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DOI
10.1007/978-3-031-07254-3_21

Publication date
2023

Document Version
Final published version

Published in
European Workshop on Structural Health Monitoring, EWSHM 2022, Volume 1

Citation (APA)
Milanoski, D., Galanopoulos, G., Zarouchas, D., & Loutas, T. (2023). Damage Diagnostics on Post-buckled Stiffened Panels Utilizing the Digital-Twin Concept. In P. Rizzo, & A. Milazzo (Eds.), *European Workshop on Structural Health Monitoring, EWSHM 2022, Volume 1* (pp. 213-222). (Lecture Notes in Civil Engineering; Vol. 253 LNCE). Springer. https://doi.org/10.1007/978-3-031-07254-3_21

Damage Diagnostics on Post-buckled Stiffened Panels Utilizing the Digital-Twin Concept

Dimitrios Milanoski[1(✉)], Georgios Galanopoulos[1], Dimitrios Zarouchas[2,3], and Theodoros Loutas[1]

[1] Applied Mechanics Laboratory, Department of Mechanical Engineering and Aeronautics, University of Patras, 26504 Rio, Greece
d.milanoski@upatras.gr
[2] Structural Integrity and Composites Group, Faculty of Aerospace Engineering, Delft University of Technology, Kluyverweg 1, 2629HS Delft, The Netherlands
[3] Center of Excellence in Artificial Intelligence for Structures, Prognostics and Health Management, Faculty of Aerospace Engineering, Delft University of Technology, Kluyverweg 1, 2629HS Delft, The Netherlands

Abstract. A digital twin representative of a typical composite stiffened panel is utilized to monitor skin-to-stringer disbonds. A validated finite element model of the composite panel estimates the longitudinal strains of the pristine state, at the exact location where integrated fiber Bragg grating sensors are permanently installed. Experimental strains are acquired and compared to those provided by the digital twin in order to reveal the presence of disbonds. The integrated sensor grid is used in a manner that some sensors identify the load acting on the panel, leveraging on the digital twin baseline, whilst the remaining ones are dedicated for diagnostic purposes. Two damaged single-stringer panels are tested under compression-compression fatigue conditions. Static strains are received during quasi-static test intervals among the fatigue cycles. The historical strain data are analyzed in a near real-time manner to detect and localize the induced damage throughout the test span.

Keywords: Structural health monitoring · Digital twin · Composite stiffened panels · Fiber Bragg grating sensors

1 Introduction

Engineering communities are progressively adopting the concurrent concepts of Industry 4.0, Internet-of-Things, towards an overall shift to the digital transformation [21]. In this technological melting pot, the *digital twin* (DT) concept, introduced in the previous decade [8,20], is increasingly finding a wide range of applications among different industrial sectors [10]. The position paper by AIAA and AIA thoroughly presents the value of DT in alignment with the

P. Rizzo and A. Milazzo (Eds.): EWSHM 2022, LNCE 253, pp. 213–222, 2023.
https://doi.org/10.1007/978-3-031-07254-3_21

needs of the aerospace industry [1]. In an attempt to encompass all the documented definitions, a short one was given: "*A DT is a virtual representation of a connected physical asset*". Beyond that point, a cooperative framework is occasionally developed to connect the virtual with the physical counterpart [19]. Structural Health Monitoring (SHM) methodologies shall thrive in the existence of a DT, which provides valuable feedback to the physical asset based on measurements received from the latter. However, the context within a DT is capable of generalizing its response should be wisely considered [22]. The DT becomes a powerful tool if further meta-modeling actions are pursued based on a validated numerical model, e.g. finite element (FE) model. The idea of training offline meta-models (also referred as surrogate models) with data generated by FE models is currently gaining spiraling attention [2,4,7,11,12,14,16–18]. Diagnostics, as well as prognostics, are tackled utilizing surrogate models in an attempt to leverage in-situ sensor measurements and provide near real-time predictions.

