On Random Vibration Based Robust Damage Detection for a Population of Composite Aerostructures Under Variable and Non-measurable Excitation

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Abstract. The problem of random vibration response based robust and unsupervised damage detection for a population of composite aerostructures is addressed. The focus is on the achievement of robustness which is of paramount importance as manufacturing variability within the population and flight condition variability are practically inevitable. Two robust damage detection methods are postulated based on Multiple-Input Single-Output (MISO) Transmittance Function (TF) stochastic AutoRegressive with eXogenous pseudo-eXcitation (ARX) type representations for eliminating the effects of non-measurable excitation. Robustness to manufacturing variability is achieved via Multiple Model (MM) representations (the MM-TF-ARX method) or Principal Component Analysis (the PCA-TF-ARX method). The achievable detection performance is assessed via Monte Carlo ANSYS-based simulations with a population of 120 composite beams subject to manufacturing thickness variability, two distinct turbulence-like excitation profiles, and three early-stage crack damage scenarios. The results, in terms of Receiver Operating Characteristics curves, indicate excellent damage detection performance for the MM-TF-ARX method, yet inferior for its PCA-TF-ARX counterpart.

Keywords: Population based SHM · Composite structures · Robust damage detection · Vibration-based SHM · Statistical time series methods

1 Introduction

As composite aerostructures are increasingly used by aircraft manufacturers [1], the development of suitable and effective Structural Health Monitoring (SHM) systems becomes essential for purposes related to safety and proper maintenance. Within this context random vibration based SHM is an important technology offering potential in-flight operation under naturally available excitation, reduced cost, and large area coverage due to its 'global' nature.

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Yet, a number of difficulties are also encountered. First, damage diagnosability and performance for early-stage/incipient damage may be insufficient. This may be especially true under uncertainty, including that stemming from non-measurable and varying characteristics of in-flight loading/excitation conditions, as well as other potential factors such as varying temperature. Indeed, varying excitation conditions hinder effective diagnosis as they may significantly affect the vibration response characteristics on which damage diagnosis is based. Furthermore, uncertainty sources like varying temperature [2,3] affect the structural dynamics and thus the vibration response characteristics as well. The end result is that the effects of these factors on the vibration response characteristics may completely 'mask' those due to incipient damage, thus rendering effective diagnosis highly challenging. For this reason considerable efforts are devoted on the development of robust damage diagnosis methods capable of counteracting the effects of uncertainty [2–7], and to a lesser extent those of varying excitation conditions [8–10].

A related important issue stems from the need for population-based SHM for nominally identical aerostructures; this is highly desirable from a fleet asset management viewpoint as SHM system tuning on each individual structure may be avoided and other advantages, such as information sharing, may be obtained. Yet, additional uncertainty (geometric, manufacturing, and so on), is then inevitably introduced [4–7], further increasing the problem difficulty.

The *goal* of the present study is the postulation and critical assessment of robust damage detection methods for effectively addressing the aforementioned issues. The postulated methods are designed to be robust to the excitation profile while also accounting for population uncertainty, and, potentially, other additional uncertainty as well. They are of the data-based type, that is based on small-scale identified models using a limited number of sensors, as well as unsupervised, that is with training based on signal records associated only with the healthy structural state. Robustness to the excitation profile is achieved via proper Multiple-Input Single-Output (MISO) Transmittance Function (TF) models, which in contrast to commonly used transmittance [3,6,11], aim at effective and complete cancellation of potentially variable excitation effects. The models are of the stochastic AutoRegressive with eXogenous excitation (ARX) type, designated as MISO TF-ARX. Robustness to population uncertainty is then achieved by embedding the problem within our recently introduced Multiple Model (MM) or a Principal Component Analysis (PCA) based framework [5], with the resulting methods being designated as MM-TF-ARX and PCA-TF-ARX, respectively.

