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Polynomial Chaos-Kriging metamodel for quantification of the debonding area in large wind turbine blades

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Abstract

This study aims to investigate the performance of a data-driven methodology for quantifying damage based on the use of a metamodel obtained from the Polynomial Chaos-Kriging method. The investigation seeks to quantify the severity of the damage, described by a specific type of debonding in a wind turbine blade as a function of a damage index. The damage indexes used are computed using a data-driven vibration-based structural health monitoring methodology. The blade's debonding damage is introduced artificially, and the blade is excited with an electromechanical actuator that introduces a mechanical impulse causing the impact on the blade. The acceleration responses' vibrations are measured by accelerometers distributed along the trailing and the wind turbine blade. A metamodel is formerly obtained through the Polynomial Chaos-Kriging method based on the damage indexes, trained with the blade's healthy condition and four damage conditions, and validated with the other two damage conditions. The Polynomial Chaos-Kriging manifests promising results for capturing the proper trend for the severity of the damage as a function of the damage index. This research complements the damage detection analyses previously performed on the same blade.

Keywords

Structural health monitoring, wind turbine blades, damage quantification, damage features, data-driven metamodel, Polynomial Chaos-Kriging

Introduction

Currently, society aims for a future where the generation of energy is clearer. Thus, there is an expansion in offshore wind turbines, making studies in this area necessary. In addition, the maintenance of wind turbine blades involves, in most part, methods based on visual inspection, which can be dangerous and expensive.[1] Therefore, a system for monitoring wind turbines' conditions is of great industrial interest, demanding further development of methodologies for detecting and quantifying damage to these structures.[2]

Structural health monitoring (SHM) methods are used to diagnose and extract meaningful information about the health from a structure of interest, based on the measured data from sensors distributed and permanently installed along with the structure.[3] SHM techniques have four functional levels of the classification proposed by Rytter[4]: level 1—damage detection, level 2—damage location, level 3—damage quantification, and level 4—remaining useful life estimate. In the literature, the first three levels are also categorized as diagnosis and the last as prognosis. This work focuses on damage quantification to complement a methodology for damage detection by Garcia and Tcherniak[1] and thus provides a full damage diagnosis of debonding wind turbine blades. The contribution concerns the damage quantification, obtaining the severity by the damage indices (DIs), assuming the inherent uncertainties to obtain a robust damage quantification. This

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work does not focus on high levels of SHM such as the damage location or the remaining useful life estimate. In the literature,[5–7] it is possible to find works on damage location in structures of composite materials.

The damage detection methodology used by Garcia and Tcherniak[1] followed the idea of vibration-based structural health monitoring (VSHM), which measures vibration responses from an artificial excitation. Thus, the structure's health/current state can be analyzed by monitoring its vibration response changes. The methodology was applied to an SSP 34-m wind turbine blade. Conventional classification of VSHM methodologies is the division between model-based[8] and non-model-based (or data-driven) methods.[9,10] In the methodology of this work, a data-driven approach is used. Non-model-based methods depend exclusively on the data measured from the structure under study. These methods also involve constructing a model, but that model is based on data rather than numerical or analytical models.[9] The structure's initial state measurements are considered reference states, where these observations can be compared with the structure measurements in operation. Any deviation of the new observations from the reference state might be considered an indication of damage. Tcherniak and Mølgaard[11] carried out an analysis of an unsupervised methodology that combined the correlation between the signals measured from different accelerometers. This study demonstrated that methodologies based on data-driven techniques have a big potential for detecting damage on large structures. Currently, many data-driven methodologies are being developed, for example, Soize and Orcesi[12] presented a machine learning approach using only an experimental database, consisting of a small number of records, to detect changes in the rigidity of engineering structures.

The damage quantification is not yet extensively addressed by the scientific community, but it is crucial to improve the safety and useful life of structures, thus motivating the scientific community to develop some damage quantification methods. Paixão et al.[13] used AutoRegressive (AR) models on Lamb wave signals measured on a composite material plate to calculate damage-sensitive features for calculating indexes using the Mahalanobis square distance. Quantification was achieved by learning a defined curve, using cubic spline functions to predict the delamination area. da Silva et al.[14] executed a similar idea when manipulating the possibility of extrapolating these trend curves to future prognostic states when the delamination grows in the same place and with a similar effect. These studies demonstrated that the resources that use AR models are precisely correlated with the structural state and with a smooth tendency that allows the use of cubic spline functions.

Many studies have addressed experiments in wind turbines in the literature, but there is a lack of methodologies to quantify the damage to them. One of the difficulties in quantifying wind turbine blades' damage is that these structures work under variability (temperature, climate, etc.). Therefore, it is of great importance to consider uncertainty quantification (UQ). A method with valid results in obtaining UQ models is the Polynomial Chaos Expansion (PCE). The PCE method with application in engineering was introduced by Ghanem and Spanos.[15] They proposed a new method using convergent orthogonal expansion for solving problems involving material variability. The material property was modeled as a random field. The results found had a good agreement with the results obtained through a Monte Carlo simulation. Ghanem and Spanos[16] used the PCE to quantify the uncertainty applied to some problems involving mechanical systems. The use of different types of orthogonal polynomials to represent non-Gaussian processes was introduced by Xiu and Karniadakis,[17] which presents a method for solving stochastic differential equations based on Galerkin projections on a polynomial chaos basis. They represented stochastic processes based on an Askey family of orthogonal polynomials that reduced the system's dimensionality and led to the exponential convergence of the error. This new methodology, which is reviewed by Xiu,[18] presents satisfactory computational cost and precision results. One of the significant advantages seen in using the PCE is its rapid convergence and expressing the final solution as a random process and not just as a set of statistics. Bogoevska et al.[19] mention that operational structures such as wind turbines have complex dynamic behavior that challenges the applicability of existing SHM strategies for condition evaluation. Thus, Bogoevska et al.[19] propose a structure based on the symbiotic treatment of environmental/operational variables acting on the structure's vibration response. A probabilistic model of the PCE was used for UQ in the identified structural performance indicators. Avendaño-Valencia et al.[20] emphasized that effective fatigue monitoring and prediction algorithms for structures such as wind turbines require an accurate representation of their dynamic response on the short- and long-term scale. The long term can be achieved in a computationally efficient way through the use of metamodels. That article discussed a two-step methodology, in which the first consisted of projecting the power spectral density (PSD) of the measured dynamic response of the wind turbine linearly in an alternative representation space through principal component analysis (PCA). In the second stage, the coefficients of the PCA-based projection were used as a vector of characteristics, represented by a probability density model in the characteristic space, which is associated with environmental/operational variables measured by the supervisory control and data acquisition (SCADA) of the wind turbine through the PCE. The proposed methodology facilitated the detection of different wind turbine modes, although it can still be used for fatigue simulation and prediction, only by sampling from the resource space. This methodology was demonstrated with real data measured on a wind turbine located in Lübbenau, Germany, measured over 3 months.

In this study, the methodology discussed for quantifying the size of damage like trailing edge (TE) debonding of a wind turbine blade is based on obtaining a metamodel using the Polynomial Chaos-Kriging (PC-Kriging) method. PCE and Kriging are two popular non-intrusive metamodeling techniques (they do not modify or adapt the original model equations). The PCE replaces the computational model with a series of orthonormal polynomials in the input variables, where the polynomials are chosen in coherence with the probability distributions of these input variables.[16,21] The Kriging method assumes that the computational model behaves as a realization of a Gaussian random process whose parameters are estimated from the available computer executions, that is, input vectors and response values.[22] The PC-Kriging presents itself as a new non-intrusive metamodel approach combining PCE and Kriging. The PCE is close to the computational model's global behavior, while Kriging is responsible for its local variability. Combining these two methods leads to better accuracy, or at least as good, as either method alone.[23,24] That is why the choice of applying both methods as a combined approach in this work.