The present paper exploits a validated nonlinear FE model of a composite single-stringer panel (SSP) subjected to uniaxial compression that leads to the overall buckling of the panel. Damage diagnostics are performed in a manner of comparing strain readings received from the real panel with those of a pristine baseline, provided by the FE model. The DT concept is adopted such that exogenous details that affect the SHM (strain) measurements, i.e. compressive load magnitude and the buckling mode shape, are predicted by the pristine FE model. Fiber Bragg grating sensors (FBGs), embedded in a commercial glass-epoxy fiber-optic sensor (FOS) tape, i.e. SMARTAPE™ [9] provided by SMARTEC S.A., are placed along the two feet of the SSP. The sensor grid is divided into the reference sensors, aiming to identify the exogenous details, and the evaluation sensors which are used to assess the presence of skin-to-stringer damage. The two groups are correlated, as the evaluation sensors rely on the predictions yielded by the reference sensors in order to properly compare the experimental strains with the analogous from the pristine DT. The proposed strain-based methodology leverages on the local redistribution of the strain field

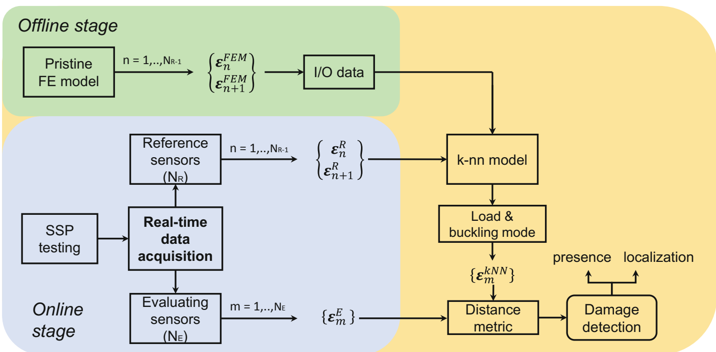

Fig. 1. Outlook of the proposed SHM methodology.

in the proximity of damage [3,14]. We illustrate the scenario of harnessing the reference sensors, which are placed far from potentially damaged regions, and their readings may be safely correlated to the pristine FE model. The developed methodology is treated as a typical supervised classification problem with models trained from the pristine FE model. The conceptual idea is shown in Fig. 1.

2 Supervised Baseline Model

In this section, the development of a supervised classification SHM methodology is described. Training data points are generated by a validated FE model corresponding to the pristine state of the SSP [13,14]. Real-time strains, interrogated by a reference sensor group, are utilized to associate the recorded strains to a load level as well as the buckling mode of the SSP before proceeding to the diagnostic actions.

2.1 Intuition

The composite SSP is imposed to extensive compressive loads which lead to buckling of the panel. The particular SSP, as previewed in Fig. 2a, is already studied and a FE model has been verified in our previous works [15]. Experimental observations accompanied by the numerical model revealed the buckling behavior of the structure. More specifically, the buckling shape is majorly controlled by the first mode shape, i.e. forming one half-wave. However, it is probable that the panel buckles towards one direction or the exact opposite, as shown in Fig. 2b,c. Henceforth we consider Mode 0 the buckling condition under which regions with positive coordinates along the x-axis present negative out-of-plane

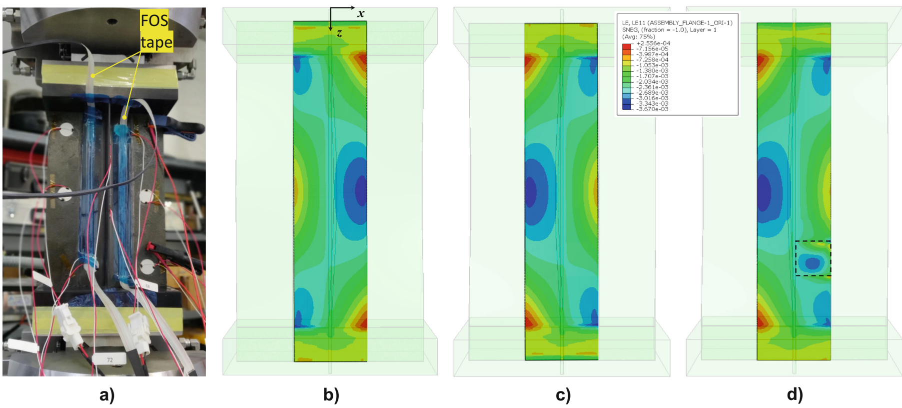

Fig. 2. a) Preview of the sensorized composite SSP. Simulated pristine strain field along the stringer flange for buckling b) Mode 0, c) Mode 1 and d) visualization of strain modification in the vicinity of skin-to-stringer damage.

displacements along the y-axis. Thus, the strain distributions along the stringer feet present a distinct behavior in accordance with the mode shape. Supplementary, it can be clearly noticed that the skin/stringer delamination (Fig. 2d) only disturbs the strain field in its vicinity.

