SENSOR SELECTION BASED ON PRINCIPAL COMPONENT ANALYSIS FOR FAULT DETECTION IN WIND TURBINES

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ABSTRACT. Growing interest for improving the reliability of safety-critical structures, such as wind turbines, has led to the advancement of structural health monitoring (SHM). Existing techniques for fault detection can be broadly classified into two major categories: model-based methods and signal processing-based methods. This work focuses in the signal-processing-based fault detection by using principal component analysis (PCA) as a way to condense and extract information from the collected signals. In particular, the goal of this work is to select a reduced number of sensors to be used. From a practical point of view, a reduced number of sensors installed in the structure leads to a reduced cost of installation and maintenance. Besides, from a computational point of view, less sensors implies lower computing time, thus the detection time is shortened.

The overall strategy is to firstly create a PCA model measuring a healthy wind turbine. Secondly, with the model, and for each fault scenario and each possible subset of sensors, it measures the Euclidean distance between the arithmetic mean of the projections into the PCA model that come from the healthy wind turbine and the mean of the projections that come from the faulty one. Finally, it finds the subset of sensors that separate the most the data coming from the healthy wind turbine and the data coming from the faulty one.

Numerical simulations using a sophisticated wind turbine model (a modern 5MW turbine implemented in the FAST software) show the performance of the proposed method under actuators (pitch and torque) and sensors (pitch angle measurement) faults of different type: fixed value, gain factor, offset and changed dynamics.

KEYWORDS: fault detection; sensor selection; principal component analysis; wind turbines; FAST

1 INTRODUCTION

The past few years have seen a rapid growth in interest in wind turbine fault detection [1] through the use of condition monitoring and structural health monitoring (SHM) [2, 3]. The SHM techniques are based on the idea that the change in mechanical properties of the structure will be captured by a change in its dynamic characteristics [4]. Existing techniques for fault detection can be broadly classified into two major categories: model-based methods and signal processing-based methods. For model-based fault detection, the system model could be mathematical—or knowledge-based [5]. Faults are detected based on the residual generated by state variable or model parameter estimation [6, 7, 8]. For signal processing-based fault detection, mathematical or statistical operations are performed on the measurements (see, for example, [9, 10]), or artificial intelligence techniques are applied to the measurements to extract the information about the faults (see [11, 12]).

With respect to signal-processing-based fault detection, principal component analysis (PCA) is used in this framework as a way to condense and extract information from the collected signals. Following this structure, the goal of this work is to enhance the method proposed by the authors in [13] –which is focused on the development of a wind turbine fault detection strategy that combines a data driven baseline model based on PCA and hypothesis testing– by selecting a reduced number of sensors to be used. A different approach in the frequency domain can be found in [14], where a Karhunen-Loeve basis is used.

Most industrial wind turbines are manufactured with an integrated system that can monitor various turbine parameters. These monitored data are collated and stored via a supervisory control and data acquisition (SCADA) system that archives the information in a convenient manner. These data quickly accumulates to create large and unmanageable volumes that can hinder attempts to deduce the health of a turbine's components. It would prove beneficial if the data could be analyzed and interpreted automatically (online) to support the operators in planning cost-effective maintenance activities [15, 16]. This work describes a strategy to reduce and select the number of sensors to be used when the fault detection strategy introduced in [13] is used to identify incipient faults in the main components of a turbine. The SCADA data sets are already generated by the integrated monitoring system, and therefore, no new installation of specific sensors or diagnostic equipment is required. The strategy presented in [13] is based on principal component analysis and statistical hypothesis testing. The final section of the work shows the performance of the selected and reduced number of sensors when the fault detection strategy is applied to an enhanced benchmark challenge for wind turbine fault detection, see [1]. This benchmark proposes a set of realistic fault scenarios considered in an aeroelastic computer-aided engineering tool for horizontal axes wind turbines called FAST, see [17].

2 WIND TURBINE BENCHMARK MODEL

A complete description of the wind turbine benchmark model, as well as the used baseline torque and pitch controllers, can be found in [1]. In this benchmark challenge, a more sophisticated wind turbine model—a modern 5 MW turbine implemented in the FAST software—and updated fault scenarios are presented. These updates enhance the realism of the challenge and will therefore lead to solutions that are significantly more useful to the wind industry. Hereafter, a brief review of the reference wind turbine is given and the generator-converter actuator model and the pitch actuator model are recalled, as the studied faults affect those subsystems. A complete description of the tested fault scenarios is given.

