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Experimental damage detection in a wind turbine blade model using principal components of response correlation functions

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Abstract. The utilization of vibration signals for structural damage detection (SDD) is appealing due to the strong theoretical foundation of such approaches, ease of data acquisition and processing efficiency. Different methods are available for defining damage sensitive features (DSFs) based on vibrations, such as modal analysis or time series methods. The present paper proposes the use of partial autocorrelation coefficients of acceleration responses as DSFs. Principal component (PC) analysis is used to transform the initial DSFs to scores. The resulting scores from the healthy and damaged states are used to select the PCs which are most sensitive to damage. These are then used for making decisions about the structural state by means of statistical hypothesis testing conducted on the scores. The approach is applied to experiments with a laboratory scale wind turbine blade (WTB) made of glass-fibre reinforced epoxy composite. Damage is non-destructively simulated by attaching small masses and the WTB is excited with the help of an electrodynamic shaker using band-limited white noise. The SDD results for the selected subsets of PCs show a clear improvement of the detectability of early damages compared to other DSF selections.

1. Introduction

Vibration-based structural health monitoring (SHM) is the process of acquiring vibrational measurements, extracting information and knowledge from these observations and determining the current structural performance [1]. It is based on the premise that damage leads to changes in stiffness, mass or energy dissipation mechanisms of a structure and, thus, vibrational response are affected. This enables to define damage sensitive features (DSFs) which describe the current structural state by processing these signals.

Although traditional structural damage detection (SDD) with the help of modal parameters, i.e. natural frequencies, mode shapes and their spatial derivatives, is a mature approach [2], the estimation of these parameters entails practical difficulties due to computational demands and hindrances preventing wider automation of the process [3]. Parametric and non-parametric time series representations of vibration signals, as data-driven approaches, avoid this estimation of modal characteristics. Autoregressive (AR) models are one example of parametric models, for which the theoretical relationship between the structural stiffness and AR coefficients (ARCs) was demonstrated by Nair et al. [4]. However, the use of such models for SHM purposes requires a priori model structure selection, identification and validation. Non-parametric time series representations are less demanding and computationally efficient. They can be classified according to their working domain as frequency, mixed time-frequency and time domain approaches.



Decisions about the current structural state can be made with the help of statistical hypothesis tests of distance measures, e.g. the Mahalanobis distance, between DSF vectors from the healthy and current state [5], where statistical assumptions about the DSF vectors are used to define thresholds for these distances. Even though this is a structured approach with minimal user intervention, the performance with respect to the detectability of early damages depends significantly on the DSF vector dimension and the damage sensitivity of the individual DSF vector entries. The use of principal component analysis (PCA) received considerable attention in the field of SHM in the past for several purposes. The general aim of PCA is to identify a projection defined by orthogonal basis vectors which maximizes the variation in the data for the first few dimensions [6]. This property has been used to reduce the effects of changes in environmental and operational conditions on DSFs [7], where it is generally assumed that the highest variations are a result of these changes and removing the a few first coefficients counteracts the adverse effects. Bandara et al. [8] used PCA for the reduction of frequency response function data for SDD by means of artificial neural networks in a three storey bookshelf structure. Statistical hypothesis testing and PCA of mechanical response data obtained from piezoelectric transducers attached to a small aluminium plate under Lamb wave excitation was applied by Mujica et al. [9]. They used univariate statistical tests of the transformed data, the so called scores, for making decisions about the current structural state.

The present paper discusses the application of partial autocorrelation coefficient (PACC) estimates from acceleration time series as DSF vectors. Due to the high dimensionality of this non-parametric time series representation, dimensionality reduction is achieved by means of PCA, where only selected principal component (PC) estimates from the healthy system are used to transform the DSF vectors to scores. The most damage sensitive PCs for the considered damage scenarios are selected with respect to the corresponding statistical threshold. Then, decisions about the structural state are made by multivariate statistical tests of scores from the current state against the healthy state. The approach is applied to data gathered from dynamic experiments of a laboratory scale wind turbine blade (WTB) under band limited white noise shaker excitation. Damage is simulated non-destructively by attaching small magnets as additional masses.

The paper is structured as follows. First, the proposed methodology is introduced. Second, the structure under study and the experimental setup is presented. Then, the SDD results are discussed. Finally, the paper is rounded up with a set of conclusions and prospects for the future work.