Some works were carried out using the combination of the PCE and Kriging methods, and thus, it was possible to identify some advantages and disadvantages of this combination. Some of the PC-Kriging method's main advantages are the ease of model construction, the low computational cost, the analytical calculation of classical statistical measures of the quantity of interest, and its simplicity compared to other machine learning techniques. However, the PC-Kriging is very sensitive to data quality, just like any other machine learning technique, and impossible to apply to large problems, these being some of its disadvantages.[25,26] Kersaudy et al.[27] evaluated the specific absorption rate (SAR) using a surrogate model to reduce the computational cost. Thus, it was considered a sparse representation of the PCE using minimal angle regression as a selection algorithm to retain the most influential polynomials, and the selected polynomials are used as regression functions for the universal Kriging model. This combination proposal was applied to three benchmark examples, and the performances were compared with a standard Kriging model and a sparse PCE classic. The combination of the methods showed an adequate performance. In the literature, some studies used PC-Kriging for quantification problems considering uncertainties. Schöbi et al.[28] developed a new structural reliability method based on the PC-Kriging approach, which was coupled to an active learning algorithm known as adaptive Kriging-Monte Carlo Simulation (AK-MCS). The problem was formulated so that the calculation of small probabilities of failure and extreme quantiles were unified. Dubreuil et al.[29] carried out a parametric study of engineering models under uncertainty, using the PC-Kriging approach. The advantage of the approach developed in this article was the reduction in computational cost, which was demonstrated in several numerical examples and also illustrated in the parametric study of an aircraft wing under uncertainty.

The main contribution of this work is to propose a PC-Kriging framework for damage quantification. To the best of the authors' knowledge, this methodology is not yet explored in the context of SHM, despite its great potential for damage quantification, once it considers the propagation of uncertainties in the model with a relative low computational cost, becoming something viable for the industrial context. In particular, this article explores applying the PC-Kriging method for quantification damage to a wind turbine blade, using a data-driven methodology. In our limited knowledge, there is no similar application in the SHM literature using this method to quantify the delaminated area.

In this study, PC-Kriging is used to define a trend curve that associates a local DI with an estimate of the damaged area, considering the uncertainties. Each DI is calculated based on the data-driven algorithm using the Mahalanobis distance (MD), considering a baseline condition as a reference condition. Roberts et al.[30] carried out an investigation on the environmental and operational variability on the vibration features in a wind turbine blade in operation. The study was carried out with the structure undamaged and incrementally damaged under 43 r/min operating condition. In this study, a global DI has been considered by combining the damage-sensitive features extracted from the vibration responses from all the sensors. The DT is calculated based on the observations considered for the learning. In the literature, there are some works about wind turbine blades in operation that investigate other techniques to mitigate environmental variations and operations.[31,32] One of the major challenges in regression problems for damage detection and quantification is the valid correlation of the parameters, the damaged area with the metric DI, which has sensitive features about severity. The Gaussian process regression (GPR) method depends on the data's quality to determine a correct trend, so one of the advantages of PC-Kriging is that the PCE determines the data trend. Even though PC-Kriging has several advantages,[33] there are still not enough results in the literature on the use of PC-Kriging for problems of quantification of damage in SHM, so application work using PC-Kriging is of great importance for advances in the use of this method.

The work is organized as follows: first, a statement of the problem in question is performed, then the methodologies that will be adopted for the detection and quantification of damage in wind turbine blades are presented. The experiment setup and the introduction of artificial damage, and the data collection procedure are presented. Finally, the results are investigated, and the conclusions have discussed the performances of the proposed VSHM methodology for detecting damage in different locations of the accelerometer and the methodology used to quantify the damage.

Problem statement

The study presented in this work is carried out on an SSP 34-m wind turbine blade. The blade is instrumented with 20 triaxial accelerometers, 10 along the TE and 10 along the leading edge (LE). The results of this study consist of two parts:

1. Damage detection: the methodology by Garcia and Tcherniak[1] is used. Such methodology consists of four steps: data collection, the reference state, feature extraction, and inspection phase and decision-making. Each of these steps is detailed throughout the text. An actuator is used to excite the blade, which is an impact test. An investigation is carried out on the sensitivity of detection and damage progression.
2. Damage quantification: to quantify the damage's size, a metamodel obtained from the PC-Kriging method is used. The metamodel generates a trend curve related to the DIs obtained in the detection part with the severity of the damage.

Figure 1 shows a schematic of the entire methodology of this work. The methodology is divided into two steps: (1) learning and (2) validation. The PC-Kriging metamodel is obtained in the learning step using training data from the structure under the baseline condition and known progressive damage conditions. In the validation step, the structure is under an unknown condition, and the objective is to find out if there is any damage. For this, a hypothesis test is performed with a defined threshold value. When damage is detected, the DI is estimated from the DI using the trained metamodel. The damage quantification part is the main contribution of this work.

Damage assessment

Methodology for damage assessment in wind turbine blades

The methodology presented in this study is available in Garcia and Tcherniak's study.[1] This methodology is considered a simple non-parametric method for data compression and information extraction. The procedure is divided into four steps: data collection, the reference state, feature extraction, and inspection phase for decision-making.[34]

Data collection. The first step is to collect the data from the structure/system. Acceleration signals are measured and discretized into a vector. Each measured signal is first standardized to have zero mean and unit variance and second transformed into the frequency domain. Each signal vector realization is arranged in the columns of the matrix $\mathbf{Z}$, that is

$$\mathbf{Z} = (\mathbf{Z}_1, \mathbf{Z}_2, \ldots, \mathbf{Z}_M) \tag{1}$$

The matrix $\mathbf{Z}$ is constructed from signal vectors obtained on the pristine/healthy state of the wind turbine blade, and it is used for creating the reference state.

Creation of the reference state. A reference state is created based on the matrix $\mathbf{Z}$, where the observation signal vectors can be compared. First, each vector signal $\mathbf{Z}_m$ is embedded into a matrix $\check{\mathbf{Z}}_m$ by W-lagged copies of itself. All matrices $\check{\mathbf{Z}}_m$ are used to create the full embedded matrix $\check{\mathbf{Z}}$, that is

$$\check{\mathbf{Z}} = (\check{\mathbf{Z}}_1, \check{\mathbf{Z}}_2, \ldots, \check{\mathbf{Z}}_M) \tag{2}$$

The covariance matrix of $\check{\mathbf{Z}}$, which defines the covariance between the different signal vector realizations, is estimated by

$$\mathbf{C}_Z = \frac{\check{\mathbf{Z}}^t \check{\mathbf{Z}}}{N} \tag{3}$$

The eigendecomposition of $\mathbf{C}_Z$ is written as

$$\mathbf{E}_Z^t \mathbf{C}_Z \mathbf{E}_Z = \Lambda_Z \tag{4}$$

where Λ_Z contains all eigenvalues stored in the diagonal matrix and $\mathbf{E}_Z$ contains all eigenvectors $\mathbf{E}^k$ with dimension $\{\mathbf{E}^k : 1 < k \leqslant MW\}$. The principal component $\mathbf{A}^k$ associated with each eigenvector $\mathbf{E}^k$ is computed by projecting the matrix $\check{\mathbf{Z}}$ onto $\mathbf{E}_Z$ as described by

$$\mathbf{A} = \check{\mathbf{X}}\mathbf{E}_X \tag{5}$$

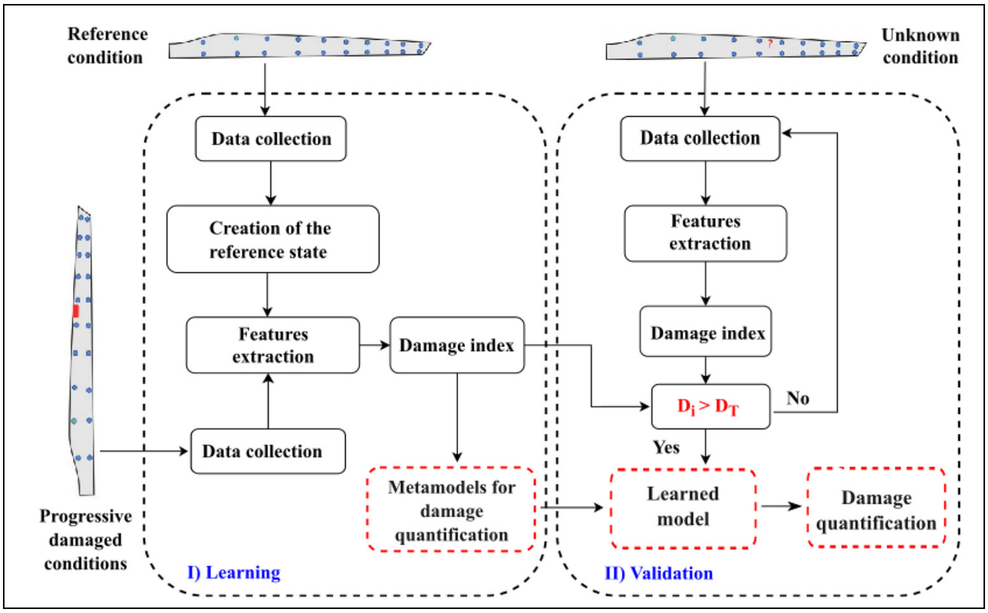

Figure 1. Schematic representation of the proposed methodology for quantifying damage to wind turbine blades.