2.1 Reference Wind Turbine

The numerical simulations use the onshore version of a large wind turbine that is representative of typical utility-scale land- and sea-based multimegawatt turbines described by [18]. This wind turbine is a conventional three-bladed upwind variable-speed variable blade-pitch-to-feather-controlled turbine of 5 MW. In this work we deal with the full load region of operation (also called region 3). That is, the proposed controllers main objective is that the electric power follows the rated power. In the simulations, new wind data sets with turbulence intensity set to 10% are generated with TurbSim [19]. The wind speed covers the full load region, as its values range from 12.91 m/s up to 22.57 m/s.

2.2 Generator-Converter Model and Pitch Actuator Model

On one hand, the generator-converter system can be approximated by a first-order ordinary differential equation, see [1], which is given by:

$$\dot{\tau}_r(t) + \alpha_{gc}\tau_r(t) = \alpha_{gc}\tau_c(t) \tag{1}$$

where τ_r and τ_c are the real generator torque and its reference (given by the controller), respectively. In the numerical simulations, $\alpha_{gc} = 50$, see [18]. Moreover, the power produced by the generator, $P_e(t)$, is given by (see [1]):

$$P_e(t) = \eta_g\omega_g(t)\tau_r(t) \tag{2}$$

where η_g is the efficiency of the generator and ω_g is the generator speed. In the numerical experiments, $\eta_g = 0.98$ is used, see [1].

On the other hand, the hydraulic pitch system consists of three identical pitch actuators, which are modeled as a linear differential equation with time-dependent variables, pitch angle $\beta(t)$ and its reference $\beta_r(t)$. In principle, it is a piston servo-system, which can be expressed as a second-order ordinary differential equation [1]:

$$\ddot{\beta}(t) + 2\xi\omega_n\dot{\beta}(t) + \omega_n^2\beta(t) = \omega_n^2\beta_r(t) \tag{3}$$

where ω_n and ξ are the natural frequency and the damping ratio, respectively. For the fault-free case, the parameters $\xi = 0.6$ and $\omega_n = 11.11$ rad/s are used, see [1].

2.3 Fault Scenarios

Both actuator and sensor faults are considered. All the described faults originate from actual faults in wind turbines [1]. Table 1 summarizes all the considered fault scenarios.

2.3.1 Actuator Faults

Pitch actuator faults are studied as they are the actuators with highest failure rate in wind turbines. A fault may change the dynamics of the pitch system by varying the damping ratio (ζ) and natural frequencies (ω_n) from their nominal values to their faulty values. The parameters for the pitch system under different conditions are given in Table 1. The normal air content in the hydraulic oil is 7%, whereas the high air content in oil fault (F1) corresponds to 15%. Pump wear (F2) represents the situation of 75% pressure in the pitch system while the parameters stated for hydraulic leakage (F3) correspond to a

Table 1: Fault scenarios.

Fault	Type	Description
1	Pitch actuator	Change in dynamics: high air content in oil (ω_n = 5.73rad/s, ξ = 0.45)
2	Pitch actuator	Change in dynamics: pump wear (ω_n = 7.27rad/s, ξ = 0.75)
3	Pitch actuator	Change in dynamics: hydraulic leakage (ω_n = 3.42rad/s, ξ = 0.9)
4	Generator speed sensor	Scaling (gain factor equal to 1.2)
5	Pitch angle sensor	Stuck (fixed value equal to 5deg)
6	Pitch angle sensor	Stuck (fixed value equal to 10deg)
7	Pitch angle sensor	Scaling (gain factor equal to 1.2)
8	Torque actuator	Offset (offset value equal to 2000Nm)

pressure of only 50%. The three faults are modeled by changing the parameters ω_n and ζ in the relevant pitch actuator model.

For the test, the change in dynamics faults given in Table 1 are introduced only in the third pitch actuator (thus β_1 and β_2 are always fault-free).

A torque actuator fault (F8) is also studied. This fault is an offset on the generated torque, which can be due to an error in the initialization of the converter controller. This fault can occur since the converter torque is estimated based on the currents in the converter. If this estimate is initialized incorrectly it will result in an offset on the estimated converter torque, which leads to the offset on the generator torque. The offset value is 2000 Nm.

