

Wind turbine fault detection through principal component analysis and multivariate statistical inference

Francesc Pozo¹, Yolanda Vidal¹ and Leonardo Acho¹

¹ CoDALab, Department of Mathematics, Escola d'Enginyeria de Barcelona Est (EEBE), Universitat Politècnica de Catalunya (UPC), Sant Ramon de Penyafort / Eduard Maristany, 08019 Barcelona, Spain, francesc.pozo@upc.edu

Keywords: wind turbine, fault detection, principal component analysis, multivariate statistical hypothesis testing.

Abstract

This work addresses the problem of online fault detection of an advanced wind turbine benchmark under actuators (pitch and torque) and sensors (pitch angle measurement) faults of different type: fixed value, gain factor, offset and changed dynamics. The fault detection scheme starts by computing the baseline principal component analysis (PCA) model from the healthy or undamaged wind turbine. Subsequently, when the wind turbine is inspected or supervised, new measurements are obtained and projected into the baseline PCA model. When both sets of data—the baseline and the data from the current wind turbine—are compared, a multivariate statistical hypothesis testing is used to make a decision on whether or not the wind turbine presents some damage, fault or misbehavior. The effectiveness of the proposed fault-detection scheme is illustrated by numerical simulations on a well-known large offshore wind turbine in the presence of wind turbulence and realistic fault scenarios. The obtained results demonstrate that the proposed strategy provides an early fault detection, thereby giving the operators sufficient time to make more informed decisions regarding the maintenance of their machines.

1. INTRODUCTION

Wind energy is currently the fastest growing source of renewable energy in the world. As wind turbines (WT) increase in size, and their operating conditions become more extreme, a number of current and future challenges exist. A major issue with wind turbines, specially those located offshore, is the relatively high cost of maintenance [1]. Since the replacement of main components of a wind turbine is a difficult and costly affair, improved maintenance procedures can lead to essential cost reductions. Autonomous online fault detection algorithms allow early warnings of defects to prevent major component failures. Furthermore, side effects on other components can be reduced significantly. Many faults can be detected while the defective component is still operational. Thus necessary repair actions can be planned in time and need not to be taken immediately and this fact is specially important for off-shore turbines where bad weather conditions can prevent any repair actions. Therefore the implementation of fault detection (FD) systems is crucial.

The past few years have seen a rapid growth in interest in wind turbine fault detection [2] through the use of condition monitoring and structural health monitoring (SHM) [3,4]. 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 [5]. 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 [6]. Faults are detected based on the residual generated by state variable or model parameter estimation [7–9]. For signal processing-based fault detection, mathematical or statistical operations are performed on the measurements (see, for example, [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, this work is focused on the development of a wind turbine fault detection strategy that combines a data driven baseline model—reference pattern obtained from the healthy wind turbine—based on PCA and multivariate hypothesis testing. A different approach in the frequency domain can be found in [13], 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 [14–16]. This work describes a technique that can be used to identify incipient faults in the main components of a turbine through the analysis of this SCADA data. 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 developed is based on principal component analysis and multivariate statistical hypothesis testing. The final section of the work shows the performance of the proposed techniques using an enhanced benchmark challenge for wind turbine fault detection, see [2]. 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].

The structure of the work is the following. In Section 2 the wind turbine benchmark is recalled as well as the fault scenarios studied in this work. Section 3 presents the design of the proposed fault detection strategy. The simulation results obtained with the proposed approach applied to the wind turbine benchmark are given in Section 4. Concluding remarks are given in Section 5.

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 [2]. 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, generator-converter model and pitch actuator model

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. The wind turbine characteristics are given in [19, 1]. 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 [20]. The wind speed covers the full load region, as its values range from 12.91 m/s up to 22.57 m/s.

The generator-converter system can be approximated by a first-order ordinary differential equation, see [2], which is given by:

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

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 [2]):

$$P_e(t) = \eta_g \omega_g(t) \tau_r(t) \quad (2)$$

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 [2].

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 [2]:

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

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 [2].

2.2 Fault scenarios

Both actuator and sensor faults are considered. All the described faults originate from actual faults in wind turbines [2]. Table 1 summarizes all the considered fault scenarios.

Table 1 : Fault scenarios.

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

2.2.1 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 (ξ) 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 pressure of only 50%. The three faults are modeled by changing the parameters ω_n and ξ 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.