The reference state is formulated based on the reconstructed components obtained by the linear combination of a set of principal components. The reconstructed components are computed by convolving the principal components $\mathbf{A}^k$ with the associated $\mathbf{E}^k$

$$R^k_{m,l} = \frac{1}{W_n} \sum_{w=1}^{W} A^k_{l-w+1} E^k_{m,w} \tag{6}$$

where W_n is a normalization factor described by

$$W_n = \begin{cases} n & 1 \leq n \leq W-1 \\ W & W \leq n \leq N \end{cases} \tag{7}$$

The reconstructed components are arranged in columns into the matrix $\mathbf{R}$ with dimension $[L \times (MW)]$. Each column corresponds to the reconstructed component of the signal associated with the respective principal component. Therefore, $\mathbf{R}$ can be used as the reference state of the structure to which the observation signal vectors are compared.[1]

Feature extraction. A feature vector (FV) is obtained for each new observation signal vector, which will be subjected to damage evaluation by comparing its similarity to the reference state defined by $\mathbf{R}$. An FV is calculated by multiplying an observation signal vector $\mathbf{z}$ with each RC in the reference state $\mathbf{R}$, as shown in equation (8) where $j = 1, \ldots, W$

$$T_j = \sum_{n=1}^{N} z_n R_{nj} \tag{8}$$

Each T_j value represents the inner product between an observation signal vector and each RC. All T_j are arranged into a vector $\mathbf{T}$ with dimension W. The FV $\mathbf{T}$ characterizes the observation signal vector onto the feature space.

Inspection phase and decision-making. The baseline feature matrix $\mathbf{T}_B$ is created. Once the baseline is defined, an observation FV is then compared with the baseline $\mathbf{T}_B$. Using the MD, DI is obtained

$$\mathcal{D}_i = \sqrt{(\mathbf{T}^i - \boldsymbol{\mu}_B)^t \boldsymbol{\Sigma}^{-1} (\mathbf{T}^i - \boldsymbol{\mu}_B)} \tag{9}$$

where $\boldsymbol{\mu}_B$ is the mean row of the baseline feature matrix $\mathbf{T}_B$, $\boldsymbol{\Sigma}$ is its corresponding covariance matrix, and $\mathcal{D}_i$ is the DI.

It is necessary to set a threshold against which DIs can be assessed to label an observation as an outlier or inlier. A probabilistic threshold D_T based on the probability density function (PDF) of the distances measured by the baseline FVs for the baseline matrix is calculated $\mathbf{T}_B$. As the DIs are always positive ($\mathcal{D}_i > 0$), a lognormal PDF was used to approximately adjust the data considered as a learning set (observations from the healthy wind turbine blade), to define a limit to distinguish between observations of the healthy and damaged structure. The threshold D_T is determined by a particular risk level which defines the false alarm probability equal to α in the lognormal density function. The threshold is calculated by the inverse of the lognormal cumulative density function which gives the value with probability $1-\alpha$ in the cumulative density function.[1] Thus, the definition of whether or not there is damage is given by the decision below

$$\mathbf{H_0} : \mathcal{D}_i \leqslant D_T \Rightarrow \text{Undamaged wind turbine blade}$$

$$\mathbf{H_1} : \mathcal{D}_i > D_T \quad \Rightarrow \text{Damaged wind turbine blade}$$

We emphasize that once the DI used is based on a previous paper, the points are only summarized in the present work and invite the reader to get more details in Garcia and Tcherniak's study.[1]

Damage quantification methodology

After detecting the initial TE debonding in the wind turbine blades using a data-driven approach, the user needs to decide if there is an imminent structural failure or if the system can be kept in operation under monitoring to track the damage progression and its impact on structural safety conditions. Therefore, it is imperative to obtain the quantification of the debonding length.

Computer simulation of many problems in modern engineering and applied sciences have a high computational cost. In this context, the metamodeling tries to reduce computational costs and perform sophisticated analyses, such as reliability analysis and design optimizations.[35] One method for obtaining metamodels is investigated: PC-Kriging. In the next subsection, the method algorithm is presented.

PC-Kriging. The PCE method works as a type of "response surface," which locally interpolates the model hypersurface. This method obtains the computational model by sum the orthonormal polynomials to the input variables. This orthogonal expansion decouples stochastic and deterministic objects; that is, the polynomial basis is random, and the numerical coefficients are deterministic, obtained from the data. This property made the metamodel construction easier.

In this context, consider a finite-variance computational model $\mathcal{M} : \mathcal{D}_X \subset \mathbb{R}^M \mapsto \mathbb{R}$, which receives as input an M-dimensional vector $X = (X_1, \cdots, X_M) \in \mathbb{R}^M$ with a given PDF f_X defined on the support $\mathcal{D}_x$, and returns as output the scalar quantity of interest $Y = \mathcal{M}(X) \in \mathbb{R}$, such as illustrated in Figure 2.

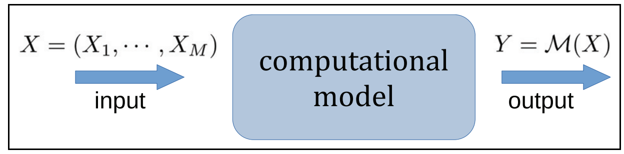

Figure 2. Computational model under uncertainty.

According to Marelli and Sudret,[36] the PCE of $\mathcal{M}(X)$ is given by

$$Y = \mathcal{M}(X) \approx \mathcal{M}^{PC}(X) = \sum_{\alpha \in \mathcal{A}} y_\alpha \Psi_\alpha(X) \tag{10}$$

where $\mathcal{A} \subset \mathbb{N}^M$ is a subset of the polynomial indexes, $\Psi_\alpha(X)$ is a family of orthonormal polynomials with respect to f_X, and y_α are real-valued deterministic coefficients to be determined.

The appropriate family of polynomials is chosen according to the probability distributions of the input variables.[18,21] One of the significant advantages seen in using the PCE is its rapid convergence and expressing the final solution as a random process and not just as a set of statistics.

The Kriging method, also known as GPR, is a nonparametric Bayesian approach that has the advantages of working on small data sets and providing measurements that consider the predictions' uncertainties. A Kriging model is called ordinary Kriging when the trend is a single parameter with an unknown value. When the trend is a sum of functions, it is called universal Kriging.

The combination of the PCE and Kriging methods results in the method called PC-Kriging. This combination results in technique metamodeling more accurately than the PCE and Kriging separately. The PC-Kriging uses the PCE-type regression to capture the computational model's global behavior and the interpolation-type Kriging to capture the variations. The PC-Kriging is considered a universal Kriging technique that obtains the trend from a set of orthonormal polynomials.[23] One of the PC-Kriging's main advantages is the ease in building the model and the low computational cost; however, PC-Kriging may not perform well on high-dimensional problems.

The construction of the metamodel by PC-Kriging consists of two stages: (1) the determination of a set of polynomials that defines the trend and (2) the determination of the ideal correlation parameters and the trend parameters. The polynomials that define the trend are calculated using the PCE by employing the least-angle regression (LARS) algorithm. The trend parameters and correlation parts are calculated as in the universal Kriging algorithm by solving the log-likelihood function's maximization using a gradient-based optimization algorithm. These two steps are processed in series, as the set of polynomials can be determined independently of Kriging's settings.[24–26,33]

The idea of applying PC-Kriging in the damage quantification level is to employ a metamodel to capture the trend between the local DI and damage size, which has been observed by Garcia and Tcherniak.[1] The local DI is used as input, and the damage size is used as output for the construction of a PC-Kriging model. The PC-Kriging can be described as

$$\mathcal{S} \cong \sum_{\alpha \in \mathcal{A}} y_\alpha \Psi_\alpha(\mathcal{D}_i) + \sigma^2 \mathcal{Z}(\mathcal{D}_i, \omega) \tag{11}$$

where $\mathcal{D}_i \in \mathbb{R}$ is the local DI with a given PDF f_X and $\mathcal{S}$ is the damage size, with $\mathcal{S} \in \mathbb{R}$. The $\sum_{\alpha \in \mathcal{A}} y_\alpha \Psi_\alpha(\mathcal{D}_i)$ is a weighted sum of orthonormal polynomials that describes the PC-Kriging model trend, where $\Psi_\alpha(\mathcal{D}_i)$ are orthonormal polynomials in relation to f_X, $\alpha \in \mathcal{A}$ are the indices, and y_α are the corresponding coefficients; σ^2 is the variance of the process, and $\mathcal{Z}(\mathcal{D}_i, \omega)$ is a Gaussian random process with zero mean. ω describes outcomes of the underlying probability space with a correlation family $\mathcal{R}$ and its hyperparameters θ. That is, the correlation function $\mathcal{R} = \mathcal{R}(x, x', \theta)$ describes the correlation between two samples of the input space. For example, x and x' depend on the hyperparameter θ.[22] The PC-Kriging can be interpreted as a universal model of Kriging with a specific trend.