2.2 Feature Extraction

In Fig. 3a the sensor grid used in this study is schematically depicted along with the numerical strains at the reference sensor locations for the two modes. The blue plus signs represent the $s = 5$ reference sensors (R1, ..., R5) whilst the red ones denote the evaluation sensors (E1, ..., E5). In Fig. 3b the simulated strains at the location of the reference sensors are plotted for both of the buckling modes. It can be observed that a distinct correlation among the strains of consecutive sensors is met, based on which mode is considered. In Fig. 3c a comprehensive three-dimensional view of the consecutive strains is depicted per mode with respect to the load. The strain pairs $(\epsilon_{R_n}, \epsilon_{R_{n+1}})$ follow a distinct path per mode and diverging in the post-buckling regime as long the load magnitude increases. Thus, these quantities constitute a mode-sensitive feature. Conclusively, test observations will be lying closer to the path of the corresponding mode shape as well as to a distinct load magnitude as may be visualized with the example observations (gray crosses indicate the projections of the test data) of Fig. 3c.

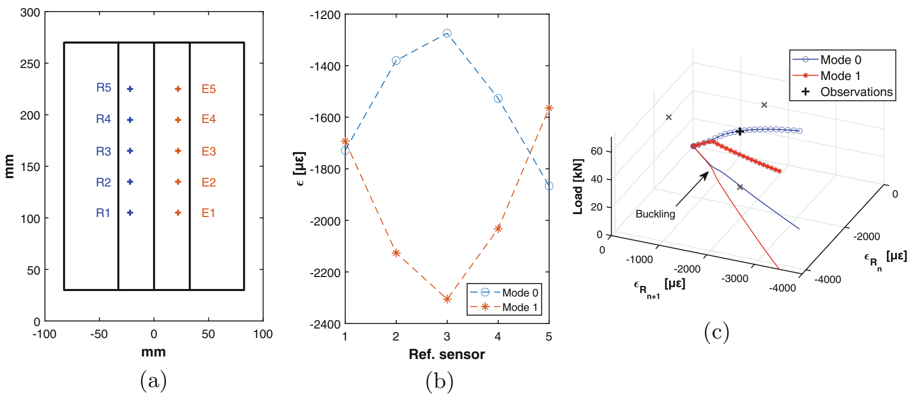

Fig. 3. a) Schematic representation of the sensor grid, b) simulated strains of the reference sensors per buckling mode and c) feature space including the effect of load.

2.3 *k*-Nearest Neighbors Models

One of the most common distance-based classification algorithms is the k-nearest neighbors (k-NN). The algorithm classifies an example point based on the most common assigned labels among its k-nearest neighbors. Training data points are received by the pristine FE model and we construct input-output $\{X_n, Y_n\}$ pairs as follows:

$$X_n = \begin{bmatrix} \epsilon_{R_n}^{(1)} & \epsilon_{R_{n+1}}^{(1)} \\ \epsilon_{R_n}^{(2)} & \epsilon_{Rn+1}^{(2)} \\ \vdots & \vdots \\ \epsilon_{R_n}^{(N)} & \epsilon_{R_{n+1}}^{(N)} \\ \epsilon_{R_n}^{(N+1)} & \epsilon_{R_{n+1}}^{(N+1)} \\ \vdots & \vdots \\ \epsilon_{R_n}^{(2N)} & \epsilon_{R_{n+1}}^{(2N)} \end{bmatrix}, Y_n = \begin{pmatrix} 1 \\ 2 \\ \vdots \\ N \\ 1 \\ \vdots \\ N \end{pmatrix}, n = 1, ..., s-1 \tag{1}$$