2.2.2 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. FAULT DETECTION STRATEGY

The overall fault detection strategy is based on principal component analysis and multivariate statistical hypothesis testing. A baseline pattern or PCA model is created with the healthy state of the wind turbine in the presence of wind turbulence. When the current state of the wind turbine has to be diagnosed, the collected data is projected using the PCA model. The final diagnosis is performed using multivariate statistical hypothesis testing.

The main paradigm of vibration based structural health monitoring is based on the basic idea that a change in physical properties due to structural changes or damage will cause detectable changes in dynamical responses. First of all, the healthy structure is excited by a signal to create a pattern. Subsequently, the structure to be diagnosed is excited by the same signal and the dynamic response is compared with the pattern. This scheme is also known as guided waves in structures for structural health monitoring [21].

However, in our application, the only available excitation of the wind turbines is the wind turbulence. Therefore, guided waves in wind turbines for SHM cannot be considered as a realistic scenario. In spite of that, the new paradigm is based on the fact that, even with a different wind turbulence, the fault detection strategy based on PCA and statistical hypothesis testing will be able to detect some damage, fault or misbehavior. More precisely, the key idea behind the detection strategy is the assumption that a change in the behavior of the overall system, even with a different excitation, has to be detected. The results presented in Section 4 confirm this hypothesis.

3.1 Data driven baseline modeling based on PCA

Let us start the PCA modeling by measuring, from a healthy wind turbine, a sensor during $(nL - 1)\Delta$ seconds, where Δ is the sampling time and $n, L \in \mathbb{N}$. The discretized measures of the sensor are a real vector

$$\left(x_{11} \ x_{12} \ \cdots \ x_{1L} \ x_{21} \ x_{22} \ \cdots \ x_{2L} \ \cdots \ x_{n1} \ x_{n2} \ \cdots \ x_{nL} \right) \in \mathbb{R}^{nL} \quad (4)$$

where the real number x_{ij} , $i = 1, \dots, n$, $j = 1, \dots, L$ corresponds to the measure of the sensor at time $((i - 1)L + (j - 1))\Delta$ seconds. When the measures are obtained from $N \in \mathbb{N}$ sensors also during $(nL - 1)\Delta$ seconds, all the collected data coming from the N sensors is disposed in a matrix $\mathbf{X} \in \mathcal{M}_{n \times (N \cdot L)}$ as follows:

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

where the superindex $k = 1, \dots, N$ of each element x_{ij}^k in the matrix represents the number of sensor.

The objective of the principal component analysis is to find a linear transformation orthogonal matrix $\mathbf{P} \in \mathcal{M}_{(N \cdot L) \times (N \cdot L)}(\mathbb{R})$ that will be used to transform or project the original data matrix \mathbf{X} according to the subsequent matrix product:

$$\mathbf{T} = \mathbf{X}\mathbf{P} \in \mathcal{M}_{n \times (N \cdot L)}(\mathbb{R}) \quad (6)$$

where \mathbf{T} is a matrix having a diagonal covariance matrix.

3.1.1 Group scaling

Since the data in matrix \mathbf{X} is affected by diverse wind turbulence, come from several sensors and could have different scales and magnitudes, it is required to apply a preprocessing step to rescale the data using the mean of all measurements of the sensor at the same column and the standard deviation of all measurements of the sensor [22].

More precisely, for $k = 1, 2, \dots, N$ we define

$$\mu_j^k = \frac{1}{n} \sum_{i=1}^n x_{ij}^k, \quad j = 1, \dots, L, \quad (7)$$

$$\mu^k = \frac{1}{nL} \sum_{i=1}^n \sum_{j=1}^L x_{ij}^k, \quad (8)$$

$$\sigma^k = \sqrt{\frac{1}{nL} \sum_{i=1}^n \sum_{j=1}^L (x_{ij}^k - \mu^k)^2} \quad (9)$$

where μ_j^k is the mean of the measures placed at the same column, that is, the mean of the n measures of sensor k in matrix \mathbf{X}^k at time instants $((i-1)L + (j-1))\Delta$ seconds, $i = 1, \dots, n$; μ^k is the mean of all the elements in matrix \mathbf{X}^k , that is, the mean of all the measures of sensor k ; and σ^k is the standard deviation of all the measures of sensor k . Therefore, the elements x_{ij}^k of matrix \mathbf{X} are scaled to define a new matrix $\check{\mathbf{X}}$ as

$$\check{x}_{ij}^k := \frac{x_{ij}^k - \mu_j^k}{\sigma^k}, \quad i = 1, \dots, n, \quad j = 1, \dots, L, \quad k = 1, \dots, N. \quad (10)$$