The PC-Kriging algorithm can be done in two ways: sequential and optimal. In sequential PC-Kriging (SPCK), the set of polynomials and the Kriging metamodel are determined sequentially. First, the ideal set of polynomials is determined by the PCE based on LARS. Every set of polynomials is incorporated into the PC-Kriging equation, and then, the PC-Kriging metamodel is calibrated as a usual Kriging model, including the calculation of the coefficients y_α. In the optimal PC-Kriging (OPCK), the model is obtained iteratively. As in SPCK, the ideal set of polynomials is determined by LARS. The LARS algorithm results in a dispersion of the set of polynomials classified according to their correlation with the current residual in each LARS iteration (in decreasing order). Each polynomial is then added individually to the trend of a PC-Kriging model. In each iteration, a new PC-Kriging model is calibrated. At the end of this process, the PC-Kriging models are compared using their leave-one-out (LOO) error estimators. The PC-Kriging metamodel optimal is chosen according to the one that minimizes the LOO error.[35] The LOO error can be defined as[24]

$$\epsilon_{LOO} = \frac{1}{N} \sum_{i=1}^{N} (\mathcal{Y}^{(i)} - \mu_{\hat{y},(-i)}(\mathcal{X}^{(i)}))^2 \tag{12}$$

where $\mu_{\hat{y},(-i)}(\mathcal{X}^{(i)})$ is the prediction mean $\mu_{\hat{y}}$ of sample $\mathcal{X}^{(i)}$ by a Kriging metamodel based on the experimental design $\mathcal{X}^{(-i)} = \mathcal{X} \backslash \mathcal{X}^{(i)}$ and $\mathcal{Y} = \{\mathcal{Y}^{(i)}, i = 1, \cdots, N\}$ is the exact model response.

Schöbi et al.[24] compared the performances of the Kriging, PCE, SPCK, and OPCK methods, in terms of generalization of relative error in the analytical reference functions. The results showed that PC-Kriging is better than, or at least as good as, Kriging and PCE methods separately for small experimental projects. Moreover, it was concluded that OPCK is preferable to SPCK because it reduces the number of polynomials in the regression part and, therefore, reduces the metamodel's complexity. Based on this conclusion, the OPCK algorithm was employed in this work.

The implementation of the PC-Kriging algorithms was performed using the UQLab (https://www.uqlab.com/), which is a MATLAB-based software framework designed to bring UQ techniques and algorithms to a broad audience. The UQLab offers an extensive list of algorithms for UQ, including the PC-Kriging method.[37]

Experimental application

The data set used in the experimental application proposed in this work belongs to Bruel & Kjaer. This data set has been explored recently to validate different methodologies.[1,38,39] A brief description of the experimental setup will be provided below. A detailed description of the experimental setup can be found in Nielsen et al.'s study.[40]

The experimental application of the methodology proposed was performed in the SSP 34-m wind turbine blade. SSP Technology A/S manufactured the blade, and the experiments were performed on a test rig at the wind energy department, the Technical University of Denmark. The blade of the wind turbine and the experiment's facilities can be seen in Figure 3(b).

The blade was instrumented with 20 triaxial accelerometers, model Bruel & Kjaer Type 4524-B, positioned as represented in the scheme in Figure 3(a). Ten accelerometers were placed in the TE and 10 in the LE. In the experiment, acceleration signals were collected for the blade's impact response under healthy and progressive damaged conditions. Figure 3(c) show the electromechanical actuator used to generate the structure's impact, and it was placed on the surface outside of the blade at the position indicated in Figure 3(a).

Experimental data are always contaminated by noise, so it was necessary to repeat the measurements several times. In this experiment, to speed up the validation, the time between the actuator impacts varied from 1 to 5 min. In real applications, the time between measurements can be increased, depending on industrial requirements. In total, 386 signals were collected for seven structural health conditions simulated, being a healthy condition, and six with damage (see Table 1).

One of the main types of damage in wind turbine blades is the adhesive joint debonding.[41] This type of damage occurs when an adhesive bond between the laminates of the pressure and suction sides of the blade breaks which can happen on both LE and TE. Small debonding size can grow up to a level at which repair is impossible, and the entire blade should be replaced.[1] First, a series of holes through the adhesive between the blade's pressure and suction sides were drilled. Then, using a saw and a chisel, the holes were merged, forming an opening that was gradually extended from 20 up to 120 cm by increments of 20 cm. The debonded parts were connected by bolts, placed at 10-cm intervals. The healthy condition was then simulated by tightening all the bolts, and the progressive damaged conditions were reproduced by loosening some bolts. The number of loosened bolts defined the damage size. The location of the damage can be seen in Figure 3(a). More details about the experiment can be found in Garcia and Tcherniak's study.[1]

Table 1. Number of signals measured on each experimental test.[1]

Condition	Damage size (cm)	Number of signals
H	–	53
D20	20	70
D40	40	61
D60	60	60
D80	80	49
D100	100	54
D120	120	39
Total		386

Results and discussions

This section presents the damage detection results and the quantification of the area of the TE debonding. To obtain the results, MATLAB software is used. For damage quantification results, the UQLab toolbox is

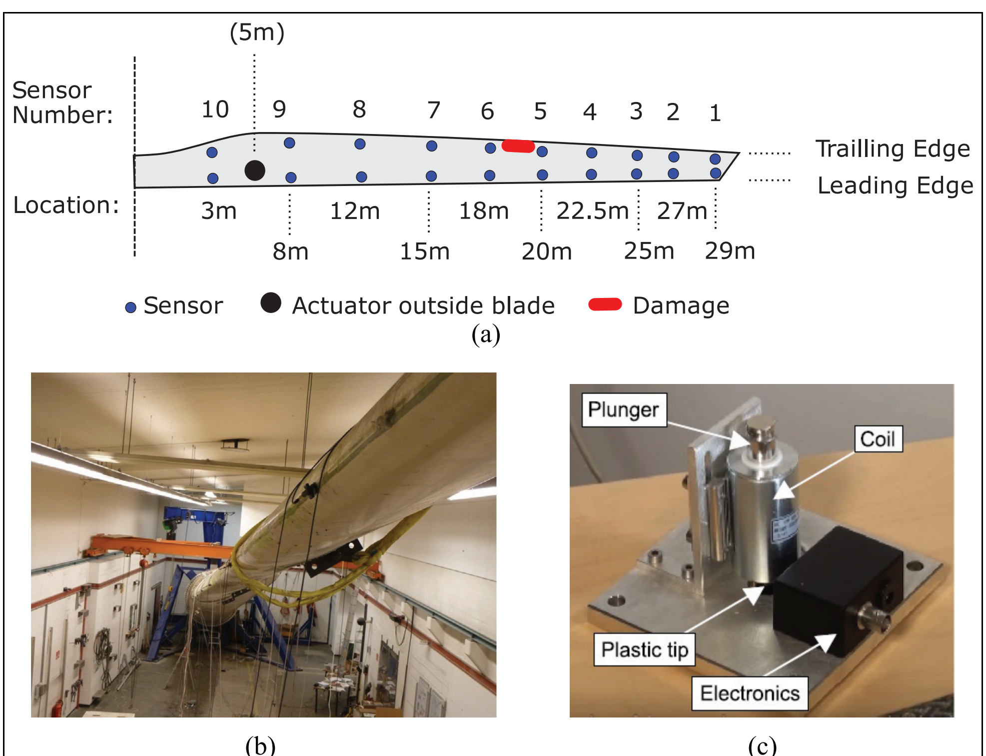

Figure 3. Experimental setup of the SSP 34-m wind turbine blade manufactured by SSP Technology A/S. The blade was instrumented with 10 accelerometers along the leading edge (LE) and 10 along the trailing edge (TE) and was excited by an electromechanical actuator. The debonding damage was introduced into the blade.[1] (a) Accelerometers, damage and actuator locations scheme. (b) Test rig setup. (c) Electromechanical actuator.