The assessment of the methods is based on Monte Carlo experiments with an ANSYS-based finite element model and a population of 120 nominally identical composite beams subject to manufacturing variability. Two distinct turbulence-like random excitation profiles are employed, with vibration associated with engine rotation also included in one. Three early-stage damage scenarios (corresponding to 1mm wide and 1, 3 and 5 cm long longitudinal through-the-thickness crack on the 150 cm long beam) are considered, while detection performance is

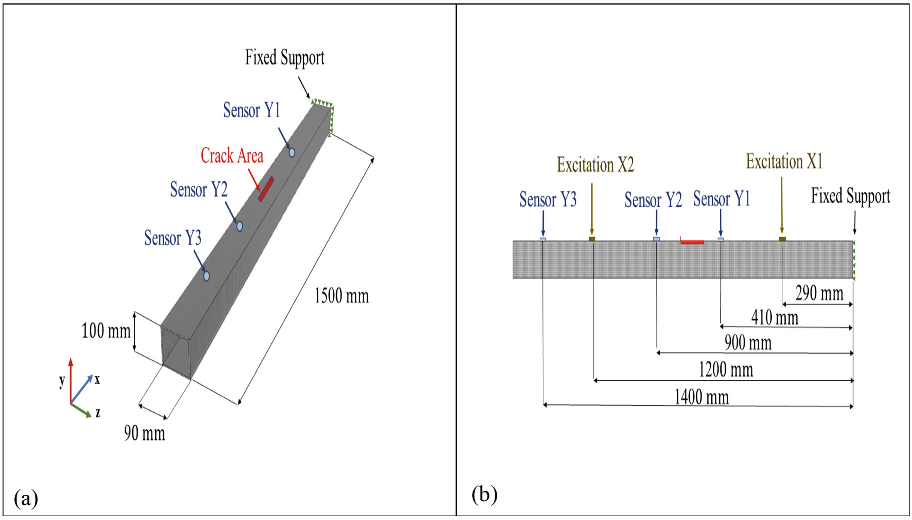

Fig. 1. Schematic representation of the composite aerostructure on which the excitation, sensor, and crack locations are indicated.

evaluated via Receiver Operating Characteristic (ROC) curves. Some of the main questions addressed in the study are:

(i) What are the performance characteristics achievable by the postulated methods in terms of True Positive Rate (TPR) and False Positive Rate (FPR)?
(ii) What is the methods' sensitivity to damage? Are damages as small as 1/150 of the beam length detectable?
(iii) Is it possible to have the damage detection methods trained with one random excitation profile but still being effective when operating under the other?

2 The Population of Composite Aerostructures, the Damage Scenarios, and the Random Vibration Signals

2.1 The Population of Composite Aerostructures and the Damage Scenarios

A population of 120 nominally identical composite aerostructures is considered. Each structure (Fig. 1) is a hollow Carbon/Epoxy beam representing the topology of the main part of a tail boom consisting of an eight ply generally orthotropic laminate with lamination configuration $[0/90/45/-45]_S$ and made of UD Carbon/Epoxy prepreg. The structure's nominal dimensions are $1\,500 \times 100 \times 90$ mm, the nominal thickness is 3.1 mm, and the nominal mass is 2.73 kg (Fig. 1). Population geometric uncertainty is introduced by having thickness varying within the $\pm 11\%$ range of its nominal value. Dynamic responses are

Table 1. Details of the Monte Carlo experiments and the vibration signal characteristics.

Structural health state	# of structures	# of test cases under E1/E2 (per 'rotation')	# aggregate test cases under E1/E2
Baseline/Learning Phase			
Healthy (HB)	40	40/0	1 360/0
Inspection/Diagnosis Phase			
Healthy (HI)	20	40/40	1 360/1 360
1 cm crack (D1)	20	40/40	1 360/1 360
3 cm crack (D2)	20	40/40	1 360/1 360
5 cm crack (D3)	20	40/40	1 360/1 360

[1]Newmark integration: time step $\Delta t = 1/30\,000$ (s), $\alpha = 0.2525$, $\gamma = 0.005$, $\delta = 0.505$.
[2]Signal pre-processing: 24-th order Chebyshev II low-pass filtering with cut-off 1 000 Hz, re-sampling at $f_s = 2\,000$ Hz; final signal length $N = 2\,000$ samples (1 s).
[3]Each Inspection Test Case is repeated 34 times ('rotations') with different Baseline Test Cases.
[4]E1, E2: turbulence-like excitation profiles with a 434 Hz sinusoidal added on E2.

simulated via a finite element model implemented in ANSYS and consisting of Shell-181 elements [12] with a mesh size of 5 mm. Each beam is considered under Clamped-Free boundary conditions in order to simulate its connection to the aircraft fuselage.

Three early-stage damage scenarios, referred to as D1, D2, and D3 and corresponding to 1 mm wide and 1, 3, and 5 cm longitudinal through-the-thickness crack on the 150 cm long beam, are considered. 60 of the 120 aerostructures are damaged (20 per damage scenario; see Table 1). Damage is implemented by removing material at a specific location on the top side of each beam (Fig. 1). The inflation layers are created around the crack area in order to ensure high model fidelity and resolution [13].