2. Methodology

For the proposed SDD methodology, it is assumed that the utilized vibrational responses are stationary. A discrete time series $x[t]$ can be divided into n segments $x_i[t]$ with $i=1, 2, \dots, n$ and a common number of samples. Then, removing the estimated means, $\hat{\mu}_{x_i}$, and dividing by the estimated standard deviations, $\hat{\sigma}_{x_i}$, gives the normalized time series segments $z_i[t]$. PACCs, $\alpha_i[\tau]$, are defined as the correlations between time series segments $z_i[t]$ and $z_i[t-\tau]$ shifted by a time lag, τ , without the effects of intermediate variables $z_i[t-1]$, $z_i[t-2]$, ..., $z_i[t-\tau+1]$. The sample PACC, $\hat{\alpha}_i[\tau]$, can be efficiently computed by the recursion [10]:

$$\hat{\alpha}_i[\tau] = \frac{\hat{r}_i[\tau] - \sum_{k=1}^{\tau-1} \hat{a}_{i,\tau-1,k} \hat{r}_i[\tau-k]}{1 - \sum_{k=1}^{\tau-1} \hat{a}_{i,\tau-1,k} \hat{r}_i[k]} \quad (1)$$

where \hat{r}_i is the sample autocorrelation function of $z_i[t]$, and $\hat{a}_{i,l,k}$ denotes the estimated l -th coefficient of an AR model of order k of the i -th segment. This underlines the close relationship between autocorrelations, AR models and PACCs, which can be estimated from each other [11]. In the present study, consecutive PACCs are used to construct a DSF matrix, \mathbf{A} , comprising DSF vectors, α_i , estimated from different time series segments, i , as:

$$\mathbf{A}^T = [\alpha_1 - \hat{\mu}_a \quad \alpha_2 - \hat{\mu}_a \quad \dots \quad \alpha_n - \hat{\mu}_a] \text{ with } \alpha_i = [\hat{\alpha}_i[1] \quad \hat{\alpha}_i[2] \quad \dots \quad \hat{\alpha}_i[m]]^T \quad (2)$$

where $\hat{\boldsymbol{\mu}}_{\alpha}$ is the estimated mean DSF vector. The feature matrix, \mathbf{A} , of dimension $n \times m$ can be linearly transformed into a new matrix, \mathbf{S} , with the help of a linear transformation matrix, \mathbf{T} , as:

$$\mathbf{S} = \mathbf{A}\mathbf{T} \quad (3)$$

PCA enables to identify a transformation matrix such that the new features are linearly independent and the variances are maximized for the first few dimensions. where \mathbf{S} is in this case called the score matrix. This is done by performing singular value decomposition (SVD) of the sample variance-covariance matrix, $\hat{\boldsymbol{\Sigma}}$, as

$$\hat{\boldsymbol{\Sigma}} = \mathbf{T}\boldsymbol{\Lambda}\mathbf{T}^T \text{ with } \boldsymbol{\Lambda} = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_m) \text{ and } \mathbf{T} = [\mathbf{t}_1 \quad \mathbf{t}_2 \quad \dots \quad \mathbf{t}_m] \quad (4)$$

where λ_k are the eigenvalues sorted in descending order and \mathbf{t}_k are the corresponding normalized eigenvectors, or PCs. In the present study, the transformation matrix, \mathbf{T}_h , estimated from the PCACs of the healthy state, \mathbf{A}_h , is used. Then, it is proposed to make decisions about the structural state by statistical hypothesis testing of the scores in the current structural state, \mathbf{S}_c , with respect to the healthy state, \mathbf{S}_h . In order to improve the detectability of early damages, only a subset of all PCs is used, which includes only these PCs that are the most sensitive to damage. For the selection of this subset, the scores for the healthy and a selected damage state, \mathbf{S}_h and \mathbf{S}_d , are computed as:

$$\mathbf{S}_h = \mathbf{A}_h \mathbf{T}_h \text{ and } \mathbf{S}_d = \mathbf{A}_d \mathbf{T}_h \quad (5)$$

where both feature matrices, \mathbf{A}_h and \mathbf{A}_d , are obtained by removing the estimated DSF mean of the healthy state only.