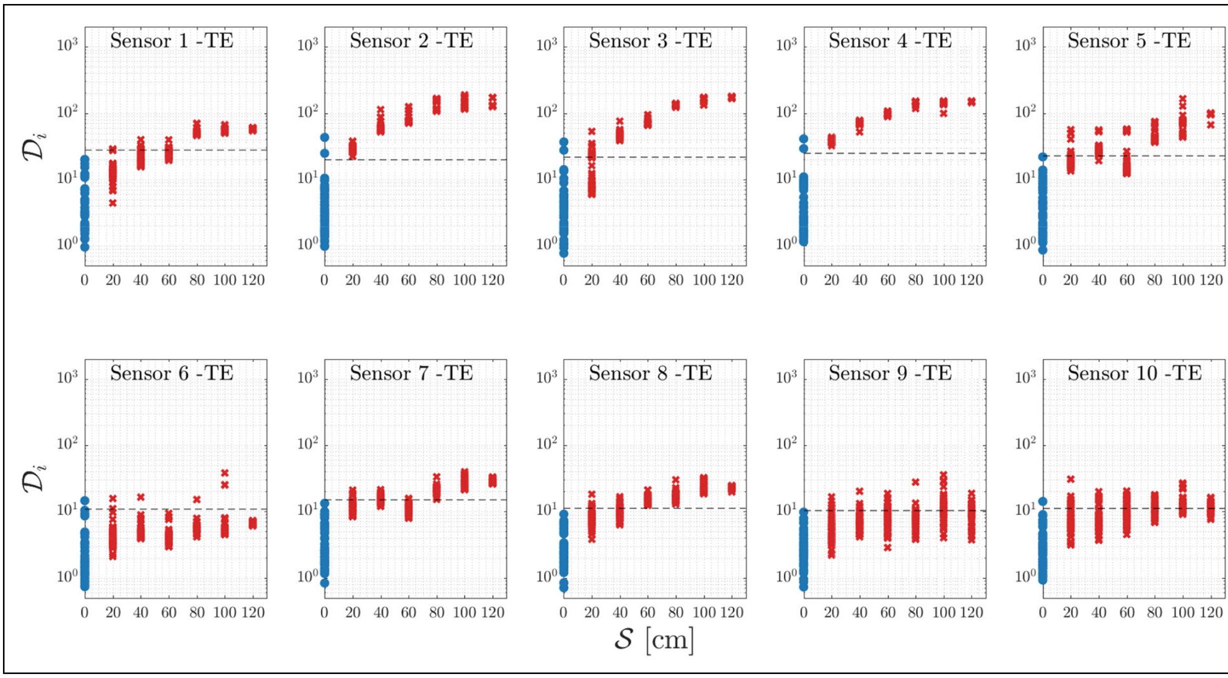

Figure 4. Damage index ($\mathcal{D}_i$) by damage size ($\mathcal{S}$) for accelerometers in the trailing edge (TE). The damage index in the healthy (●) and damaged (x) conditions. The dashed line (-----) corresponds to the threshold defined by a risk of false alarm probability equal set to $\alpha = 0.01$.

used. It is used to estimate the TE debonding size, using the DI and optimizing the PC-Kriging model.

Damage detection

The methodology for damage detection described previously is applied in the SSP 34-m wind turbine blade data set. The data set provides acceleration signals collected from sensors placed in the TE and LE. Garcia and Tcherniak[1] defined the parameters chosen for the best methodology performance, which are employed in this work. In the reference state's Creation, it is considered $M = 10$ signal vector realizations with a sliding window size of $W = 10$. The FV dimension is set to $p = 5$. The baseline matrix construction is performed using $s = 26$ FVs of dimension $p = 5$ extracted from healthy condition signals. In the inspection phase, the risk of false alarm probability is set to $\alpha = 0.01$ in the lognormal density function. A detailed discussion of each of these parameters on the methodology performance can be found in Garcia and Tcherniak's study.[1]

Figure 4 shows the DI by damage size obtained, considering the accelerometers in the TE to the actuator's position. Figure 5 shows the DI by damage size obtained, considering the LE's accelerometers. In these cases, the threshold is calculated by a risk of false alarm probability equal to $\alpha = 0.01$. It can be seen that the accelerometers along the TE detected the damage better than the accelerometers along the LE.

The damage detection results present three scenarios: (1) DIs can detect and track the severity of the damage. This case can be seen in Figure 4, in sensors 2 and 4. (2) The damage is not well detected, as it has many false negatives. However, as the damage increases, there is a tendency for the DIs, so the damage's progression is somehow detected. In this case, there is a time-dependent feature for damage detection. This can be seen in Figure 4, in sensors 1, 3, and 8, and Figure 5 in sensors 4 and 5. (3) A final scenario is when the DIs cannot detect the damage or track its progress. In Figure 4, this can be seen in sensors 6 and 9 and Figure 5, in almost all sensors. It is observed that the accelerometers 1, 2, 3, and 4 in the TE, and located before the damage toward the tip of the blade, obtained better results. This conclusion is in line with the results of García et al.[42]. In García et al.'s study,[42] elastic waves were simulated in a similar experiment. The elastic waves traveled along the blade until they interacted with the damaged region to continue toward the tip of the blade. For this reason, the accelerometers located

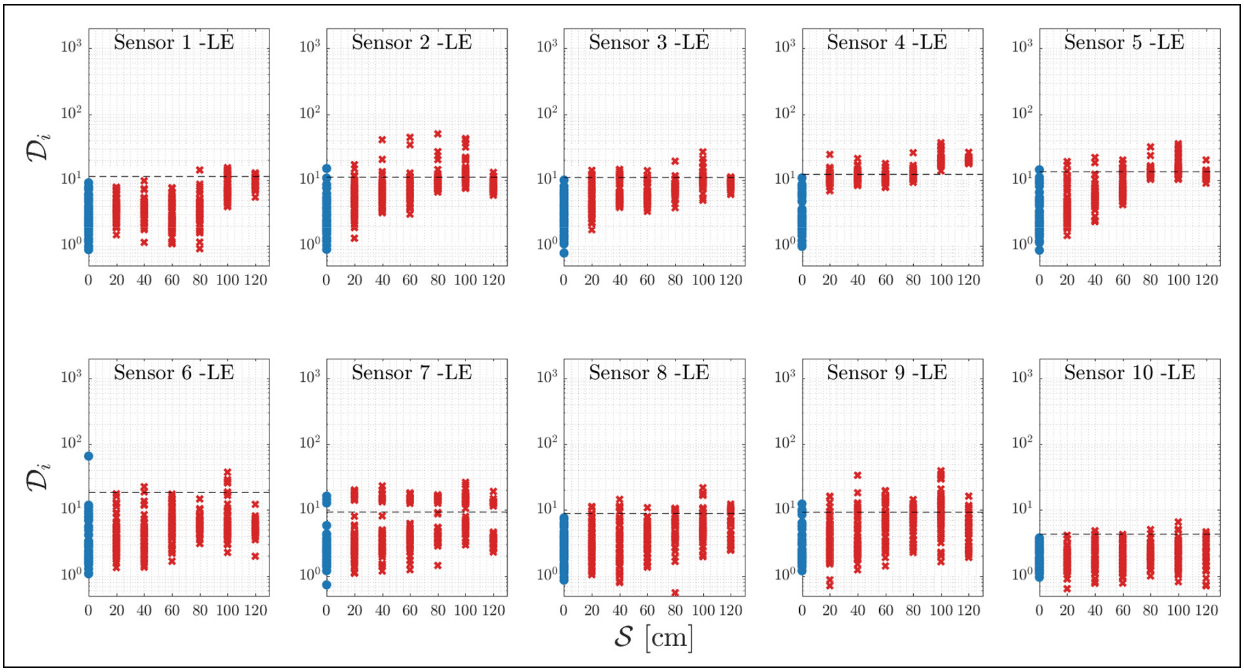

Figure 5. Damage index ($\mathcal{D}_i$) by damage size ($\mathcal{S}$) for accelerometers in the leading edge (LE). The damage index in the healthy (●) and damaged (x) conditions. The dashed line (- - - - -) corresponds to the threshold defined by a risk of false alarm probability equal set to $\alpha = 0.01$.

before the damage performed better. These results of damage detection influence the results of damage quantification because DIs are used.