Each structure in the population is excited at two distinct points (X1 and X2), with the resulting vibration acceleration measured in the same direction as the excitation at points Y1, Y2, and Y3 (Fig. 1).

2.2 Effects of Uncertainty and Damage on the Dynamics

The effects of geometric uncertainty and damage on the Y2/Y1 and Y2/Y3 Frequency Response Functions (FRFs) of the MISO Transmittance Function (defined with Y1, Y3 as pseudo-inputs and Y2 as output) for all population members are depicted in Fig. 2 separately for each damage scenario with the Healthy (H) curves being also superimposed. The following observations are in order: (a) In all (H, D1, D2, D3 cases) the geometric uncertainty causes considerable uncertainty on the Transmittance FRFs; (b) Even in the absence of

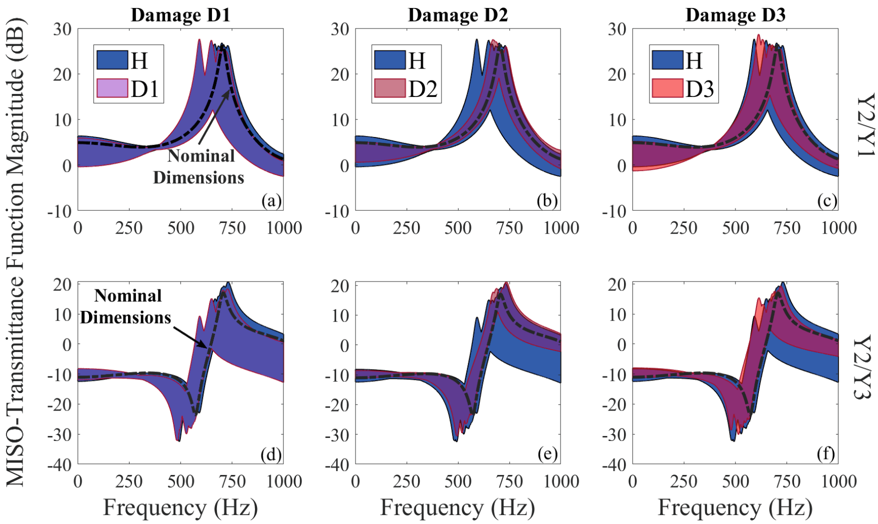

Fig. 2. The population uncertainty effects on the analytical MISO Transmittance frequency response Functions under the healthy and each damage state: Y2/Y1 Transmittance (upper row) and Y2/Y3 Transmittance (lower row). The black dashed lines indicate the functions for the nominal structure.

estimation error, the Transmittance FRF uncertainty zones corresponding to the healthy case and each one of the damage scenarios are very significantly overlapping, especially for the smaller damage scenarios. These observations clearly suggest a challenging damage detection problem.

2.3 The Vibration Signals

Each structure is excited by realizations of one of two distinct excitation profiles, E1 or E2, which provide random, turbulence-like, excitation with a damped sinusoidal 434 Hz added on E2 in order to simulate rotating part, like engine, effects. Welch-based Power Spectral Density (PSD) estimates of the employed excitation realizations are presented in Fig. 3; these are treated as non-measurable in damage detection. The random vibration signals are obtained via Newmark integration and are subsequently low-pass filtered and sampled at $f_s = 2\,000$ Hz (resulting signal length $N = 2\,000$ samples or 1 s; details in Table 1).

3 The Robust Damage Detection Methods and Performance Assessment

3.1 The Methods

The data-based damage detection methods postulated utilize random vibration response signals from three locations (Y1, Y2, Y3) on the structure, with Y1

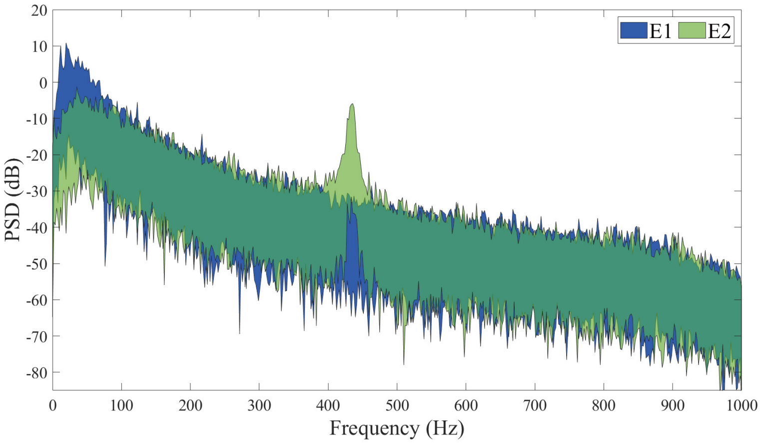

Fig. 3. Welch-based Power Spectral Density estimates of the excitation profiles E1 (blue) and E2 (green) (80 estimates per profile).