When the data are normalized using Equation (10), the scaling procedure is called variable scaling or group scaling [23]. For the sake of clarity, and throughout the rest of the work, the scaled matrix $\check{\mathbf{X}}$ is renamed as simply \mathbf{X} . Since the scaled matrix \mathbf{X} is a mean-centered matrix [23], it is possible to calculate its covariance matrix as follows:

$$\mathbf{C}_\mathbf{X} = \frac{1}{n-1} \mathbf{X}^T \mathbf{X} \in \mathcal{M}_{(N \cdot L) \times (N \cdot L)}(\mathbb{R}) \quad (11)$$

The subspaces in PCA are defined by the eigenvectors and eigenvalues of the covariance matrix as follows:

$$\mathbf{C}_\mathbf{X} \mathbf{P} = \mathbf{P} \Lambda \quad (12)$$

where the columns of $\mathbf{P} \in \mathcal{M}_{(N \cdot L) \times (N \cdot L)}(\mathbb{R})$ are the eigenvectors of $\mathbf{C}_\mathbf{X}$. The diagonal terms of matrix $\Lambda \in \mathcal{M}_{(N \cdot L) \times (N \cdot L)}(\mathbb{R})$ are the eigenvalues λ_i , $i = 1, \dots, N \cdot L$, of $\mathbf{C}_\mathbf{X}$ whereas the off-diagonal terms are zero, that is,

$$\Lambda_{ii} = \lambda_i, \quad i = 1, \dots, N \cdot L \quad (13)$$

$$\Lambda_{ij} = 0, \quad i, j = 1, \dots, N \cdot L, \quad i \neq j \quad (14)$$

The eigenvectors p_j , $j = 1, \dots, N \cdot L$, representing the columns of the transformation matrix \mathbf{P} are classified according to the eigenvalues in descending order and they are called the principal components or the loading vectors of the data set. The eigenvector with the highest eigenvalue, called the first principal component, represents the most important pattern in the data with the largest quantity of information.

Matrix \mathbf{P} is usually called the principal components of the data set or loading matrix and matrix \mathbf{T} is the transformed or projected matrix to the principal component space, also called score matrix. Using all the $N \cdot L$ principal components, that is, in the full dimensional case, the orthogonality of \mathbf{P} implies $\mathbf{P}\mathbf{P}^T = \mathbf{I}$, where \mathbf{I} is the $(N \cdot L) \times (N \cdot L)$ identity matrix. Therefore, the projection can be inverted to recover the original data as

$$\mathbf{X} = \mathbf{TP}^T \quad (15)$$

However, the objective of PCA is, as said before, to reduce the dimensionality of the data set \mathbf{X} by selecting only a limited number $\ell < N \cdot L$ of principal components, that is, only the eigenvectors related to the ℓ highest eigenvalues. Thus, given the reduced matrix

$$\hat{\mathbf{P}} = (p_1 | p_2 | \dots | p_\ell) \in \mathcal{M}_{N \cdot L \times \ell}(\mathbb{R}) \quad (16)$$

matrix $\hat{\mathbf{T}}$ is defined as

$$\hat{\mathbf{T}} = \mathbf{X}\hat{\mathbf{P}} \in \mathcal{M}_{n \times \ell}(\mathbb{R}) \quad (17)$$

3.2 Fault detection based on multivariate hypothesis testing

The current wind turbine to diagnose is subjected to a wind turbulence as described in Sections 2 and 3.1. When the measures are obtained from $N \in \mathbb{N}$ sensors during $(vL - 1)\Delta$ seconds, a new data matrix \mathbf{Y} is constructed as in Equation (5):

$$\mathbf{Y} = \left(\begin{array}{cccc|cccc|ccc} y_{11}^1 & y_{12}^1 & \dots & y_{1L}^1 & y_{11}^2 & \dots & y_{1L}^2 & \dots & y_{11}^N & \dots & y_{1L}^N \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{i1}^1 & y_{i2}^1 & \dots & y_{iL}^1 & y_{i1}^2 & \dots & y_{iL}^2 & \dots & y_{i1}^N & \dots & y_{iL}^N \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{v1}^1 & y_{v2}^1 & \dots & y_{vL}^1 & y_{v1}^2 & \dots & y_{vL}^2 & \dots & y_{v1}^N & \dots & y_{vL}^N \end{array} \right) \in \mathcal{M}_{v \times (N \cdot L)}(\mathbb{R}) \quad (18)$$