Damage quantification

The damage quantification methodology used is based on the construction of a PC-Kriging metamodel, which obtains the TE debonding size as a function of the local DI. The local DI is used as input for building a PC-Kriging metamodel. The following conditions' local DI is considered in the model learning stage: H, D40, D80, D100, and D120. The damaged conditions D20 and D60 are used in the validation steps to validate the prediction of damage quantification using metamodel.

In the first stage of the PC-Kriging metamodel construction, the polynomials set defining the trend through the PCE are defined using the LARS algorithm. In the second stage, the ideal correlation parameters and the tendency parameters are calculated the same way they are calculated in the universal Kriging algorithm.

For this work results, an OPCK approach is used; that is, the metamodel is obtained iteratively, and the one chosen is the one that minimized the LOO error. The OPCK is chosen because it already has better performance in the literature than the SPCK.[24] Figure 6 shows a schematic representation of the OPCK algorithm. The DI is always positive, so in the PCE settings, the distribution used is lognormal, and the moments of the PCE settings are the mean and standard deviation of the learning data. In the Kriging configuration, a correlation function based on an exponential and ellipsoidal family is used to optimize the maximum likelihood estimate performed by a gradient method to define the GPR model.[22] The trained models represent a mean and 95% confidence interval of the predicted distribution. Figure 7 attests to the severity, that is, the size of the TE debonding as a function of the DI obtained by the PC-Kriging method for the sensors in the TE, and Figure 8 presents the results for each sensor in the LE.

Figures 7 and 8 show that most of the DIs used in the learning and validation stages are within the region of the confidence interval, inferring an adequate selection of the learning parameters. It is also noted that the PC-Kriging model captured the DI trend adequately well.

The root mean squared error (RMSE) metric is chosen to validate the model prediction for validation conditions D20 and D60. This metric is a frequently used measure of the differences between values estimated by

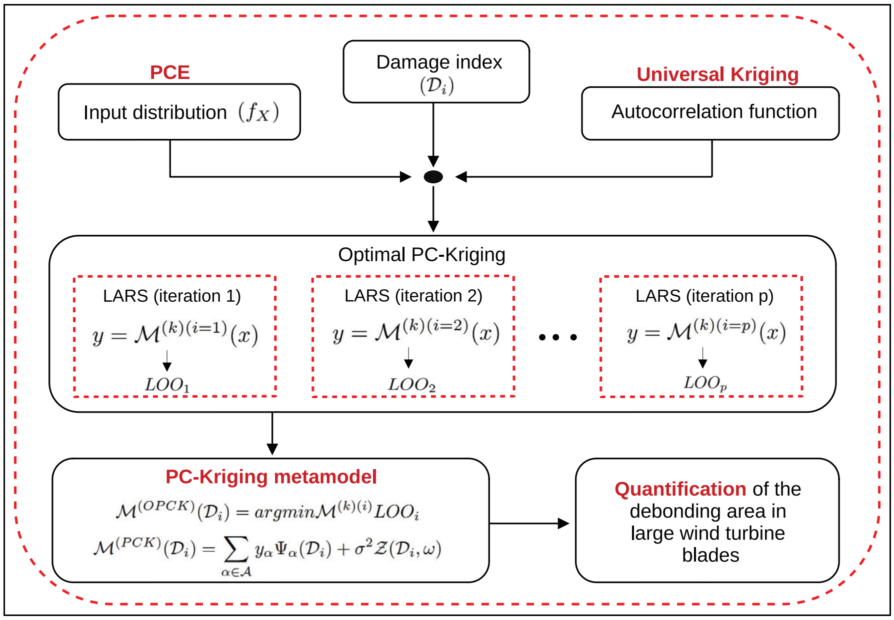

Figure 6. Schematic representation of the optimal Polynomial Chaos-Kriging algorithm.

a model or an estimator and the values measured. The RMSE in this work can be defined as

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\mathcal{S}_{est} - \mathcal{S}_{mea})^2}{n}} \tag{13}$$

where $\mathcal{S}_{est}$ are estimated values for the quantification of the debonding area, $\mathcal{S}_{mea}$ are measured values of the debonding area, and n is number of observations. The validations of the PC-Kriging model prediction for the validation conditions in the TE and LE are presented in Figures 9 and 10. Ideally, the points would concentrate on the diagonal line, as this is where the estimated damage size coincides with the measured damage size. Table 2 presents the RMSE values and the mean of the estimated value for the validation conditions (D20 and D60) for each sensor in the TE and LE.

The sensors located in the TE also had a better performance for the quantification of the damage. The results show that the location of the sensor in the TE and LE influences the results. The sensors that fall under scenarios (1) and (2) referred to in damage detection are the ones that present the best results. In TE, sensors 1, 2, 3, 4, and 8 had the best results. Sensor 10 had the worst result in the TE, which did not detect the damage well. The LE sensors' results were not good, with sensors 4 and 5 that best quantified the damage, and these sensors were the ones that detected a trend in the progression of damage. The presence of noise in the environment can corrupt the response signals and consequently impair the detection and quantification of damage. Some RMSE with high values can be justified by noise in the experiment.[43] It is essential to consider the noise disturbance[44,45] and uncertainties in the experiment. This is also one of the reasons for doing the regression using PC-Kriging, as it accounts for all the variability within the different observations. PC-Kriging provides an average function, but in addition, it provides a confidence interval to account for uncertainties in forecasts. In general, the metamodel obtained by PC-Kriging presents promising results for quantifying the damage to the DIs that present good detection of the damage or capture the damage progression trend.

Conclusion

This work approached the debonding area's quantification due to the debonding in wind turbine blades, using a new methodology considering the uncertainties and interpolation through a metamodel obtained by the PC-Kriging method. The metamodel obtained relates the DIs to TE debonding. To obtain the DIs, the methodology presented by Garcia and Tcherniak[1] was used. This methodology was applied to an SSP 34-m wind turbine blade, instrumented with one actuator, 10 accelerometers in the TE, and 10 in the LE. It is observed that the accelerometers located in the TE detected the damage better than those located in the LE. The excellent performance of accelerometer 4 in the TE stands out; it is located close to and before the damage and far from the actuator. It is also noted that the damage

