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Sensitivity analysis of sensor location for damage detection in a wind turbine blade


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Abstract: This work performs the sensitivity analysis of sensors located in a damaged composite wind turbine blade to identify the sensors with the most significant influence on a global damage index (DI). The methodology used obtains DIs from data-driven vibration Structural Health Monitoring (VSHM). First, a global DI with data from the sensors is used. From this global DI, the Polynomial Chaos–Kriging method is used to obtain a metamodel that quantifies the damage severity as a function of the DI. Subsequently, the global sensitivity analysis (GSA) is performed to analyse the influence of each sensor on the DI. The GSA method used is the Sobol' indices. The results obtained from the sensitivity analysis of the sensors are satisfactory because the Sobol' indices show that the sensors located in the damage path have greater sensitivity and influence on the DI. Studies of this nature are critical, as they make it possible to optimise the location of sensors for better damage detection and contribute to cost reduction.

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1. Introduction

Currently, the society aims for a future where electric energy generation is clean. In this sense, there is an expansion of wind farms, which need offshore wind turbines to generate energy. The blade of wind turbines are made of composite material, making studies in this area necessary. The structural health monitoring of wind turbine blades is of great importance for the industry, as it can prevent accidents and reduce costs. Thus, it is necessary to carry out methodologies for the damage detection and quantification of these structures. After detecting damage, the user needs to decide if there is an impending structural failure or if the system can be kept in operation under monitoring to track the progression of the damage and its impact on structural safety conditions. Therefore, it is important to obtain the quantification of the damage severity. For this, it is essential to instrument the blades with sensors to collect the data. Therefore, studies of the sensitivity analysis of the sensors in the damage index (DI) contribute to optimising the location of the sensors and consequently in the reduction of material costs.

To the best of our knowledge, few works in the literature propose the sensitivity analysis of sensors in an index for damage detection in composite wind turbine blades. In [1], uncertainty quantification and sensitivity analysis were performed on a wind turbine blade of 5 Megawatt, using a Polynomial Chaos Expansion-based approach. This work achieved a sensitivity analysis using Sobol' indices to identify the most influential random parameters. Another study example is available in [2], where the global sensitivity analysis of the geometry variables of the performance of wind turbine blades was performed.

This work aims to analyse the influence of sensors on the DI and thus optimise the damage quantification results obtained in previous work [3]. This work provides advances in damage detection and quantification methodologies is of great importance for society and industry, in particular for large wind turbine blades.

2. Methodology

The methodology of this work followed the following steps: obtaining of global damage Index (DI) for damage detection, damage quantification, and sensitivity analysis of global DI using Sobol' indices.

2.1 Damage detection and quantification methodology

The methodology to obtain the DI was based in [4], which proposes a local DI. As in this work we aim to perform the sensitivity analysis of the DI, it is convenient to use a global DI, which combines the characteristics extracted from all sensor paths. With this global DI, a metamodel is trained to quantify the damage. To obtain the metamodel to quantify the damage PC-Kriging method is used. The Polynomial Chaos Expansion (PCE) method works as a "response surface". This method obtains the computational model by summing the orthonormal polynomials to the input variables. This orthogonal expansion decouples stochastic and deterministic objects; the polynomial basis is random, and the numerical coefficients are deterministic, obtained from the data. This

property made the metamodel construction easier other methods [5]. The Kriging method, also known as Gaussian Process Regression (GPR), is a non-parametric Bayesian approach that has the advantages of working on small data sets and providing measurements that consider the predictions' uncertainties. The combination of the Polynomial Chaos Expansion (PCE) and Kriging methods results in the method called Polynomial Chaos-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 behaviour and the interpolation type Kriging to capture the variations [6]. One of PC-Kriging's main advantages is the ease in building the model and the low computational cost. Applying PC-Kriging in the damage quantification level is to employ a metamodel to capture the trend between the local DI and damage size. The global DI is used as input, and the damage size is used as output to construct a PC-Kriging model. The implementation of the PC-Kriging algorithms was performed using the UQLab [7].