and Y3 treated as pseudo-inputs and Y2 as output (see Fig. 1) within a MISO Transmittance Function (TF) framework that eliminates varying excitation profile effects. The TF is modeled as a stochastic MISO ARX type model of the form [14, pp. 154–157]:

$$\text{TF-ARX}(n, n, n): \ \sum_{i=0}^{n} a_i \cdot y_2[t-i] = \sum_{i=0}^{n} b_i^1 \cdot y_1[t-i] + \sum_{i=0}^{n} b_i^3 \cdot y_3[t-i] + w[t]$$

with t designating discrete time, $y_j[t]$ $(j = 1, 2, 3)$ the measured signals, $w[t]$ zero-mean white Gaussian noise with variance σ_w^2, a_i, b_i^1, b_i^3 $(i = 0, \dots, n)$ the AR and the two sets of X parameters, respectively ($a_0 \equiv 1$). Both damage detection methods employ the model parameter vector consisting of the AR/X parameters, or versions thereof, as feature vector.

The first, MM-TF-ARX, method operates within a MM framework [5] within which the healthy population structural dynamics under uncertainty are modeled via a p-dimensional MM representation (consisting of p conventional models obtained via a corresponding number of Y1, Y2, Y3 signal sets) within the feature space and constructed in an initial Baseline/Learning Phase. When a fresh signal set is available from a structure in unknown state, a corresponding conventional model is estimated and a distance metric D (minimum Mahalanobis pseudo-distance) between it and the MM representation is computed. Damage is then detected if and only if D is higher than a user selected threshold (Inspection/Diagnosis Phase).

The second, PCA-TF-ARX, method, employs PCA for feature vector transformation and dimensionality reduction [5]. The principal components corresponding to the largest m eigenvalues of the AR/X parameter covariance matrix – responsible for a user-selected fraction of the total variability under the healthy

Table 2. Details on the damage detection methods.

Method	Feature	Feature dimensionality	Distance Metric
MM-TF-ARX	AR/X parameter vector	31	Mahalanobis
PCA-TF-ARX	AR/X parameter vector	30	Mahalanobis

TF-ARX Modeling: selected model TF-ARX(10,10,10); RSS/SSS(%)= 0.08; BIC= −3.4; SPP= 190.

structural state – are assumed to be associated with uncertainty. Feature vector transformation and dimensionality reduction (by m) is then achieved by using the matrix consisting of the eigenvectors corresponding to the retained eigenvalues and the healthy population dynamics are represented by the sample-mean conventional model within the transformed and reduced feature space (Baseline/Learning Phase). When a fresh signal set is available from a structure in unknown state, a corresponding conventional model is estimated, transformed, and reduced in the exact same way. Damage detection is then based on computing a distance metric D (Mahalanobis pseudo-distance) between it and the sample-mean model representation of the healthy dynamics, with damage confirmed if D is higher than a user selected threshold (Inspection/Diagnosis Phase).

3.2 Damage Detection Performance Assessment

Vibration-signal-based TF-ARX(n, n, n) $(n = 1, 2, \ldots)$ modeling (signal details in Table 1) of the healthy population dynamics under the E1 excitation profile leads to a TF-ARX$(10, 10, 10)$ model with characteristics indicated in Table 2 along with feature dimensionality for each method. The MM representation dimensionality is selected equal to the number of experiments/Test Cases in the Baseline Phase, that is $p = 40$ (Table 1). The numbers of Experiments/Test Cases under each of the E1 and E2 excitation profiles and each condition (Healthy, D1, D2, D3) in the Inspection Phase are also shown in the same Table. Signal sets used in the Baseline Phase are excluded from the Inspection Phase. For the PCA-TF-ARX method only the principal component corresponding to the largest eigenvalue is dropped ($m = 1$; see the feature dimensionality in Table 2) as only the geometric uncertainty remains active due to the fact that the excitation effects are cancelled out through the MISO TF.