It is worth remarking that the natural number v (the number of rows of matrix \mathbf{Y}) is not necessarily equal to n (the number of rows of \mathbf{X}), but the number of columns of \mathbf{Y} must agree with that of \mathbf{X} ; that is, in both cases the number N of sensors and the number of samples per row must be equal.

Before the collected data arranged in matrix \mathbf{Y} is projected into the new space spanned by the eigenvectors in matrix \mathbf{P} in Equation (12), the matrix has to be scaled to define a new matrix $\check{\mathbf{Y}}$ as in Equation (10):

$$\check{y}_{ij}^k := \frac{y_{ij}^k - \mu_j^k}{\sigma^k}, \quad i = 1, \dots, v, \quad j = 1, \dots, L, \quad k = 1, \dots, N, \quad (19)$$

where μ_j^k and σ^k are defined in Equations (7) and (9), respectively.

The projection of each row vector $r^i = \check{\mathbf{Y}}(i, :) \in \mathbb{R}^{N \cdot L}$, $i = 1, \dots, v$ of matrix $\check{\mathbf{Y}}$ into the space spanned by the eigenvectors in $\hat{\mathbf{P}}$ is performed through the following vector to matrix multiplication:

$$t^i = r^i \cdot \hat{\mathbf{P}} \in \mathbb{R}^\ell \quad (20)$$

For each row vector r^i , $i = 1, \dots, v$, the first component of vector t^i is called the first score or score 1; similarly, the second component of vector t^i is called the second score or score 2, and so on.

3.2.1 The random nature of the scores

Since the turbulent wind can be considered as a random process, the dynamic response of the wind turbine can be considered as a stochastic process and the measurements in r^i are also stochastic. Therefore, the vector r^i acquires this stochastic nature and it will be regarded as an ℓ -dimensional random vector to construct the stochastic approach in this work. As an example, in Figure 1, two three-dimensional samples are represented; one is the three-dimensional baseline sample (left) and the other is referred to faults 1, 4 and 7 (right).

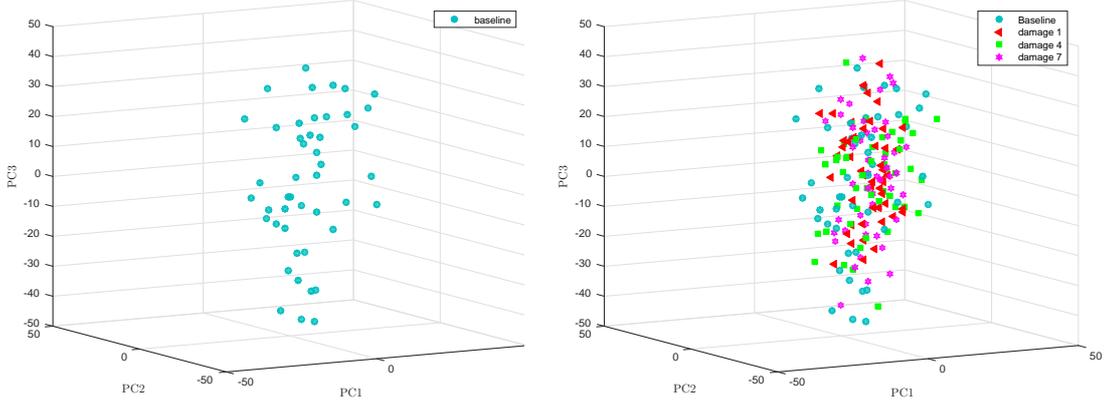


Figure 1 : Baseline sample (left) and sample from the structure to be diagnosed (right).

3.2.2 Testing a multivariate mean vector

In this work, the framework of multivariate statistical inference is used with the objective of the classification of wind turbines in healthy or faulty. With this goal, a test for multivariate normality is first performed. A test for the plausibility of a value for a normal population mean vector is then performed.