It can be assumed that the covariance structure for the initial features in the healthy state and states with small damage extent is almost equal, thus the computed scores \mathbf{S}_d are nearly linearly independent. This enables to estimate the contribution of k -th PC to a multivariate distance between healthy and damaged score features in terms of Fisher's criterion, FC_k , as:

$$FC_k = \frac{n_d n_h (n_d + n_h - 2)}{n_d + n_h} \frac{(\hat{\mu}_{k,d} - \hat{\mu}_{k,h})^2}{(n_d - 1)\hat{\sigma}_{k,d}^2 + (n_h - 1)\hat{\sigma}_{k,h}^2} \text{ where } \hat{\mu}_k = n^{-1} \sum_{i=1}^n \mathbf{s}_{i,k} \text{ and } \hat{\sigma}_k^2 = n^{-1} \sum_{i=1}^n (\mathbf{s}_{i,k} - \hat{\mu}_k)^2 \quad (6)$$

The subscripts h and d refer to the healthy and damage state, respectively. The estimated mean, $\hat{\mu}_k$, and the estimated variance, $\hat{\sigma}_k^2$, are calculated from the score vectors, $\mathbf{s}_{i,k}$, of the corresponding k -th PC computed using n samples. Then, the cumulative sum of Fisher's criteria sorted in descending order, FC_k^{sort} , divided by a statistical threshold with the number of degrees-of-freedom (DOFs) corresponding to the number of coefficients can be used to define the relative Fisher's criteria, FC_k^{rel} , as:

$$FC_k^{rel} = \sum_{j=1}^k FC_k^{sort} \bigg/ F_{T_{k,n_d+n_h-2}}^2 (1 - \alpha) \quad (7)$$

Here, it is assumed that a single score, \mathbf{s}_i , follows a multivariate Gaussian distribution $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with true mean, $\boldsymbol{\mu}$, and true variance-covariance matrix, $\boldsymbol{\Sigma}$. The statistical threshold is therefore selected using the cumulative distribution function, $F_{T_{k,n_d+n_h-2}}^2 (1 - \alpha)$, of Hotelling's probability distribution, $T_{k,n_d+n_h-2}^2$, at a selected level of significance, α , and with k and n_d+n_h-2 DOFs. The number of considered PCs is k , and the number of samples used for estimating the mean and variance in the healthy and damage state is n_d and n_h , respectively.

Note it requires $FC_k^{rel} > 1$ for damage detection and that the selection of m_{select} PCs for optimal damage detection requires maximising FC_k^{rel} with respect to k :

$$m_{select} = \max_k FC_k^{rel} \quad (8)$$

The assumption that the covariance structure of PACCs for the damaged structure is the same as for the healthy one is leading to the diagonalization of scores from the damage state and makes it easy to determine which scores contribute the most to FC_k^{rel} . However, the during the simulated SDD stage, this assumption can be relaxed. The multivariate mean of DSF vector estimated from a system in the current state, $\boldsymbol{\mu}_c$, can then be tested against the healthy state, $\boldsymbol{\mu}_h$, by the following statistical hypothesis:

$$\begin{aligned} H_0 : \boldsymbol{\mu}_c = \boldsymbol{\mu}_h & \quad \text{tested with} \quad T^2 \leq F_{T^2, m_{select}, n_c+n_h-2} (1-\alpha) \Rightarrow H_0 \text{ is accepted} \\ H_1 : \boldsymbol{\mu}_c \neq \boldsymbol{\mu}_h & \quad \text{Else} \quad \Rightarrow H_0 \text{ is rejected} \end{aligned} \quad (9)$$

where the healthy state is represented by the null hypothesis, H_0 , and the alternative hypothesis, H_1 , corresponds to the damage state. In practical applications these true statistical properties are generally not available. Thus, the hypothesis is tested by means of the estimated quantities and the T^2 statistic [12]:

$$T^2 = \frac{n_c n_h}{n_c + n_h} (\hat{\boldsymbol{\mu}}_c - \hat{\boldsymbol{\mu}}_h)^T \hat{\boldsymbol{\Sigma}}_{pl}^{-1} (\hat{\boldsymbol{\mu}}_c - \hat{\boldsymbol{\mu}}_h) \sim T_{m_{select}, n_c+n_h-2}^2 \quad (10)$$