2.3.2 Sensor Faults

The generator speed measurement uses encoders and its elements are subject to electrical and mechanical failures, which can result in a changed gain factor on the measurement. The simulated fault, F4, is a gain factor on ω_g equal to 1.2.

Faults 5 and 6 result in blade 3 having a stuck pitch angle sensor, which holds a constant value of 5° (F5) and 10° (F6), respectively.

Finally, the fault of a gain factor on the measurement of the third pitch angle sensor is studied (F7). The measurement is scaled by a factor of 1.2.

3 SENSOR SELECTION

The goal of this section is to present a method to select a reduced number of sensors to be used in the fault detection method. From a practical point of view, a reduced number of sensors installed in the structure leads to a reduced cost of installation and maintenance. Besides, from a computational point of view, less sensors implies less computing time so the detection time is also reduced.

Classical approaches to sensor or variable selection may be summarized in the following example. Let us assume we have N sensors or variables that are measuring during $(n-1)\Delta$ seconds, where Δ is the

Table 2: Assumed available measurements. These sensors are representative of the types of sensors that are available on a MW-scale commercial wind turbine.

Number	Sensor Type	Symbol	Units
1	Generated electrical power	$P_{e,m}$	kW
2	Rotor speed	$\omega_{r,m}$	rad/s
3	Generator speed	$\omega_{g,m}$	rad/s
4	Generator torque	$\tau_{c,m}$	Nm
5	first pitch angle	$\beta_{1,m}$	deg
6	second pitch angle	$\beta_{2,m}$	deg
7	third pitch angle	$\beta_{3,m}$	deg
8	fore-aft acceleration at tower bottom	$a^b_{fa,m}$	m/s^2
9	side-to-side acceleration at tower bottom	$a^b_{ss,m}$	m/s^2
10	fore-aft acceleration at mid-tower	$a^m_{fa,m}$	m/s^2
11	side-to-side acceleration at mid-tower	$a^m_{ss,m}$	m/s^2
12	fore-aft acceleration at tower top	$a^t_{fa,m}$	m/s^2
13	side-to-side acceleration at tower top	$a^t_{ss,m}$	m/s^2

sampling time and $n \in \mathbb{N}$. The discretized measures of each sensor can be arranged as a column vector $\mathbf{x}^i = (x^i_1, x^i_2, \ldots, x^i_n)^T,\ i = 1, \ldots, N$ so we can build up a $n \times N$ matrix as follows:

$$X = \left(\begin{array}{c|c|c|c} \mathbf{x}^1 & \mathbf{x}^2 & \cdots & \mathbf{x}^N \end{array} \right) = \begin{pmatrix} x^1_1 & x^2_1 & \cdots & x^N_1 \\ x^1_2 & x^2_2 & \cdots & x^N_2 \\ \vdots & \vdots & \ddots & \vdots \\ x^1_i & x^2_i & \cdots & x^N_i \\ \vdots & \vdots & \ddots & \vdots \\ x^1_n & x^2_n & \cdots & x^N_n \end{pmatrix} \in \mathcal{M}_{n\times N}(\mathbb{R}) \tag{4}$$

It is worth noting that each column in matrix X in equation (4) represents the measures of a single sensor or variable. In general, when a large number of variables or sensors is available the results are usually slightly changed if just a subset of the sensors is used. Consequently, a simple approach is to calculate the subset of σ sensors that maximizes the multiple correlation of the $N-\sigma$ non-selected sensors with respect to the σ selected sensors. A similar approach, based on principal component analysis (PCA), that is also used in the field of feature extraction is to compute the first principal components and observe the coefficients of the corresponding eigenvectors. More precisely, if the unit eigenvector related to the largest eigenvalue is

$$u_1 = \alpha_1 s_1 + \alpha_2 s_2 + \cdots + \alpha_N s_N, \ \sum_{i=1}^{N} \alpha_i^2 = 1,$$

the sensor associated with the smallest coefficient $\alpha = \min_{i=1,\ldots,N} \alpha_i$ can be neglected. A comprehensive list of methods for deciding which variables or sensors to reject can be found in [20]. However, when multiway principal component analysis is applied to data coming from N sensors at L discretization instants and n experimental trials, the information can be stored in an unfolded $n \times (N \cdot L)$ matrix as follows:

$$\mathbf{X} = \left(\begin{array}{cccc|ccc|c|ccc} x_{11}^1 & x_{12}^1 & \cdots & x_{1L}^1 & x_{11}^2 & \cdots & x_{1L}^2 & \cdots & x_{11}^N & \cdots & x_{1L}^N \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1}^1 & x_{i2}^1 & \cdots & x_{iL}^1 & x_{i1}^2 & \cdots & x_{iL}^2 & \cdots & x_{i1}^N & \cdots & x_{iL}^N \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1}^1 & x_{n2}^1 & \cdots & x_{nL}^1 & x_{n1}^2 & \cdots & x_{nL}^2 & \cdots & x_{n1}^N & \cdots & x_{nL}^N \end{array} \right) \tag{5}$$

(6)

In this case, a column in matrix $\mathbf{X}$ in equation (7) no longer represents the values of a variable at different time instants but the measurements of a variable at one particular time instant in the whole set of experimental trials. Consequently, even though PCA can be applied to this kind of matrices as a way to reduce the dimensionality of the data and to create a new coordinates space where the data is best represented, the eigenvalues and eigenvectors of the covariance matrix $\mathbf{C_X} = \frac{1}{N \cdot L - 1} \mathbf{X}^T \mathbf{X}$ cannot be directly used to infer what variables or sensors could be neglected. Besides, we are not only interested in the sensors that best model the healthy structure but the sensors that best discriminate the faulty structure.

The overall strategy to select the best subset of sensors that discriminate the healthy and the faulty wind turbine is to create a multiway PCA model measuring a healthy wind turbine. With the model, and for each fault scenario, me measure the euclidean distance between the arithmetic mean of the projections into the PCA model that come from the healthy structure and the mean of the projections that come from the faulty one. The subset of sensors related to the maximum distance between the means of each pair of projections will be the selected sensors. The detailed algorithmic procedure is described in the next section.

3.1 Sensor selection algorithm

Sensor selection can be essentially viewed as a combinatorial problem involving some kind of performance criterion over all possible options. In the subsequent algorithm, some parameters must be selected, such as the cardinal of the initial set of variables or sensors N, the number of sensors σ to be combined or the number ℓ of principal components.

1. Consider a set $\mathcal{S} = \{s_1, s_2, \dots, s_{13}\}$ of $N = 13$ sensors as in Table 2.

2. Consider a number of sensors σ to be combined, $\sigma = 2, \dots, N$.

3. Consider the set $\Omega^\sigma = \left\{\mathcal{S}_1^\sigma, \mathcal{S}_2^\sigma, \dots, \mathcal{S}_{\binom{N}{\sigma}}^\sigma\right\}$ formed by the $\binom{N}{\sigma}$ $\sigma-$subsets of σ elements out of the set $\mathcal{S}$. For instance, $\mathcal{S}_1^2 = \{s_1, s_2\}$. In a general case, we will write $\mathcal{S}_k^\sigma = \{s_{(1)}, s_{(2)}, \dots, s_{(\sigma)}\},\ k = 1, \dots, \binom{N}{\sigma}$, where $s_{(1)}$ refers to the first sensor in $\mathcal{S}_k^\sigma$, $s_{(2)}$ to the second sensor in the set and so on.

4. For each $\sigma-$subset $\mathcal{S}_k^\sigma \in \Omega^\sigma,\ k = 1, \dots, \binom{N}{\sigma}$, measure, from a healthy wind turbine, sensors $s_{(1)}, s_{(2)}, \dots, s_{(\sigma)}$ during $(nL - 1)\Delta$ seconds.

5. Arrange the collected data coming from the σ sensors in a matrix $\mathbf{X} \in \mathcal{M}_{n\times(\sigma\cdot L)}(\mathbb{R})$ as follows:

$$\mathbf{X} = \left(\begin{array}{cccc|ccc|c|ccc} x_{11}^{(1)} & x_{12}^{(1)} & \cdots & x_{1L}^{(1)} & x_{11}^{(2)} & \cdots & x_{1L}^{(2)} & \cdots & x_{11}^{(\sigma)} & \cdots & x_{1L}^{(\sigma)} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1}^{(1)} & x_{i2}^{(1)} & \cdots & x_{iL}^{(1)} & x_{i1}^{(2)} & \cdots & x_{iL}^{(2)} & \cdots & x_{i1}^{(\sigma)} & \cdots & x_{iL}^{(\sigma)} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1}^{(1)} & x_{n2}^{(1)} & \cdots & x_{nL}^{(1)} & x_{n1}^{(2)} & \cdots & x_{nL}^{(2)} & \cdots & x_{n1}^{(\sigma)} & \cdots & x_{nL}^{(\sigma)} \end{array}\right) \tag{7}$$