Damage detection assessment results are obtained for 2 720 Inspection Test Cases (inspection experiments) per health state (HI, D1, D2, D3); resulting into a total of 10 880 Inspection Test Cases. These are obtained by using 34 different sets of the $p = 40$ Baseline Test Cases ('rotation' procedure) under the E1 excitation profile in order to ensure that the aggregate results and conclusions are independent of any specific set of Baseline Test Cases.

The results are presented in terms of ROC curves and distance metric D plots. Those obtained by the MM-TF-ARX method (Fig. 4) are truly excellent,

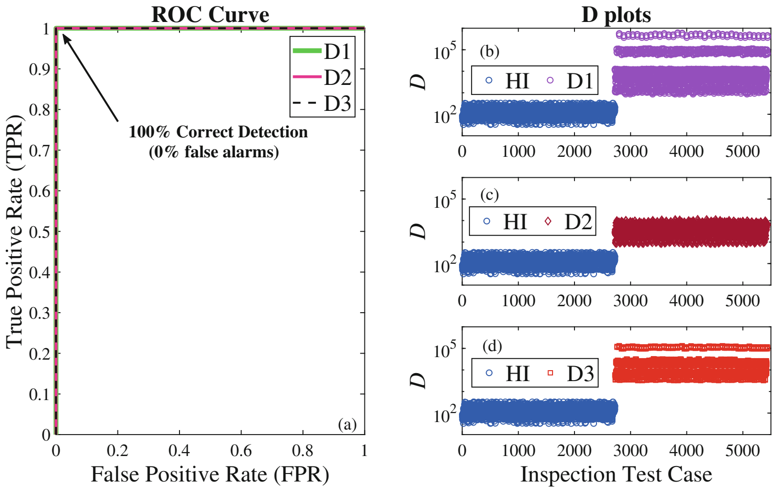

Fig. 4. Damage detection performance for the MM-TF-ARX method: ROC curve for each damage scenario (a), distance metric for the Healthy and D1 states (b), Healthy and D2 states (c), and Healthy and D3 states (d). (2 720 Inspection Test Cases per health condition; E1 and E2 excitation profiles).

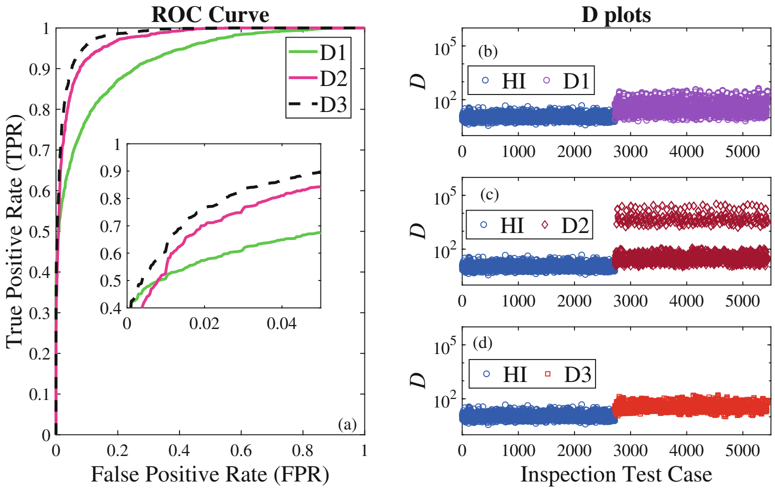

Fig. 5. Damage detection performance for the PCA-TF-ARX method: ROC curve for each damage scenario (a), distance metric for the Healthy and D1 states (b), Healthy and D2 states (c), and Healthy and D3 states (d). (2 720 Inspection Test Cases per health condition; E1 and E2 excitation profiles).

achieving 100% TPR (correct detection rate) for 0% FPR (false alarm rate) for all three (D1, D2, D3) damage scenarios. Those obtained by the PCA-TF-ARX methods (Fig. 5) are inferior, especially for the smallest (D1) damage scenario.