Totally, $n = s-1$ 1-NN models are trained with strain pairs generated by the FE model at every sensing location; the first N rows of the input matrix correspond to strains belonging to Mode 0 whereas the remaining ones to Mode 1. The output vector assigns an integer load label to the strain pairs, which corresponds to N subdivisions of the compressive load magnitude within the range [0,70] kN. It becomes apparent that the more produced training data, the more accurate classification of observations are conducted. In our case we utilize N = 100 scenarios equally distributed along [0,70] kN. The nature of the simulated strains is deterministic but the FE strains will be contaminated with Gaussian noise in order to include stochasticity in the training data. Here, the simulated strains, per sensing location, are contaminated with zero-mean Gaussian noise and variance which corresponds to real fluctuations per sensor readings. A resultant sample with 1000 strains per load label is constructed. The methodology is implemented in MATLAB environment utilizing the integrated k-NN classifier. The final load estimation is predicted as the average from all the predictions made by the $s-1$ models.

3 Damage Diagnostics

3.1 Novelty Detection

As described previously, the evaluation sensors are dedicated to monitor the presence of damage by comparing real-time strain readings with the pristine baseline given by the FE model. In the first step, the algorithm returns load estimations as a product of classification. Then, the strain samples of the evaluation sensors, which correspond to the predicted load, are used as the pristine baseline, and the Mahalanobis distance (MD) between the observation and the sample is estimated. The latter is evaluated throughout the test span for any new observation is received by the FBGs. Readings coming from sensors close to damage are discriminated by the pristine state if the MD exceeds a statistically-determined threshold. A cross-validation set of observations is received from the reference sensors of SSP-1, where no damage exists, and the MDs are estimated. The observations are made at four different load levels in the post-buckling regime, i.e. -35, -39, -45, and -50 kN. The threshold derives from the top bound of the empirical cumulative distribution function of the previously calculated MDs assuming 95% confidence intervals. By doing so, we incorporate the intrinsic error between the FE model and the real test in the threshold determination.

3.2 Experimental Assessment

The proposed SHM methodology is tested for the case of two SSPs subjected to block loading compression-compression fatigue [5,6]. The load limits per block are presented in Table 1. Two test articles, fabricated with material system IM7/8552, have been subjected to cyclic load using a servohydraulic Instron 8802 test machine with load capacity ±250 kN. SSP-1 includes an artificial disbond (Teflon insert) whilst SSP-2 was impacted with 10 J utilizing an in-house drop tower apparatus. The nominal damage morphology, as evidenced by in-situ phased-array ultrasonic inspections, is previewed in Fig. 4 with dotted lines. Static strains have been received during quasi-static test intervals, in the range $[P_{min}, P_{max}]$ every 500 cycles, and the strain at the maximum load was stored per test to finally form the test set.

Table 1. Characteristics of the block loading fatigue tests.

Panel	f(Hz)	R-ratio	P_{min}(kN)	P_{max}(kN)	Test cycles	Failure
SSP-1	2	10	−3.5	−35.0	10,000	345,000
			−3.9	−39.0	10,000	
			−4.5	−45.0	10,000	
			−5.0	−50.0	170,000	
			−5.5	−55.0	85,000	
			−6.0	−60.0	60,000	
SSP-2	2	10	−4.0	−40.0	10,000	217,000
			−4.5	−45.0	177,000	
			−5.0	−50.0	30,000	

4 Results

4.1 Load and Mode Predictions

The collected strain data coming from the reference sensors of each SSP were treated as test set to evaluate the load acting on the panels as well as the buckling mode shape. The two SSPs buckled with a different shape to each other and the algorithm efficiently identified the response of the panel. In Fig. 5 the predicted load is plotted against the groundtruth accompanied by the predictions made by a regression-based methodology in the companion paper of our work

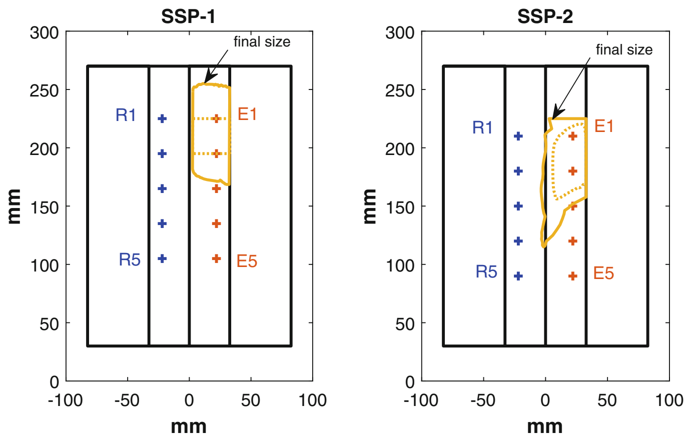

Fig. 4. Damage location in the composite panels.