6. Choose a number ℓ of principal components, $\ell = 1, \dots, \sigma \cdot L$.

7. Perform a sensor-based group scaling and find the PCA model $\mathbf{P} \in \mathcal{M}_{(\sigma\cdot L)\times(\sigma\cdot L)}(\mathbb{R})$ (also called loading matrix) as detailed in [13, Section 3.1]. Consider the reduced matrix $\hat{\mathbf{P}} := \mathbf{P}(:, 1 : \ell) \in \mathcal{M}_{(\sigma\cdot L)\times\ell}(\mathbb{R})$ related to the ℓ highest eigenvalues, formed by the first ℓ columns of matrix $\mathbf{P}$.

8. Measure, from a healthy wind turbine, sensors $s_{(1)}, s_{(2)}, \dots, s_{(\sigma)}$ during $(n_\text{h}L - 1)\Delta$ seconds. Arrange the collected data coming from the σ sensors in a matrix $\mathbf{Y}_\text{h} \in \mathcal{M}_{n_\text{h}\times(\sigma\cdot L)}(\mathbb{R})$ as follows:

$$\mathbf{Y}_\text{h} = \left(\begin{array}{cccc|ccc|c|ccc} y_{11}^{(1)} & y_{12}^{(1)} & \cdots & y_{1L}^{(1)} & y_{11}^{(2)} & \cdots & y_{1L}^{(2)} & \cdots & y_{11}^{(\sigma)} & \cdots & y_{1L}^{(\sigma)} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{i1}^{(1)} & y_{i2}^{(1)} & \cdots & y_{iL}^{(1)} & y_{i1}^{(2)} & \cdots & y_{iL}^{(2)} & \cdots & y_{i1}^{(\sigma)} & \cdots & y_{iL}^{(\sigma)} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{n_\text{h}1}^{(1)} & y_{n_\text{h}2}^{(1)} & \cdots & y_{n_\text{h}L}^{(1)} & y_{n_\text{h}1}^{(2)} & \cdots & y_{n_\text{h}L}^{(2)} & \cdots & y_{n_\text{h}1}^{(\sigma)} & \cdots & y_{n_\text{h}L}^{(\sigma)} \end{array}\right) \tag{8}$$

   Perform a sensor-based group scaling and project the data to the principal component space using the matrix product $\hat{\mathbf{T}}_\text{h} = \mathbf{Y}_\text{h}\hat{\mathbf{P}} \in \mathcal{M}_{n_\text{h}\times\ell}(\mathbb{R})$. Define $t_\text{h}^i \in \mathbb{R}^\ell,\ i = 1, \dots, n_\text{h}$ each row vector of matrix $\hat{\mathbf{T}}_\text{h}$. Note that n_h is a natural number not necessarily equal to n in Step 4.

9. Measure, from a faulty wind turbine, sensors $s_{(1)}, s_{(2)}, \dots, s_{(\sigma)}$ during $(n_\text{f}L-1)\Delta$ seconds. Arrange the collected data coming from the σ sensors in a matrix $\mathbf{Y}_\text{f} \in \mathcal{M}_{n_\text{f}\times(\sigma\cdot L)}(\mathbb{R})$ as follows:

$$\mathbf{Y}_\text{f} = \left(\begin{array}{cccc|ccc|c|ccc} z_{11}^{(1)} & z_{12}^{(1)} & \cdots & z_{1L}^{(1)} & z_{11}^{(2)} & \cdots & z_{1L}^{(2)} & \cdots & z_{11}^{(\sigma)} & \cdots & z_{1L}^{(\sigma)} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{i1}^{(1)} & z_{i2}^{(1)} & \cdots & z_{iL}^{(1)} & z_{i1}^{(2)} & \cdots & z_{iL}^{(2)} & \cdots & z_{i1}^{(\sigma)} & \cdots & z_{iL}^{(\sigma)} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{n_\text{f}1}^{(1)} & z_{n_\text{f}2}^{(1)} & \cdots & z_{n_\text{f}L}^{(1)} & z_{n_\text{f}1}^{(2)} & \cdots & z_{n_\text{f}L}^{(2)} & \cdots & z_{n_\text{f}1}^{(\sigma)} & \cdots & z_{n_\text{f}L}^{(\sigma)} \end{array}\right) \quad (9)$$