where the subscript c refers to the current state. The T^2 statistic is a standardized distance between two estimated means, $\hat{\boldsymbol{\mu}}_c$ and $\hat{\boldsymbol{\mu}}_h$. The statistical threshold is given at a selected level of significance, α , by the cumulative distribution function, $F_{T^2, m_{select}, n_c+n_h-2}$, because the T^2 statistic follows Hotelling's probability distribution, $T_{m_{select}, n_c+n_h-2}^2$, with m_{select} and n_c+n_h-2 DOFs. The estimated pooled variance-covariance matrix, $\hat{\boldsymbol{\Sigma}}_{pl}$, can be calculated with

$$\hat{\boldsymbol{\Sigma}}_{pl} = \frac{(n_c - 1)\hat{\boldsymbol{\Sigma}}_c + (n_h - 1)\hat{\boldsymbol{\Sigma}}_h}{n_c + n_h - 2} \quad (11)$$

where $\hat{\boldsymbol{\Sigma}}_c$ and $\hat{\boldsymbol{\Sigma}}_h$ are the unbiased estimates of the variance-covariance matrices in the current and the healthy state. The relative distance, a counterpart of Eq. (7) becomes:

$$T_{rel}^2 = T^2 / F_{T^2, m_{select}, n_h+n_d-2} (1-\alpha) \quad (12)$$

3. Experiment

The structure under study is the blade of a small wind turbine with 5 kW rated power output and a rotor diameter of 5 m. The WTB has a length of 2.36 m and a width of 150 mm. Defined by the aerofoil E387, the solid cross-section is constant along the blade, see Figure 1. The WTB is made of a glass-fibre reinforced epoxy composite. The total mass and mass density are estimated from measurements as 7,110 g and 2.30 g/cm³, respectively.



Figure 1. Cross section of experimental wind turbine blade.

A vertical configuration is chosen for the dynamic experiments, as shown in Figure 2. In order to create cantilever-type boundary conditions, the WTB is clamped to a massive steel base sitting on a concrete floor. The WTB is excited with the help of an electrodynamic shaker LDS V406, which is rigidly connected to a stiff vertical column made of a steel quadratic hollow section. The column is supported on the same steel base as the WTB, thus only negligible uncontrolled excitations sources are allowed. The shaker is attached to the WTB with the help of a modal stringer, where only normal forces are applied because of the thin stringer flexibility. The high-pressure side of the WTB profile is flatter than the low-pressure side, therefore the stringer is attached to the flatter side. The location is eccentric to the WTB's centre of mass in order to excite flapwise and torsional responses.

Acceleration responses are measured with four Metra uniaxial miniature piezoelectric accelerometers KS94B-100 with sensitivities of approximately 100 mV/g. They can operate in a frequency range from 0.5 Hz to 28 kHz. The accelerometers are attached to the high-pressure side of

the WTB with the help of adhesive wax. The sensor and stringer attachment locations are given in Figure 3. The sensor positions are close the selected damage location, which is also indicated in Figure 3. The response accelerations are read with a National Instruments NI-9234 data acquisition card connected to the NI cDAQ-9174 chassis and a laptop. The National Instruments software LabView is used to process the signals.

Although, damage is simulated non-destructively by adding small masses, the actual location is selected based on WTB inspection reports and damage studies of larger WTBs. The trailing-edge bondline is prone to disbonding due to the production process of large WTBs, where the upper and lower shells are bonded together. Additionally, trailing-edge buckling affects adversely the structural resistance [13]. Inspections of 99 WT's with 100 kW and 300 kW rated power output in Egypt showed frequent failures in trailing-edge bonding [14]. The maximum chord location was found to be exposed for this damage type because of the sharp geometrical changes. The simulated damage is therefore located on the trailing-edge at approximately 33% of the WTB length from the root, which corresponds to the typical maximum chord location in large WTBs. To be able to attach magnets to the WTB, a small steel washer is glued onto the surface. It is assumed that this small mass of 5 g does not affect the global WTB dynamics, thus baseline measurements are done with this mass attached. Then, damage with increasing extent is introduced by attaching small magnets and steel plates of know masses.



Figure 2. Configuration for dynamic experiments.

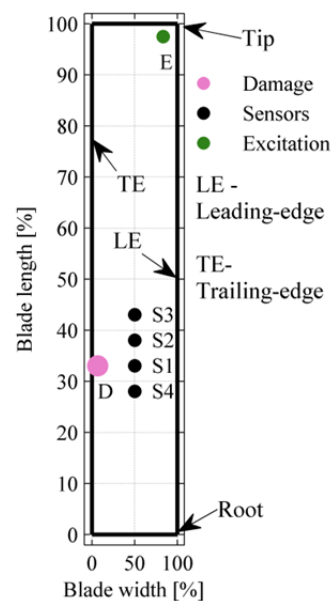


Figure 3. Schematic representation of experimental setup (not to scale).