The objective of this work is to determine whether the distribution of the multivariate random samples that are obtained from the WT to be diagnosed (healthy or not) is connected to the distribution of the baseline. To this end, a test for the plausibility of a value for a normal population mean vector will be performed. Let $s \in \mathbb{N}$ be the number of principal components that will be considered jointly. We will also consider that: (a) the baseline projection is a multivariate random sample of a multivariate random variable following a multivariate normal distribution with known population mean vector $\boldsymbol{\mu}_h \in \mathbb{R}^s$ and known variance-covariance matrix $\boldsymbol{\Sigma} \in \mathcal{M}_{s \times s}(\mathbb{R})$; and (b) the multivariate random sample of the structure to be diagnosed also follows a multivariate normal distribution with unknown multivariate mean vector $\boldsymbol{\mu}_c \in \mathbb{R}^s$ and known variance-covariance matrix $\boldsymbol{\Sigma} \in \mathcal{M}_{s \times s}(\mathbb{R})$.

As said previously, the problem that we will consider is to determine whether a given s -dimensional vector $\boldsymbol{\mu}_c$ is a plausible value for the mean of a multivariate normal distribution $N_s(\boldsymbol{\mu}_h, \boldsymbol{\Sigma})$. This statement leads immediately to a test of the hypothesis

$$\begin{aligned} H_0 : \boldsymbol{\mu}_c &= \boldsymbol{\mu}_h \text{ versus} \\ H_1 : \boldsymbol{\mu}_c &\neq \boldsymbol{\mu}_h, \end{aligned}$$

that is, the null hypothesis is ‘the multivariate random sample of the WT to be diagnosed is distributed as the baseline projection’ and the alternative hypothesis is ‘the multivariate random sample of the WT to be diagnosed is not distributed as the baseline projection’. In other words, if the result of the test is that the null hypothesis is not rejected, the current WT is categorized as healthy. Otherwise, if the null hypothesis is rejected in favor of the alternative, this would indicate the presence of some fault in the WT.

The test is based on the statistic T^2 –also called Hotelling’s T^2 – and it is summarized below. When a multivariate random sample of size $\nu \in \mathbb{N}$ is taken from a multivariate normal distribution $N_s(\boldsymbol{\mu}_h, \boldsymbol{\Sigma})$, the random variable

$$T^2 = \nu (\bar{\mathbf{X}} - \boldsymbol{\mu}_h)^T \mathbf{S}^{-1} (\bar{\mathbf{X}} - \boldsymbol{\mu}_h)$$

is distributed as

$$T^2 \hookrightarrow \frac{(\nu - 1)s}{\nu - s} F_{s, \nu - s},$$

where $F_{s, \nu - s}$ denotes a random variable with an F -distribution with s and $\nu - s$ degrees of freedom, $\bar{\mathbf{X}}$ is the sample vector mean as a multivariate random variable; and $\frac{1}{n}\mathbf{S} \in \mathcal{M}_{s \times s}(\mathbb{R})$ is the estimated covariance matrix of $\bar{\mathbf{X}}$.

At the α level of significance, we reject H_0 in favor of H_1 if the observed

$$t_{\text{obs}}^2 = \nu (\bar{\mathbf{x}} - \boldsymbol{\mu}_h)^T \mathbf{S}^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}_h)$$

is greater than $\frac{(\nu - 1)s}{\nu - s} F_{s, \nu - s}(\alpha)$, where $F_{s, \nu - s}(\alpha)$ is the upper $(100\alpha)\%$ th percentile of the $F_{s, \nu - s}$ distribution. In other words, the quantity t_{obs}^2 is the damage indicator and the test is summarized as follows:

$$t_{\text{obs}}^2 \leq \frac{(\nu - 1)s}{\nu - s} F_{s, \nu - s}(\alpha) \implies \text{Fail to reject } H_0, \quad (21)$$

$$t_{\text{obs}}^2 > \frac{(\nu - 1)s}{\nu - s} F_{s, \nu - s}(\alpha) \implies \text{Reject } H_0, \quad (22)$$

where $F_{s, \nu - s}(\alpha)$ is such that

$$\mathbb{P}(F_{s, \nu - s} > F_{s, \nu - s}(\alpha)) = \alpha,$$

where \mathbb{P} is a probability measure. More precisely, we fail to reject the null hypothesis if $t_{\text{obs}}^2 \leq \frac{(\nu - 1)s}{\nu - s} F_{s, \nu - s}(\alpha)$, thus indicating that no faults in the WT have been found. Otherwise, the null hypothesis is rejected in favor of the alternative hypothesis if $t_{\text{obs}}^2 > \frac{(\nu - 1)s}{\nu - s} F_{s, \nu - s}(\alpha)$, thus indicating the existence of some faults in the WT.