[14]. Beyond the comparison of the predictions, the computational time of each methodology has been also assessed. The current classification-based methodology outperforms the RBFs in terms of computational time and fits well for a near real-time application.

4.2 Damage Detection

The historical strain data received by the evaluation sensors were utilized for diagnostic purposes. The first two levels of SHM, i.e. damage presence and localization, are addressed in the current study. Specifically, damage presence is detected when the MD exceeds the predefined threshold, as presented in Fig. 6. For the case of SSP-1, during the early cycles where no significant damage propagation occurred, sensors E1 and E2 efficiently detected the disbond by presenting values higher than the threshold. The initial size of the rectangle disbond placed amidst the skin/stringer interface was $30 \times 30\,\mathrm{mm}^2$. As the disbond progressively increases towards E3 and E4, both sensors exhibit an incremental evolution as the strain field in their vicinity is further affected. On the contrary, sensor E5 was observed to be detached, recording negligible strains during testing, which in turn led to increased MD values throughout the duration of testing. In the case of SSP-2, the nominal damaged area, as measured by the phased-array inspection, was $1398\,\mathrm{mm}^2$ spanning in a region underneath E1, E2 and E3. The severity of the damage in this panel is clearly identified by observing the MDs of sensors E1-E4 presenting values higher than the threshold. Sensor E5 only detected damage late into the test when the initial damage has significantly propagated.

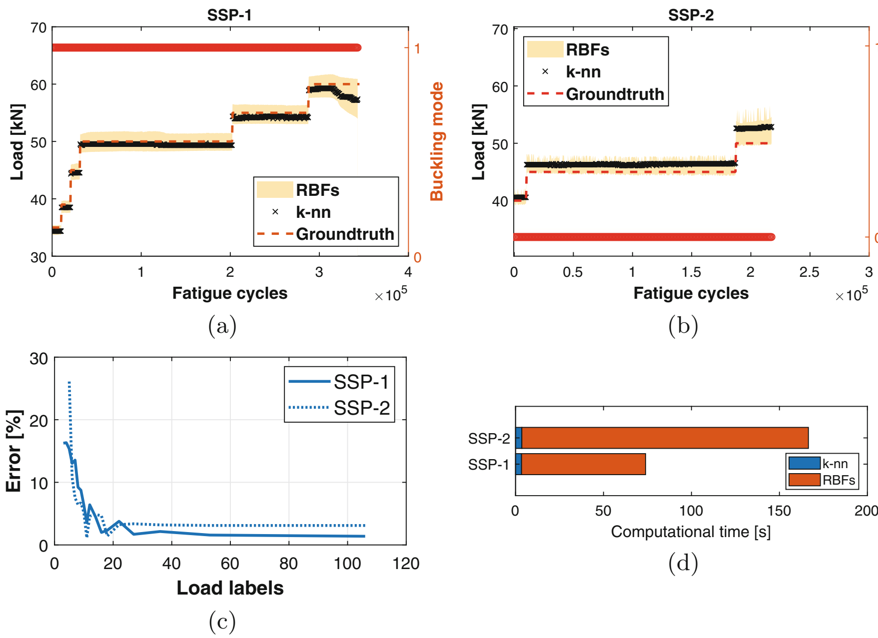

Fig. 5. Load and buckling mode shape classification predictions for a) SSP-1 and b) SSP-2. c) Average load prediction error vs. the number of training data and d) comparison of the prediction time between RBFs and the current methodology.