Perform a sensor-based group scaling and project the data to the principal component space using the matrix product $\hat{\mathbf{T}}_\text{f} = \mathbf{Y}_\text{f}\hat{\mathbf{P}} \in \mathcal{M}_{n_\text{f}\times\ell}(\mathbb{R})$. Define $t_\text{f}^i \in \mathbb{R}^\ell,\ i = 1, \dots, n_\text{f}$ each row vector of matrix $\hat{\mathbf{T}}_\text{f}$. Note again that n_f is a natural number not necessarily equal to n in Step 4 neither n_h in Step 8.

10. Define $\boldsymbol{\mu}_\text{h}$ as the mean vector value of $t_\text{h}^i \in \mathbb{R}^\ell,\ i = 1, \dots, n_\text{h}$, that is, $\boldsymbol{\mu}_\text{h} = \frac{1}{n_\text{h}} \sum_{i=1}^{n_\text{h}} t_\text{h}^i \in \mathbb{R}^\ell$.

11. Define $\boldsymbol{\mu}_\text{f}$ as the mean vector value of $t_\text{f}^i \in \mathbb{R}^\ell,\ i = 1, \dots, n_\text{f}$, that is, $\boldsymbol{\mu}_\text{f} = \frac{1}{n_\text{f}} \sum_{i=1}^{n_\text{f}} t_\text{f}^i \in \mathbb{R}^\ell$.

12. Compute the euclidean norm $\|\boldsymbol{\mu}_\text{h} - \boldsymbol{\mu}_\text{f}\|_2 =: \mathcal{N}_k^\sigma$ associated to the $\sigma-$subset $\mathcal{S}_k^\sigma \in \Omega^\sigma,\ k = 1, \dots, \binom{N}{\sigma}$.

13. Find $\kappa^\sigma \in \left\{1, \dots, \binom{N}{\sigma}\right\}$ where $\mathcal{N}_{\kappa^\sigma}^\sigma = \max_{k=1,\dots,\binom{N}{\sigma}} \mathcal{N}_k^\sigma$.

    Therefore, given a particular fault scenario, the σ sensors in the set $\mathcal{S}_{\kappa^\sigma}^\sigma$ are the sensors that separate the most the data coming from the healthy wind turbine and the data coming from the faulty one.

3.2 Results of the sensor selection

The results of the sensor selection are summarized in Tables 3 and 4 when the number of sensors to be combined is $\sigma = 3$ and $\sigma = 6$, respectively. With respect to Table 3 it is worth noting that sensors 5 and 6 –corresponding to the first and second pitch angles– appear as selected in all the 8 fault scenarios. The triad of sensors is completed in some cases with the third pitch angle (fault scenario number 1, 2, 3, 4 and 6), the generated electrical power (fault scenario number 1) and the side-to-side acceleration at tower top (fault scenario number 5 and 7). Similarly, with respect to Table 4 it is also worth remarking that sensors 5, 6 and 7 –corresponding to the first, second and third pitch angles– appear as selected in all the 8 fault scenarios. In this case, the sextuple of sensors is completed in fault scenarios 1, 2, 3 and 7 with sensors 9, 11 and 13 (side-to-side accelerations at tower bottom, mid-tower and tower top, respectively); in fault scenario 4 with sensors 1, 2 and 3 (generated electrical power, rotor speed and generator speed, respectively); in fault scenario 5 with sensors 1, 2 and 13 (generated electrical power, rotor speed and side-to-side acceleration at tower top, respectively); in fault scenario 6 with sensors 1, 3 and 13 (generated electrical power, generator speed and side-to-side acceleration at tower top, respectively); finally, in fault scenario 8 with sensors 1, 11 and 13 (generated electrical power, side-to-side acceleration at mid-tower and tower top, respectively).

