Mechanical Systems and Signal Processing 91 (2017) 326–353

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

# Damage/fault diagnosis in an operating wind turbine under uncertainty via a vibration response Gaussian mixture random coefficient model based framework ☆

Luis David Avendaño-Valencia, Spilios D. Fassois *

*Stochastic Mechanical Systems and Automation (SMSA) Laboratory, Department of Mechanical Engineering & Aeronautics, University of Patras, GR 265 04 Patras, Greece*

ARTICLE INFO

*Article history:*
Received 5 August 2016
Accepted 25 November 2016

*Keywords:*
Non-stationary identification
Vibration-based damage diagnosis
Structural health monitoring
Uncertainties
Gaussian mixture model random coefficient approach
Time-dependent ARMA models
Linear parameter varying ARMA models
Wind turbines

ABSTRACT

The study focuses on vibration response based health monitoring for an operating wind turbine, which features time-dependent dynamics under environmental and operational uncertainty. A Gaussian Mixture Model Random Coefficient (GMM–RC) model based Structural Health Monitoring framework postulated in a companion paper is adopted and assessed. The assessment is based on vibration response signals obtained from a simulated offshore 5 MW wind turbine. The non–stationarity in the vibration signals originates from the continually evolving, due to blade rotation, inertial properties, as well as the wind characteristics, while uncertainty is introduced by random variations of the wind speed within the range of 10–20 m/s. Monte Carlo simulations are performed using six distinct structural states, including the healthy state and five types of damage/fault in the tower, the blades, and the transmission, with each one of them characterized by four distinct levels. Random vibration response modeling and damage diagnosis are illustrated, along with pertinent comparisons with state–of–the–art diagnosis methods. The results demonstrate consistently good performance of the GMM–RC model based framework, offering significant performance improvements over state–of–the–art methods. Most damage types and levels are shown to be properly diagnosed using a single vibration sensor.


**Important Conventions** Bold-face upper/lower case symbols designate matrix/column-vector quantities, respectively. Matrix transposition is indicated by the superscript T. A functional argument in parentheses designates function of a real variable; for instance $x(t)$ is a function of analog time $t \in \Re$. A functional argument in brackets designates function of an integer variable; for instance $x[t]$ is a function of normalized discrete time ($t = 1, 2, \ldots$). The conversion from discrete normalized time to analog time is based upon $(t-1)T_s$, with $T_s$ designating the sampling period. A hat designates estimator/estimate of the indicated quantity; for instance $\widehat{\boldsymbol{\theta}}$ is an estimator/estimate of $\boldsymbol{\theta}$.


* Corresponding author.
*E-mail address:* fassois@mech.upatras.gr (S.D. Fassois).
*URL:* http://www.smsa.upatras.gr (S.D. Fassois).

http://dx.doi.org/10.1016/j.ymssp.2016.11.028
0888-3270/

**Nomenclature**

*Main Acronyms*

| | |
|---|---|
| AUC | area under the ROC curve |
| ARMA | Auto Regressive Moving Average |
| BIC | Bayesian Information Criterion |
| FPR | False Positive Rate |
| FS | Functional Series |
| GMM | Gaussian Mixture Model |
| LPV | Linear Parameter Varying |
| NID | Normally Independently Distributed |
| PDF | Probability Density Function |
| RC | Random Coefficient |
| ROC | Receiver Operating Characteristic |
| RSS | Residual Sum of Squares |
| SSS | Series Sum of Squares |
| TARMA | Time-dependent ARMA |
| TNR | True Negative Rate |
| TPR | True Positive Rate |
| TV-PSD | Time-Varying Power Spectral Density |

*Main symbols*

| | |
|---|---|
| $\boldsymbol{y} = [y[1] \quad y[2] \quad \cdots \quad y[N]]^T \in \mathbb{R}^N$ | $N$-sample length observation (random vibration response) vector |
| $\boldsymbol{\theta} = [\theta_1 \quad \theta_2 \quad \cdots \quad \theta_n]^T \in \mathbb{R}^n$ | parameter vector |
| $v = \{o, a, b, c, \ldots\}$ | structural state (class) ($o$: Healthy; $a$: Damage type A; $b$: Damage type B; $\ldots$) |
| $\mathfrak{m}$ | model of the vibration response |
| $\mathfrak{M}$ | GMM representation |
| $L$ | dimensionality of the GMM representation |
| $p(\boldsymbol{x})$ | Probability Density Function (PDF) associated with the corresponding random vector $\boldsymbol{x}$ |
| $P(a)$ | probability of the random event $a$ |
| $p(\boldsymbol{x}, \boldsymbol{y})$ | joint PDF of the random variables $\boldsymbol{x}$ and $\boldsymbol{y}$ |
| $p(\boldsymbol{y} \vert \boldsymbol{x})$ | conditional PDF of $\boldsymbol{y}$ given $\boldsymbol{x}$ |

## 1. Introduction

Vibration–response–based Structural Health Monitoring (SHM) aims at damage diagnosis for structures based on measured vibration response signals [1,2]. The application of this technology is of particular importance for wind turbines, since these are costly, remotely located, structures for which maintenance and repair costs are considerable [3,4]. SHM is thus important for avoiding structural damage, which may itself lead to downtimes and even catastrophic events, while keeping maintenance and repair costs low. Nonetheless, the design of vibration–response–based SHM systems for operating wind turbines poses certain challenges, including the following:

**In–operation diagnosis.** Uninterrupted operation of wind turbine facilities is necessary for maximizing power production and economic revenue. Therefore, it is most desirable to perform SHM during normal operation. Appropriate SHM methods must thus have the capability to deal with the dynamics characterizing an operating wind turbine, which feature *cyclo-stationary* and, in a broader sense, *non-stationary* behavior [5–7]. Moreover, since the actual exciting forces are not measurable, the methods must be solely based on random vibration response signals.

**Changing environmental and operational conditions.** Wind turbines operate in a constantly changing environment determined by varying winds and weather conditions. Besides, they are set to operate at different regimes in response to the varying power demands. As a consequence, the characteristics of the random vibration response may change considerably with changes in the environmental and operational conditions [7]. Thus, the SHM system must be capable of coping with such changes and distinguish them from those due to damage [1,8].

**Complex models of the dynamics.** Physics–based models of the wind turbine dynamics under varying excitation and operational conditions are generally quite complex for use in practical SHM systems. As a consequence, data–based models derived from random vibration response signals, obtained at specific locations, need to be preferably employed. Such models may also lead to more practical and potentially more effective SHM [2,9].

Most of the currently available vibration–based SHM methodologies for wind turbines utilize characteristic quantities (features) derived from frequency domain representations or modal properties of the structure. However, the extraction of frequency–domain or modal characteristics from random vibration responses of operating wind turbines requires special-