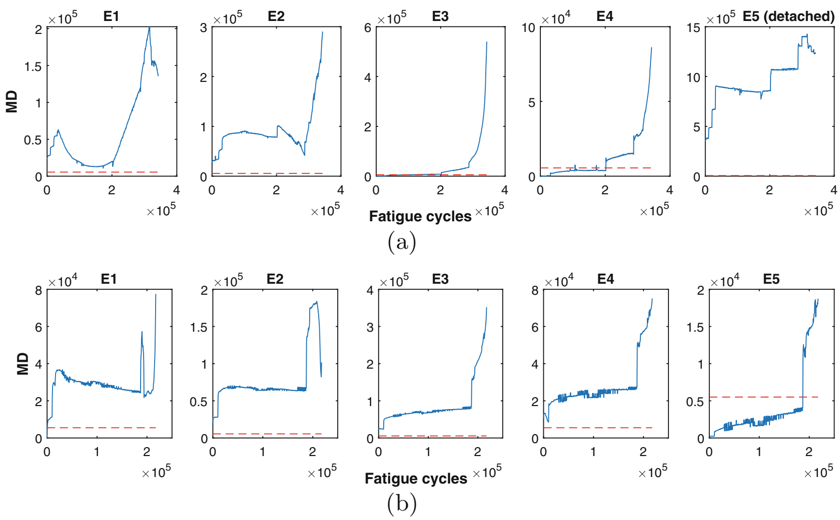

Fig. 6. Mahalanobis distance estimation on the evaluation FBG sensors for a) SSP-1 and b) SSP-2. The red dashed line represents the novelty detection threshold.

5 Concluding Remarks

A supervised classification methodology is proposed for damage diagnostics in composite stiffened panels. An off-the-self k-nn model was used, trained with longitudinal strain data solely generated from a validated FE model of the physical panel. Prior to diagnostics, the methodology identifies the applied load as well as the shape of the buckling mode that the panel follows. The load predictions were compared to an equivalent methodology proposed by the authors [14] with respect to the computational burden, showing significant reduction utilizing the proposed one. Two composite SSPs efficiently verified the current methodology; load and buckling mode predictions were found to be in accordance to the groundtruth and the evaluation sensors detected the presence of damage in their vicinity.

Funding Information. The work was financially supported by the European Union's Horizon 2020 research and innovation programme ReMAP (Grant Agreement Number: 769288).

References

1. AIAA: Digital Twin: Definition & Value. An AIAA and AIA Position Paper (December), pp. 1–16 (2020)
2. Booyse, W., Wilke, D.N., Heyns, S.: Deep digital twins for detection, diagnostics and prognostics. Mech. Syst. Signal Process. **140**, 106612 (2020). https://doi.org/10.1016/j.ymssp.2019.106612. https://linkinghub.elsevier.com/retrieve/pii/S0888327019308337
3. Broer, A., Galanopoulos, G., Benedictus, R., Loutas, T., Zarouchas, D.: Fusion-based damage diagnostics for stiffened composite panels. Struct. Health Monit. 147592172110071 (2021). https://doi.org/10.1177/14759217211007127
4. Cristiani, D., Sbarufatti, C., Cadini, F., Giglio, M.: Fatigue damage diagnosis and prognosis of an aeronautical structure based on surrogate modelling and particle filter. Struct. Health Monit. 147592172097155 (2020). https://doi.org/10.1177/1475921720971551
5. Galanopoulos, G., Milanoski, D., Broer, A., Zarouchas, D., Loutas, T.: Health monitoring of aerospace structures utilizing novel health indicators extracted from complex strain and acoustic emission data. Sensors **21**(17), 5701 (2021). https://doi.org/10.3390/s21175701
6. Galanopoulos, G., Milanoski, D., Broer, A.A.R., Zarouchas, D., Loutas, T.: Health indicators for diagnostics and prognostics of composite aerospace structures. In: 2021 IEEE 8th International Workshop on Metrology for AeroSpace (MetroAeroSpace), pp. 541–546. IEEE, June 2021. https://doi.org/10.1109/MetroAeroSpace51421.2021.9511759
7. Giannakeas, I.N., Sharif Khodaei, Z., Aliabadi, M.: Digital clone testing platform for the assessment of SHM systems under uncertainty. Mech. Syst. Signal Process. **163**, 108150 (2022). https://doi.org/10.1016/j.ymssp.2021.108150
8. Glaessgen, E.H., Stargel, D.S.: The digital twin paradigm for future NASA and U.S. air force vehicles. In: 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference 2012 (2012)