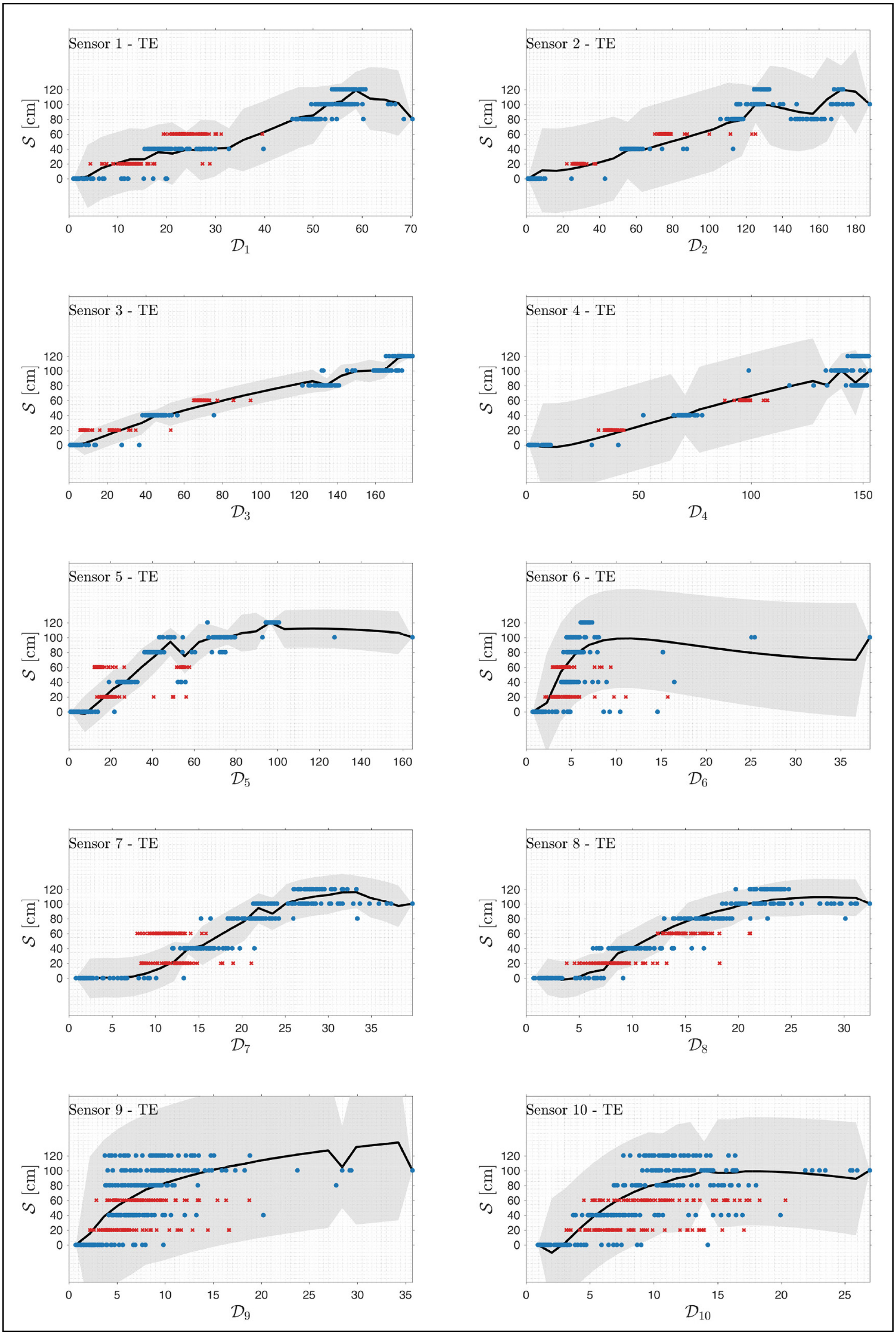

Figure 7. Damage severity ($\mathcal{S}$) by the damage index ($\mathcal{D}_i$) for accelerometers 1–10 on the trailing edge (TE). The metamodel was trained using five conditions (●) and validated with two conditions (**x**). The bold line (—) corresponds to the trend mean and the gray-colored region (■) to the 95% confidence interval.

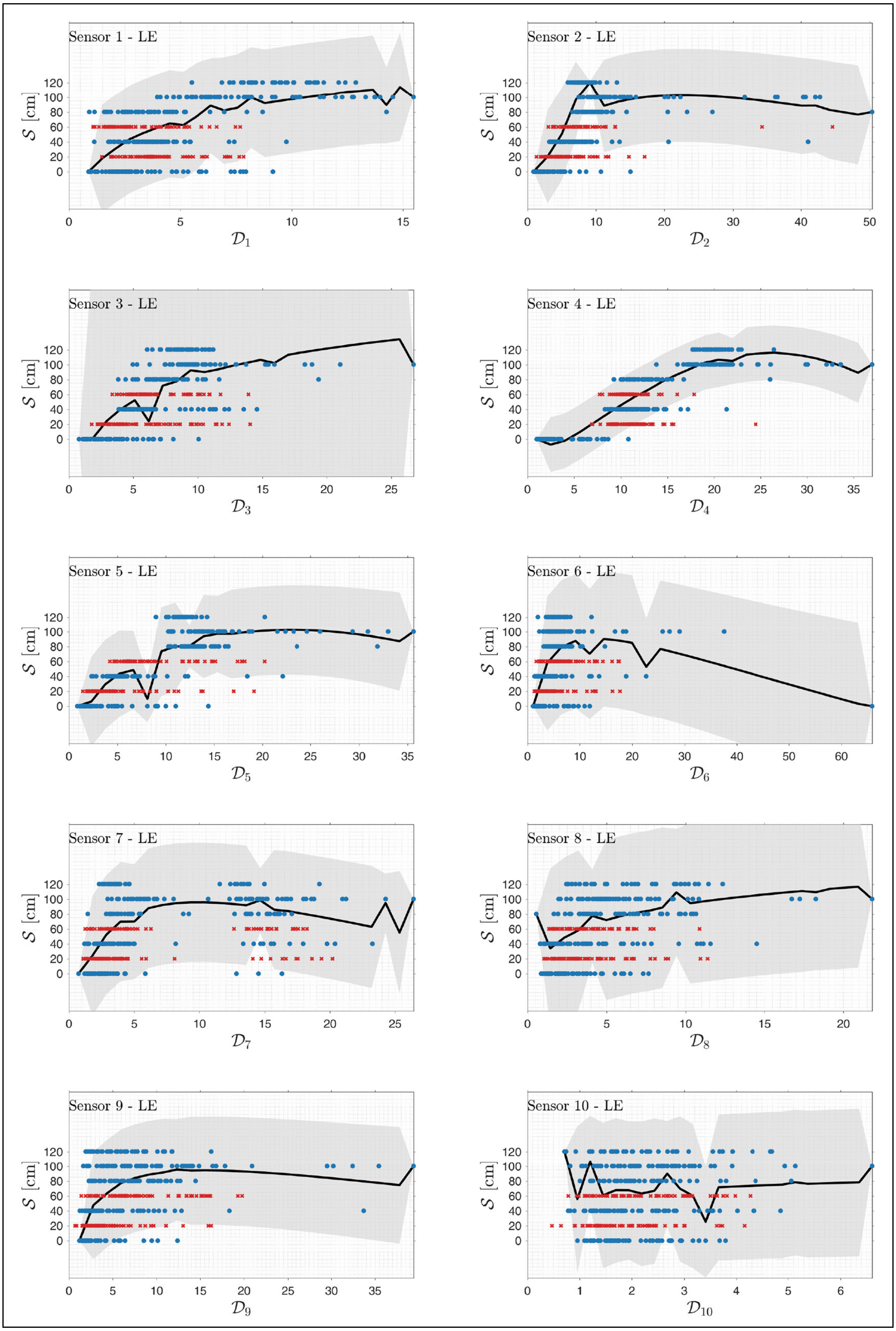

Figure 8. Damage severity ($\mathcal{S}$) by the damage index ($\mathcal{D}_i$) for accelerometers 1–10 on the leading edge (LE). The metamodel was trained using five conditions conditions (●) and validated with two conditions (x). The bold line (—) corresponds to the trend mean and the gray-colored region (■) to the 95% confidence interval.