The excitation characteristics are chosen to be band-limited white noise. Therefore, the National Instruments LabView software is used to generate zero-mean normally distributed time series with constant standard deviation. This broadband noise is then low-pass filtered with a Chebyshev filter of order eight, 100 Hz cut-off frequency and 0.6 dB band-pass ripple. The shaker is controlled by the National Instruments NI 9263 voltage output card and an amplifier with constant gain. This card is also connected to the NI cDAQ-9174 chassis and the laptop. Measurements are taken for 900 s at a sampling rate of 2048 Hz.

4. Structural Damage Detection

For the following discussion of vibration-based SDD with the help of PACCs as time series representation and statistical hypothesis testing of selected PCA scores, the initial acceleration

response signals of 900 s are divided into 100 segments of 15 s with an overlap of 40%. Although, the time series segments are directly used without subsampling or filtering, normalization is performed to account for possible variations of the shaker excitation. Therefore, the estimated means of segments are removed before dividing the time series by the estimated standard deviations.

The PACC estimates of acceleration responses from sensor ‘S1’ (see Figure 3) are shown for lags 1 to 100 in Figure 4. These estimates are given in terms of the mean and standard deviations obtained from the 100 time series segments of the healthy baseline structure. It can be seen that with increasing numbers of lags the mean values decrease while the standard deviations are nearly constant over the whole range. For the following analysis, DSF vectors, \mathbf{a}_i , are created with PACCs with consecutive lags from 1 to 100 in order to capture sufficient information.

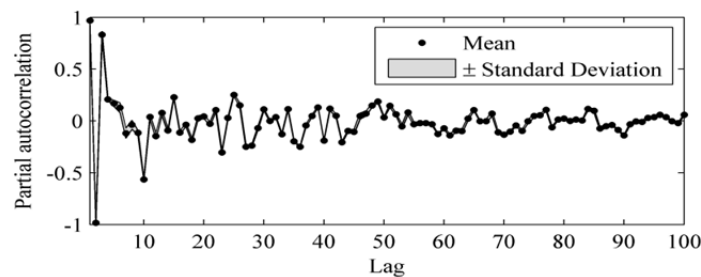


Figure 4. Mean and standard deviations of PACCs estimated from 100 samples of healthy state data.

These DSF vectors enable to construct the initial feature matrix, \mathbf{A}_h , for the healthy structure. Since the proposed SDD methodology utilizes PCA, SVD of \mathbf{A}_h is performed. This gives the transformation matrix, \mathbf{T}_h , as the eigenvectors or PCs.

The next step is the selection of PCs in order to improve the damage detectability. This requires data from the healthy and one of the simulated damage states, where masses of 1 g, 3 g and 5 g are used resulting in the maximum overall change in the WTB’s mass of less than 0.1%. Next, the corresponding score matrices, \mathbf{S}_h and \mathbf{S}_d , are calculated with the transformation matrix from the healthy state, \mathbf{T}_h . To select PCs for SDD, the relative Fisher’s criteria are calculated according to Eq. (7), where mean values and variances are estimated from the 100 samples of the healthy and the reference damage states and the significance level is chosen as 5%. The results are shown in Figure 5. For small damage extents of 1 g and 3 g the maxima are achieved by using only PCs 6 and 20. However, the larger reference damage of 5 g leads to selection of PCs 95, 92, 65 and 74. It should be noted that for all the PC selections and damage extents the relative Fisher’s criteria, FC_k^{rel} , are larger than one, thus the corresponding statistical threshold for damage detectability is always exceeded and damage successfully detected.

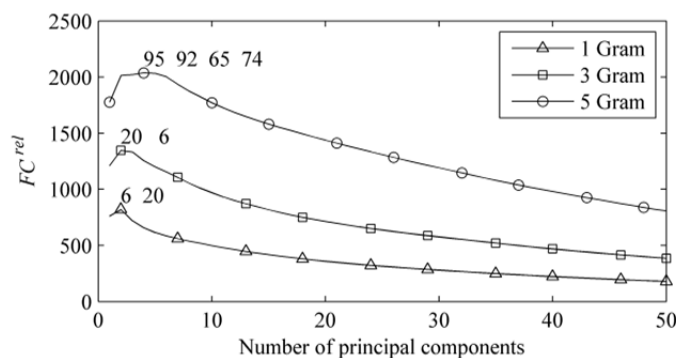


Figure 5. Relative Fisher’s criterion for various selections of PCs (selected PCs are given for the maxima).