9. Glisic, B., Inaudi, D.: Development of method for in-service crack detection based on distributed fiber optic sensors. Struct. Health Monit. **11**(2), 161–171 (2012). https://doi.org/10.1177/1475921711414233
10. Grieves, M., Vickers, J.: Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Kahlen, F.-J., Flumerfelt, S., Alves, A. (eds.) Transdisciplinary Perspectives on Complex Systems, pp. 85–113. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-38756-7_4
11. Kapteyn, M., Knezevic, D., Huynh, D., Tran, M., Willcox, K.: Data-driven physics-based digital twins via a library of component-based reduced-order models. Int. J. Numer. Methods Eng. p. nme.6423 (2020). https://doi.org/10.1002/nme.6423. https://onlinelibrary.wiley.com/doi/10.1002/nme.6423
12. Leser, P.E., et al.: Probabilistic fatigue damage prognosis using surrogate models trained via three-dimensional finite element analysis. Struct. Health Monit. **16**(3), 291–308 (2017). https://doi.org/10.1177/1475921716643298
13. Milanoski, D., Galanopoulos, G., Broer, A., Zarouchas, D., Loutas, T.: A strain-based health indicator for the SHM of skin-to-stringer disbond growth of composite stiffened panels in fatigue. In: Rizzo, P., Milazzo, A. (eds.) EWSHM 2020. LNCE, vol. 127, pp. 626–635. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-64594-6_61
14. Milanoski, D.P., Galanopoulos, G.K., Loutas, T.H.: Digital-twins of composite aerostructures towards structural health monitoring. In: 2021 IEEE 8th International Workshop on Metrology for AeroSpace (MetroAeroSpace), pp. 613–618. IEEE, June 2021. https://doi.org/10.1109/MetroAeroSpace51421.2021.9511653
15. Milanoski, D.P., Loutas, T.H.: Strain-based health indicators for the structural health monitoring of stiffened composite panels. J. Intell. Mater. Syst. Struct. **32**(3), 255–266 (2021). https://doi.org/10.1177/1045389X20924822
16. Sbarufatti, C., Corbetta, M., Millan, J.S., Frovel, M., Stefaniuk, M., Giglio, M.: Model-assisted performance qualification of a distributed SHM system for fatigue crack detection on a helicopter tail boom. In: 8th European Workshop on Structural Health Monitoring, EWSHM 2016, vol. 2, pp. 940–949 (2016)
17. Seventekidis, P., Giagopoulos, D., Arailopoulos, A., Markogiannaki, O.: Structural health monitoring using deep learning with optimal finite element model generated data. Mech. Syst. Signal Process. **145**, 106972 (2020). https://doi.org/10.1016/j.ymssp.2020.106972
18. Silionis, N.E., Anyfantis, K.N.: Static strain-based identification of extensive damages in thin-walled structures. Struct. Health Monit. 147592172110506 (2021). https://doi.org/10.1177/14759217211050605
19. Singh, V., Willcox, K.E.: Engineering design with digital thread. AIAA J. **56**(11), 4515–4528 (2018). https://doi.org/10.2514/1.J057255
20. Tuegel, E.J., Ingraffea, A.R., Eason, T.G., Spottswood, S.M.: Reengineering aircraft structural life prediction using a digital twin. Int. J. Aerosp. Eng. (2011). https://doi.org/10.1155/2011/154798
21. Wagg, D.J., Worden, K., Barthorpe, R.J., Gardner, P.: Digital twins: state-of-the-art and future directions for modeling and simulation in engineering dynamics applications. ASCE-ASME J. Risk Uncertainty Eng. Syst. Part B: Mech. Eng. **6**(3) (2020). https://doi.org/10.1115/1.4046739
22. Worden, K., Cross, E.J., Gardner, P., Barthorpe, R.J., Wagg, D.J.: On digital twins, mirrors and virtualisations. In: Barthorpe, R. (ed.) Model Validation and Uncertainty Quantification, Volume 3. CPSEMS, pp. 285–295. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-12075-7_34