2.2 Methodology for sensitivity analysis via Sobol' indices

In order to analyse the influence of each variability input data on the system's response of interest, global sensitivity analysis (GSA) is a powerful tool. The GSA can be defined by a variance decomposition method, which aims to decompose the output variance as the sum of the contributions of each input variable or their combinations. A GSA method that has recently been explored by engineering is the Sobol' indices, defined in [8], and has the idea of determining the expansion of the computational model in increasing dimensional sums in terms of conditional variances. One of its main advantages is the ability to deal with non-linear and non-parameterized models and provide a quantitative and qualitative classification. Given a mathematical model (M) that has k independent input parameters gathered into an input vector X and an output scalar $Y = M(X)$, where $X = \{X_1, X_2, \dots, X_k\}$. According to [8], you can define Y in a decomposition into sums of different dimensions. Y is defined by $Y = M_0 + \sum_i M_i(x_i) + \sum_{i < j} M_{ij}(x_i, x_j) + \dots + M_{1 \dots k}(x_1 \dots x_k)$ (1). The Eq. 1 has the property of orthogonality in terms of conditional means. In this way, it is possible to define the Sobol' decomposition in terms of conditional variances [8]. Thus, we obtain the first order Sobol' indices, which quantify the additive effect of each input separately in relation to the total variance (Eq. 2), the interaction effects of the inputs, as a second-order index (Eq. 3), and the total Sobol' indices (Eq. 4). Higher order Sobol' indices take into account the effects of the interactions of the various parameters and are defined in the same way. In the case of this work, Sobol' indices demonstrate the influence of each parameter or parameters related to the damage index. Thus, it is possible to conclude which parameters interfere more in damage classification, responding to the proposal to carry out the sensitivity analysis.

$$S_i = \frac{Var[M_i(X_i)]}{Var[M(X)]} \quad (2), \quad S_{ij} = \frac{Var[M_{ij}(X_i, X_j)]}{Var[M(X)]}, \text{ with } i \neq j \quad (3) \quad \text{and} \quad S_T = \sum_{i=1}^k S_i \quad (4).$$

3. Experimental Application

The study presented in this work is carried out on an SSP 34 m wind turbine blade. The blade was instrumented with 20 triaxial accelerometers, model Bruel & Kjaer Type 4524-B, as represented in the scheme in Fig. 1. Ten accelerometers were placed on the trailing edge (TE) and ten on the leading edge (LE). One of the main types of damage in wind turbine blades is the adhesive joint debonding. This type of damage occurs when an adhesive bond between the laminates of the pressure and suction sides of the blade breaks on both leading and trailing edges. Damage of this nature was introduced in the experiment, and signals were collected under healthy (H) and progressive damaged conditions, which gradually increased from 20 cm to 120 cm (D20, D40, D60, D80, D100, and D120).

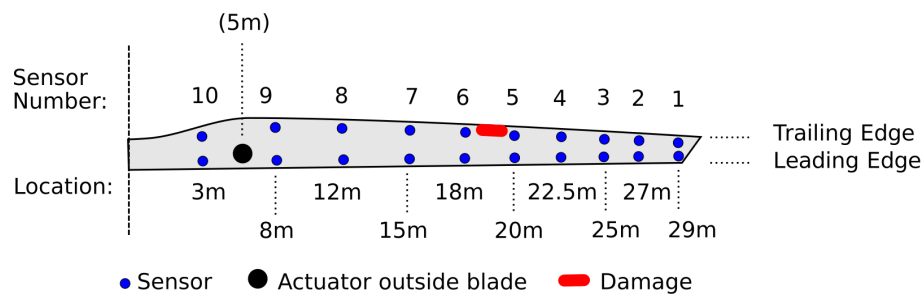


Fig. 1. Damage location scheme, actuator and accelerometers on wind turbine blade. Source: authors.

4. Results and Discussions

The global DI is used as input for building a PC-Kriging metamodel in the damage quantification. The following conditions' local damage index 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. The Root Mean Squared Error (RMSE) metric is chosen to validate the model prediction for conditions D20 and D60. This metric frequently measures the differences between values estimated by a model or an estimator and the values measured.

The Sobol' indices were used to perform the sensitivity analysis of the global DI, using a surrogate model based on PCE. The Sobol' indices show which sensors have the greatest influence on the global DI. The Sobol' indices show that sensors 1, 2, and 3 have more influence. To validate the results obtained by the Sobol' indices, we performed a new damage quantification, obtaining a new DI containing only the data of the most influential sensors. In Fig. 2 is possible to observe the results of Sobol' indices order 1 for the global DI according to the damage condition. Sobol' indices of orders greater than 1 did not give significant values. Fig. 3 attests to the severity, that is, the size of the trailing edge debonding as a function of the damage index obtained by the PC-Kriging method for the global DI with all ten sensors, and the new damage quantification obtained with the data of sensors 1, 2, and 3.