4. SIMULATION RESULTS

To validate the fault detection strategy presented in Section 3, we first consider a total of 24 samples of $\nu = 50$ elements each, according 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 eight different fault scenarios described in Table 1.

In the numerical simulations in this Section, each sample of $\nu = 50$ elements is composed by the measures obtained from the $N = 13$ sensors detailed in [19, Table 4] during $(\nu \cdot L - 1)\Delta = 312.4875$ seconds, where $L = 500$ and the sampling time $\Delta = 0.0125$ seconds. The measures of each sample are then arranged in a $\nu \times (N \cdot L)$ matrix as in Equation (18).

These 24 samples plus the baseline sample of $n = 50$ elements are used to test for the plausibility of a value for a normal population mean vector, with a level of significance $\alpha = 10\%$. Each sample of $\nu = 50$ elements is categorized as follows: (i) number of samples from the healthy wind turbine (healthy sample) which were classified by the hypothesis test as ‘healthy’ (fail to reject H_0); (ii) faulty sample classified by the test as ‘faulty’ (reject H_0); (iii) samples from the faulty structure (faulty sample) classified as ‘healthy’; and (iv) faulty sample classified as ‘faulty’. The results presented in Table 3 are

Table 2 : Scheme for the presentation of the results in Table 3.

	Healthy Sample (H_0)	Faulty 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

Table 3 : Categorization of the samples with respect to the presence or absence of a fault and the result of the test considering the first score, the second score, scores 1–2 (jointly), scores 1–7 (jointly), and scores 1–10 (jointly), when the size of the samples to diagnose is $v = 50$ and the level of significance is $\alpha = 10\%$.

	H_0	H_1		H_0	H_1
Score 1			Scores 1-2		
Fail to reject H_0	16	1	Fail to reject H_0	12	0
Reject H_0	0	7	Reject H_0	4	8
Score 2			Scores 1-7		
Fail to reject H_0	13	7	Fail to reject H_0	13	0
Reject H_0	3	1	Reject H_0	3	8
Score 3			Scores 1-12		
Fail to reject H_0	16	8	Fail to reject H_0	16	0
Reject H_0	0	0	Reject H_0	0	8

organized according to the scheme in Table 2. It can be stressed in Table 3 that the sum of the columns is constant: 16 samples in the first column (healthy wind turbine) and 8 more samples in the second column (faulty wind turbine).

Table 3 includes both the results using the univariate hypothesis testing fault detection strategy developed in [19] (for the first, second and third score) and the multivariate hypothesis testing presented in this work (scores 1-2, 1-7 and 1-12, jointly). It is worth noting that, for a fixed level of significance $\alpha = 10\%$, all decisions are correct when the first twelve scores are considered jointly.

5. CONCLUDING REMARKS

The silver bullet for offshore operators is to eliminate unscheduled maintenance. Therefore, the implementation of fault detection systems 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 multivariate statistical hypothesis testing is a valuable tool in fault detection for wind turbines. It is noteworthy that, in the simulations, when the the first twelve scores are considered jointly all the decisions are correct (there are no false alarms and no missing faults).

We believe that PCA plus multivariate statistical hypothesis testing has tremendous potential in decreasing maintenance costs. Therefore, we view the work described in this work as only the beginning of a large project. For future work, we plan to develop a complete fault detection, isolation, and reconfiguration method (FDIR). That is, a reconfigurable control strategy in response to faults. In the near future, the next step is to focus our research into efficient fault feature extraction.

ACKNOWLEDGMENTS

This work has been partially funded by the Spanish Ministry of Economy and Competitiveness through the research projects DPI2014-58427-C2-1-R and DPI2015-64170-R (MINECO/FEDER), and by the Generalitat de Catalunya through the research project 2014 SGR 859.

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