktur für unbemannte luftfahrzeuge (uav) unter verwendung von kompositwerkstoffen". *Materialwissenschaft und Werkstofftechnik*, *46*(3), pp.269-278, 2015

[2] North Atlantic Treaty Organization (NATO), "AEP-4671 Unmaned Aircraft Systems Airworthiness Requirements (USAR)*,* Edition B, Version 1*"*. Nato Standardization Office, pp. 70-79, 2019

[3] Kocev, D., Džeroski, S., White, M. D., Newell, G. R., and Griffioen, P., "Using single-and multi-target regression trees and ensembles to model a compound index of vegetation condition". *Ecological Modelling*, *220*(8), 1159-1168, 2009

[4] Teimouri, H., Milani, A.S., Loeppky, J. and Seethaler, R., "A Gaussian process–based approach to cope with uncertainty in structural health monitoring". *Structural Health Monitoring*, *16*(2), pp.174-184, 2017