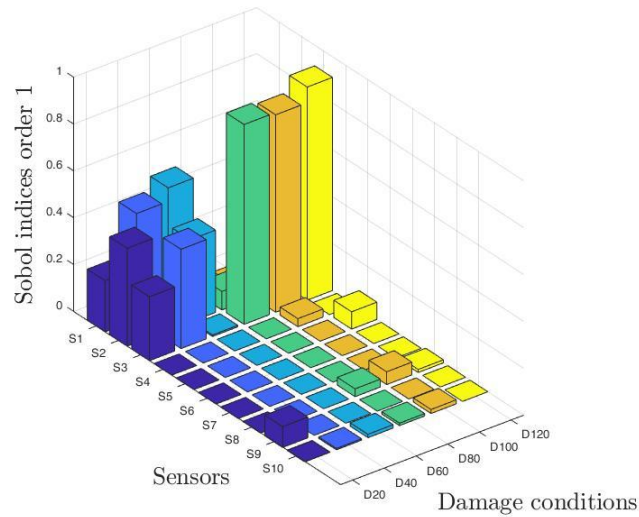


Fig. 2. Sobol' indices of order 1 for the global DI with the 10 sensors located at the trailing edge (TE), for the 6 damage conditions. Source: authors.

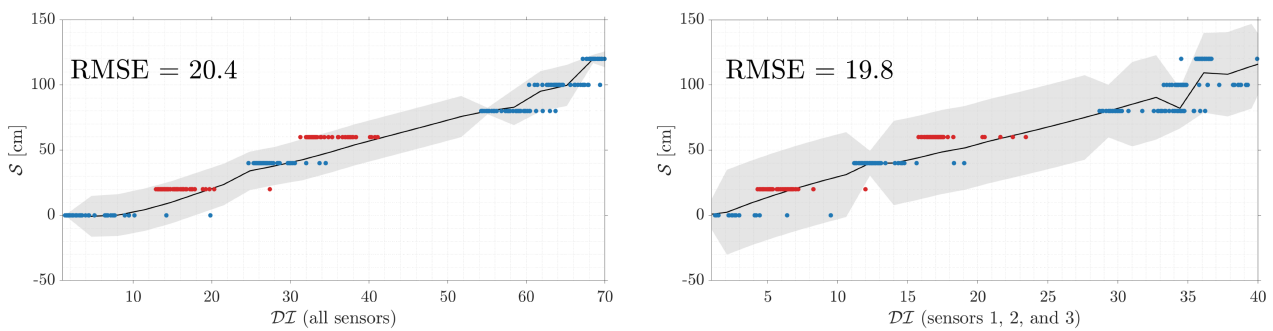


Fig. 3. Damage severity (S) by the global damage index (DI) with all accelerometers, and with 1, 2 and 3 accelerometers on the trailing edge (TE). The metamodel was trained using five conditions (●) and validated with two conditions (●). The bold line (-) corresponds to the trend mean and the gray-colored region to the 95% of confidence interval. Source: authors.

5. Conclusions

The Sobol' indices were used to perform the sensitivity analysis using the surrogate model based on PCE. The results obtained by the Sobol' indices were satisfactory, as this method was able to identify the sensor data with the greatest influence on the global damage index. To validate the information obtained by the Sobol' indices, new PC-Kriging metamodels were obtained to quantify damage, considering a new DI only with the data from the most influential sensors.

This study contributes to the data-driven SHM methodology regarding the sensor location optimization. With sensitivity analysis it is possible to identify the sensors with the most influential data to obtain a good DI. Consequently, it is possible to reduce experimental costs, which is of great industrial interest.

Declaration of Competing Interest

The authors declare no conflict of interest.

CRediT author statement

Samuel da Silva: Conceptualisation; Methodology; Data curation; Formal Analysis; Resources; Supervision; Writing – original draft; Writing – review. **Bruna Pavlack:** Methodology; Data curation; Software; Formal Analysis; Resources; Writing – original draft; Writing – review. **João Pedro Norenberg:** Data curation; Software; Formal Analysis; Writing – original draft; Writing – review. **Americo Cunha Jr:** Conceptualisation; Methodology; Data curation; Software; Formal analysis; Resources; Supervision; Writing – original draft; Writing – review. **David García Cava:** Methodology; Data curation; Writing – review; Writing – original draft.

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