Table 3: Sensor selection when the number of sensors to be combined is $\sigma = 3$ for each of the 8 fault scenarios described in Table 1.

	sensors												
Fault no.	1	2	3	4	5	6	7	8	9	10	11	12	13
1					✓	✓	✓						
2					✓	✓	✓						
3					✓	✓	✓						
4					✓	✓	✓						
5					✓	✓							✓
6					✓	✓	✓						
7					✓	✓							✓
8	✓				✓	✓							

4 FAULT DETECTION WITH A REDUCED NUMBER OF SENSORS

To analyze the effect on the overall performance of the fault detection strategy with a reduced number of sensors, we will study a total of 24 samples of $\nu = 50$ elements each, corresponding to the following distribution: 16 samples of a healthy wind turbine; and 8 samples of a faulty wind turbine with respect to each of the 8 particular fault scenarios defined in Table 1. In this section, we will consider the following particular combination of $\sigma = 6$ sensors: sensors $1, 2, 3, 4, 5$ and 6, that is, we will measure and collect the information provided by the generated electrical power, rotor speed, generator speed, generator torque and the first and second pitch angles.

For this combination, each sample of $\nu = 50$ elements is formed by the measures gathered from the sensors during $(\nu \cdot L - 1)\Delta = 312.4875$ seconds, where $L = 500$ and the sampling rate $1/\Delta = 80$ Hz. The fault detection strategy is based on the work by Pozo and Vidal [13], where multiway principal component analysis (MPCA) is first applied and then the so-called Welch-Satterthwaite method [21] to test for the equality of means.

As stated before, one configuration of $\sigma = 6$ sensors has been considered. Table 5 summarizes how the results in Table 6 are organized. More precisely, Table 6 includes –using the measures of sensors $1, 2, 3, 4, 5$ and 6– the number of samples of the healthy structure correctly classified by the test as healthy (correct decision); the number of samples of the faulty structure correctly classified as faulty (correct decision); the number of samples of the faulty structure wrongly classified as healthy (type II error or missing fault); and the number of samples of the healthy structure wrongly classified as faulty (type I error or false alarm). It is worth noting that type I errors (false alarms) and type II errors (missing faults) occur when we consider scores 2, 3 or 4, i.e., when the test is based purely on the first score all the classifications are accurate.

Table 4: Sensor selection when the number of sensors to be combined is $\sigma = 6$ for each of the 8 fault scenarios described in Table 1.

	sensors												
Fault no.	1	2	3	4	5	6	7	8	9	10	11	12	13
1					✓	✓	✓		✓		✓		✓
2					✓	✓	✓		✓		✓		✓
3					✓	✓	✓		✓		✓		✓
4	✓	✓	✓		✓	✓	✓						
5	✓	✓			✓	✓	✓						✓
6	✓		✓		✓	✓	✓						✓
7					✓	✓	✓		✓		✓		✓
8	✓				✓	✓	✓				✓		✓

Table 5: Scheme for the presentation of the results in Table 6.

	Undamaged Sample (H_0)	**Damaged Sample (H_1)**
Fail to reject H_0	Correct decision	Type II error (missing fault)
Reject H_0	Type I error (false alarm)	Correct decision

5 CONCLUDING REMARKS

The silver bullet for offshore operators is to eliminate unscheduled maintenance. Therefore, the implementation of a fault detection system is crucial. The main challenges of the wind turbine fault detection lie in its nonlinearity, unknown disturbances as well as significant measurement noise. In this work, numerical simulations (with a well-known benchmark wind turbine) show that the proposed PCA plus statistical hypothesis testing is a valuable tool in fault detection for wind turbines, even when the number of sensors that are measured are significantly reduced. It is noteworthy that, in the simulations, when the first score is used all the decisions are correct (there are no false alarms and no missing faults). We believe that PCA plus statistical hypothesis testing has tremendous potential in decreasing maintenance costs.

ACKNOWLEDGEMENTS

This work has been partially funded by the Spanish Ministry of Economy and Competitiveness through the research projects DPI2014-58427-C2-1-R, and by the Generalitat de Catalunya through the research project 2014 SGR 859.

Table 6: Categorization of the samples with respect to the presence or absence of damage and the result of the test for each of the four scores when the size of the samples to diagnose is $\nu = 50$ and the sensors used are numbers $1, 2, 3, 4, 5$ and 6.

	score 1		**score 2**		**score 3**		**score 4**	
	H_0	H_1	H_0	H_1	H_0	H_1	H_0	H_1
Fail to reject H_0	16	0	9	0	8	1	13	0
Reject H_0	0	8	7	8	8	7	3	8

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