For the preceding identification of the most damage sensitive PCs, a large number of samples is used for estimating the statistical model in the damaged state. This may not be optimal in practical applications because the need for a large number of samples will lead to delays in making a decision about the structural state. Therefore, the SDD phase discussed now uses only two sample estimates from the current structural state. To reduce the dependencies due to the overlap of time series segments, these samples are randomly selected from each state.

The detection results using two sample estimates are shown in Figure 6 in terms of the relative statistic, T_{rel}^2 , at 5% significance level in order to allow for a comparison of results obtained with different numbers of PCs. Furthermore, the damage detection threshold for T_{rel}^2 equal to one is shown, where exceedance indicates the detection of damage. The results are shown for the two previously identified optimal subsets, i.e. (6, 20) and (95, 92, 65, 74), and the full set of PCs. The healthy state results are obtained from another 900 s measurement without attached masses but using the initially obtained PCs from the first 900 s of healthy state data. Here, it can be seen that the selection of four PCs leads to a significant number, in fact 100%, of false positive alarms in contrast to the two PC subset and the full set of PCs. PC selection (95, 92, 65, 74) shows then a monotonic increase in T_{rel}^2 with increasing damage but with a high variation. The full set of PCs has a smaller variation, and for damage extents of 1 g and 2 g occasional false negatives are present. The selection with two PCs leads to a significant increase in T_{rel}^2 from the healthy state to the damage state with 1 g, which later increases slowly up to the 4 g damage. The variation for all damage extents is here the smallest of all selections. Even though there is a drop for the highest damage of 5 g compared to the smaller ones, in all cases damage is clearly indicated, while low false positive alarm rates are maintained. This selection can therefore be considered optimal for small damage extents.

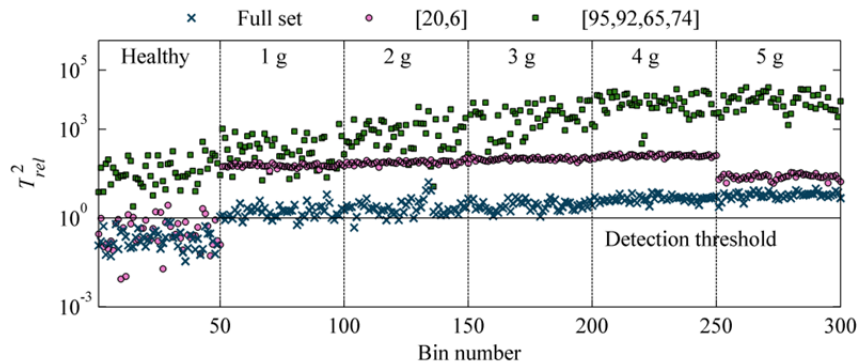


Figure 6. Relative detection rates for increasing damage extents using a subset and the full set of PCs.

5. Conclusions

This paper explored the application of PC selection of acceleration time series correlation-based DSFs for improving the detectability of structural damage. Damage decision making by means of statistical hypothesis testing of scores obtained by transforming the initial DSFs with PCA is discussed. The approach is applied to experimental data gathered from a small scale WTB under band-limited white noise excitation, where damage is non-destructively introduced by attaching small masses at the WTB's trailing edge.

The advantages of PC selection have been demonstrated with the proposed methodology, namely that optimal selections of PC subsets can be achieved for enhanced early damage detectability. Nevertheless, further studies are required to increase the understanding of the effect of different damage extents for the selection. The presented results suggest that there might not be one optimal selection for all damage extents, thus each state may require its own selection in order to achieve best detectability. Here, the orthogonality of PCs is advantages because the contribution of individual

scores is directly available without the need for considering the cross-correlations of DSF. Furthermore, only one sensor close to the actual damage location is used, and the future design of sensor setups with respect to the economic constraints and achievable damage detectability is another important aspect to be studied. However, the SDD results are promising for future developments, which can lead to beneficial applications under realistic conditions.

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