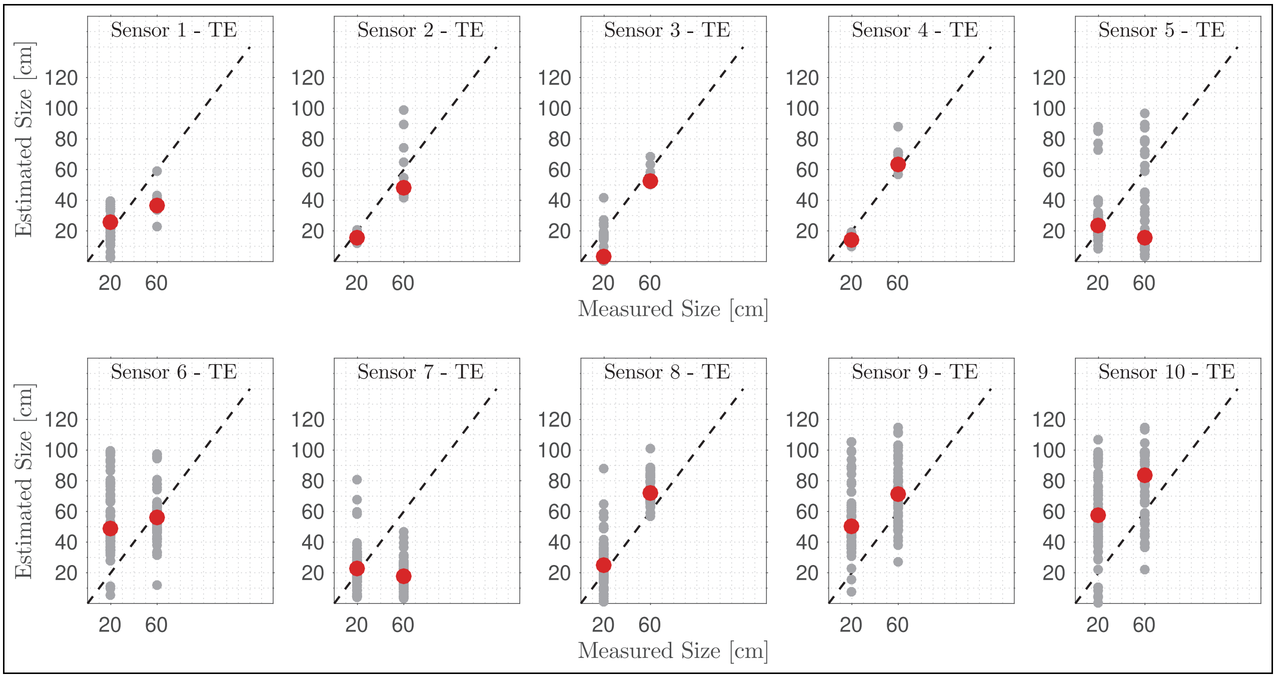

Figure 9. Validation of the estimated damage size using the PC-Kriging metamodel by the actual damage size for each sensor in the TE and validation condition. The estimated damage size for all damage indexes (*gray*) and the mean of estimated damage size (*red*) for each validation condition.

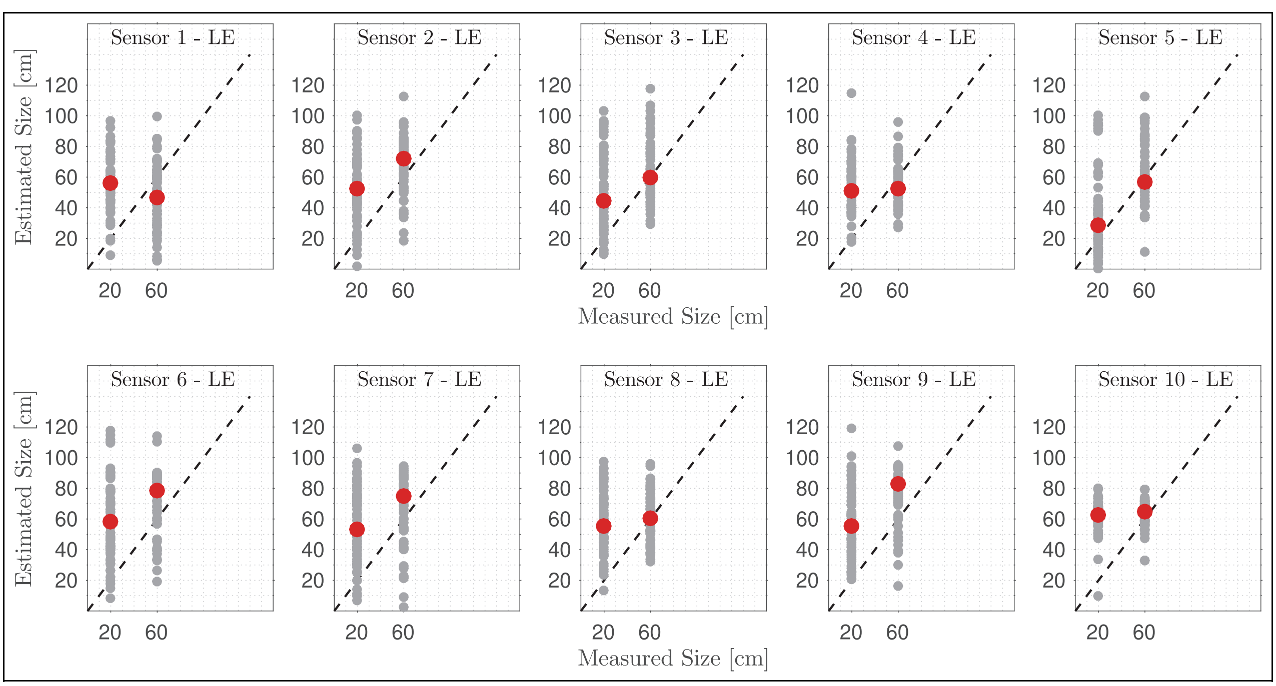

Figure 10. Validation of the estimated damage size using the PC-Kriging metamodel by the actual damage size for each sensor in the LE and validation condition. The estimated damage size for all damage indexes (*gray*) and the mean of estimated damage size (*red*) for each validation condition.

Table 2. Value of the root mean square error (RMSE) and relative error of the validation conditions (D20 and D60) for each sensor along TE and LE by the PC-Kriging metamodel.

	Sensor	1	2	3	4	5	6	7	8	9	10
	RMSE	16.8	10.0	11.4	5.83	31.1	32.0	30.6	16.4	33.6	38.5
TE	D20: Mean est. damage (cm)	25.81	15.58	3.31	13.99	23.31	49.04	22.89	25.14	50.40	57.52
	D60: Mean est. damage (cm)	36.77	47.95	52.25	63.54	15.78	56.23	17.86	72.04	71.38	83.89
	RMSE	34.3	32.3	32.3	28.5	26.5	38.5	35.5	32.9	36.1	32.4
LE	D20: Mean est. damage (cm)	56.40	52.14	44.43	50.69	28.47	58.38	52.94	55.69	55.33	62.37
	D60: Mean est. damage (cm)	46.99	72.16	59.80	52.44	56.62	78.79	74.91	60.41	82.85	64.50

TE: trailing edge; LE: leading edge; PC: Polynomial Chaos.
The sensors that have detected the damage better have the values shown in blue.

introduced is located in the TE, where the accelerometers obtained more favorable results. It is important to note that detection depends on the position of the excitation force applied to determine observability and, consequently, the sensibility of the presence of possible damage. Therefore, we cannot conclude that the best results are provided by accelerometers located in the TE due to the fact that the damage is located there. However, it can be mentioned that percentage of correct classification rates for undamaged and different damaged observations (true negatives and true positives) in the accelerometers along the TE is higher than that for accelerometers located in the LE for this particular damage scenario as seen in Garcia and Tcherniak's study.[1] On the other hand, the damage causes structural changes that can affect different vibration modes and the observability of these effects. To assist in this issue, some approaches are available, such as the use of a finite element model (FEM), which helps to understand the blade's dynamics characteristics or based on raw historical data for learning algorithms to locate damage.

The PC-Kriging method was used to obtain a metamodel that relates the DI with severity to quantify the TE debonding. A trend curve was obtained for this relationship, considering a 95% confidence interval. The PCE method captures the computational model's global behavior, while the Kriging method of the interpolation type captures local variations. For this reason, PC-Kriging, which is the combination of the two methods, presents itself as a more robust method for obtaining metamodels.

In this study, the quantification of the damage using the PC-Kriging showed better TE's accelerometers' performances, highlighting the TE's accelerometer 4. With that, it can be concluded that the accelerometers that better detected the damage obtained better DIs, and consequently resulted in a good performance for the quantification. It is also observed that the location of the accelerometers influences the results. The PC-Kriging trend curve, in general, managed to capture a monotonic increase in DIs, showing promising results for quantification. The advantages observed in the use of PC-Kriging were its simplicity and ease in constructing the metamodel since the UQLab toolbox is available, which allows an easy implementation of the method. The low computational cost is also noted to obtain the results.

This study presents a contribution to the data-driven SHM methodology regarding the quantification of damages in mechanical structures, as it addresses the use of a method that is not yet widely explored in this area. This study collaborates with the development of research in damage quantification so that better results are always obtained, and thus, it is possible to apply in the industrial context. Regarding industrial application, unfortunately, modern SHM methods have limitations, such as determining the location of the sensor that will obtain the best results. Supervised methods for damage quantification (in the case of this work, PC-Kriging) require a mathematical model obtained physically or using data-driven approaches. Both are expensive and difficult to implement in a real scenario. We require a relationship between a DI and damage size to implement a learning step to achieve the PC-Kriging model. Fortunately, some recent probabilistic machine learning algorithms can help to obtain this information, for example, the possibility of using a laboratory-to-real scale blade transfer learning approach, or to reduce discrepancies between a numerical FEM (used for learning) to transfer to a set of experimental data. In this way, the advancement in research on SHM techniques for damage quantification collaborates for use in real contexts and contributes to society.

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