4 Concluding Remarks

The problem of random vibration based robust and unsupervised damage detection of early-stage cracks D1 (1 cm), D2 (3 cm), and D3 (5 cm) for a population of nominally identical composite aerostructures under varying excitation profiles and geometric uncertainty has been considered. Two MISO Transmittance Function based methods, a MM-TF-ARX and a PCA-TF-ARX have been postulated and their achievable performance has been assessed via a total number of 10 880 Inspection Test Cases. The main lessons learnt from this study, corresponding to the questions posed in the introduction, are:

(i) The MM-TF-ARX achieves truly excellent performance characterized by 100% TPR (correct detection rate) for 0% FPR (false alarm rate) for all damage scenarios. The PCA-TF-ARX achievable performance is lower.
(ii) Damages as small as 1/150 of the beam length (D1 damage) are indeed detectable by the MM-TF-ARX method despite the excitation profile variability and the presence of geometric uncertainty. Detectability for such damages is problematic by the PCA-TF-ARX method.
(iii) Thanks to the use of the MISO Transmittance Function, the performance of both methods is not affected by the excitation profile, including the presence of sinusoidal components associated with engine operation.

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References

1. Rana, S., Fangueiro, R.: Advanced Composite Materials for Aerospace Engineering. Woodhead Publishing, UK (2016)
2. Rama Mohan Rao, A., Lakshmi, K., Krishna Kumar, S.: Detection of delamination in laminated composites with limited measurements combining PCA and dynamic QPSO. Adv. Eng. Softw. **86**, 85–106 (2015). https://doi.org/10.1016/j.advengsoft.2015.04.005
3. Aravanis, T.-C., Sakellariou, J., Fassois, S.: On the functional model-based method for vibration-based robust damage detection: versions and experimental assessment. Struct. Health Monit. **20**(2), 456–474 (2021). https://doi.org/10.1177/1475921720930206

4. Teimouri, H., Milani, A., Seethaler, R., Heidarzadeh, A.: On the impact of manufacturing uncertainty in structural health monitoring of composite structures: a signal to noise weighted neural network process. Open J. Compos. Mater. **6**, 28–39 (2016). https://doi.org/10.4236/ojcm.2016.61004
5. Vamvoudakis-Stefanou, K., Sakellariou, J., Fassois, S.: Vibration-based damage detection for a population of nominally identical structures: unsupervised Multiple Model (MM) statistical time series type methods. Mech. Syst. Signal Process. **111**, 149–171 (2018). https://doi.org/10.1016/j.ymssp.2018.03.054
6. Poulimenos, A., Sakellariou, J.: A transmittance-based methodology for damage detection under uncertainty: an application to a set of composite beams with manufacturing variability subject to impact damage and varying operating conditions. Struct. Health Monit. **18**(1), 318–333 (2019). https://doi.org/10.1177/1475921718779190
7. Vamvoudakis-Stefanou, K., Fassois, S., Sakellariou, J.: An automated hypersphere-based healthy subspace method for robust and unsupervised damage detection via random vibration response signals. Struct. Health Monit. **21**(2), 465–484 (2021). https://doi.org/10.1177/14759217211004429
8. Sierra-Pérez, J., Güemes, A., Mujica, L., Ruiz, M.: Damage detection in composite materials structures under variable loads conditions by using fiber Bragg gratings and principal component analysis, involving new unfolding and scaling methods. J. Intell. Mater. Syst. Struct. **26**(11), 1346–1359 (2015). https://doi.org/10.1177/1045389X14541493
9. Alvarez-Montoya, J., Carvajal-Castrillón, A., Sierra-Pérez, J.: In-flight and wireless damage detection in a UAV composite wing using fiber optic sensors and strain field pattern recognition. Mech. Syst. Signal Process. **136**, 106526 (2020). https://doi.org/10.1016/j.ymssp.2019.106526
10. Lin, M., Guo, S., He, S., Li, W., Yang, D.: Structure health monitoring of a composite wing based on flight load and strain data using deep learning method. Compos. Struct. **286**, 115305 (2022). https://doi.org/10.1016/j.compstruct.2022.115305
11. Zhang, H., Schulz, M., Naser, A., Ferguson, F., Pai, P.: Structural health monitoring using transmittance functions. Mech. Syst. Signal Process. **13**(5), 765–787 (1999). https://doi.org/10.1006/mssp.1999.1228
12. https://www.mm.bme.hu/~gyebro/files/ans_help_v182/ans_elem/Hlp_E_SHELL181.html. Accessed 23 Feb 2022
13. Lipian, M., Czapski, P., Obidowski, D.: Fluid-structure interaction numerical analysis of a small, urban wind turbine blade. Energies **13**(7), 1832 (2020). https://doi.org/10.3390/en13071832
14. Soderstrom, T., Stoica, P.: System Identification, 2nd edn. Prentice Hall International, UK (1989)