Mechanical Systems and Signal Processing 70-71 (2016) 557–577

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Optimal selection of autoregressive model coefficients for early damage detectability with an application to wind turbine blades

Simon Hoell, Piotr Omenzetter*

The LRF Centre for Safety and Reliability Engineering, The University of Aberdeen, Aberdeen AB24 3UE, UK

ARTICLE INFO

Article history:
Received 25 March 2015
Received in revised form
19 August 2015
Accepted 1 September 2015
Available online 26 September 2015

Keywords:
Autoregressive models
Damage detection
Hypothesis testing
Optimal feature selection
Time series
Wind turbine

ABSTRACT

Data-driven vibration-based damage detection techniques can be competitive because of their lower instrumentation and data analysis costs. The use of autoregressive model coefficients (ARMCs) as damage sensitive features (DSFs) is one such technique. So far, like with other DSFs, either full sets of coefficients or subsets selected by trial-and-error have been used, but this can lead to suboptimal composition of multivariate DSFs and decreased damage detection performance. This study enhances the selection of ARMCs for statistical hypothesis testing for damage presence. Two approaches for systematic ARMC selection, based on either adding or eliminating the coefficients one by one or using a genetic algorithm (GA) are proposed. The methods are applied to a numerical model of an aerodynamically excited large composite wind turbine blade with disbonding damage. The GA out performs the other selection methods and enables building multivariate DSFs that markedly enhance early damage detectability and are insensitive to measurement noise.

1. Introduction

The world's energy infrastructure is undergoing significant changes due to the increasing interest in, and demand for renewable energy. For the sector of wind energy, the relentless strive for more efficient energy harvesting leads to growing numbers and sizes of wind turbines (WTs) and erections in remote areas, such as offshore, where winds are stronger and more reliable and predictable. However, the increasing operation and maintenance expenditure, which can make up to 20% of the total energy production cost [1], affect adversely the production targets and expected revenues. Knowledge of the current structural state and condition obtained from interpreting remotely monitored data can counteract this issue.

The process of continuous monitoring of structures using sensors, extracting information and knowledge from these observations and determining the structural performance, condition and reliability is referred to as structural health monitoring (SHM) [2]. There has been large amount of effort during the past decade to develop effective SHM methods for application in mechanical, aerospace, civil and other structural systems [3–9]. Several non-destructive testing techniques based on different physical principles, such as thermal imaging, X-radioscopy, electrical resistance and ultrasonic waves, have been proposed for structural damage detection (SDD) in wind turbine components [10,11]. However, the majority of

* Corresponding author. Tel.: +44 1224 272529.
E-mail address: piotr.omenzetter@abdn.ac.uk (P. Omenzetter).

http://dx.doi.org/10.1016/j.ymssp.2015.09.007
0888-3270/

List of symbols

Roman letters

D	Mahalanobis distance
F	Cumulative probability distribution function; aerodynamic force acting on blade element
H	Hypothesis
K	Number of time lags
M	Aerodynamic moment acting on blade element
N	Number of surface nodes in blade finite element model
$\mathcal{N}$	Gaussian distribution
$\mathcal{P}$	Parental population for genetic algorithm
Q	Modified Ljung–Box–Pierce statistic
S	Vector cosine distance in Eq. (21)
T^2	Hotelling's T^2 statistic
a	Autoregressive coefficient; linear aerodynamic load distribution coefficient across blade
b	Uniform aerodynamic load distribution coefficient
c	Moving average coefficient; linear load distribution coefficient along blade
e	Noise term
f	Fitness function; aerodynamic nodal forces
m	Dimensionality of damage sensitive feature vector
n	Number of samples
p	Autoregressive order
q	Moving average order
r	Autocorrelation function
s	Binary selection variable in genetic algorithm
$\mathbf{s}$	Binary selection vector in genetic algorithm
t	Discrete time
x	Edge-wise coordinate in finite element blade model; edge-wise coordinate in AeroDyn model
y	Thickness-wise coordinate in finite element blade model; thickness-wise coordinate in AeroDyn model
z	Zero-mean time series; flap-wise coordinate in finite element blade model; flap-wise coordinate in AeroDyn model

Greek letters

$\boldsymbol{\Sigma}$	Variance–covariance matrix
Δ	Difference operator
α	Level of significance
β	Number of flipped entries in selection vector in genetic algorithm
κ	Number of parental individuals in genetic algorithm
υ	Damage sensitive feature
$\boldsymbol{\upsilon}$	Damage sensitive feature vector
μ	Mean value
$\boldsymbol{\mu}$	Mean value vector
ρ	Cross-correlation coefficient
σ	Standard deviation
σ^2	Variance
χ^2	Chi-square probability distribution function

Subscripts

0	Null hypothesis
1	Alternative hypothesis
N	Normal to rotor plane
P	Pitching
T	Tangential to rotor plane
c	Current state
d	Damaged state
h	Healthy state
$offsp$	Offspring
pl	Pooled
r	Blade element in AeroDyn
ref	Reference
rel	Relative
$temp$	Temporary
x	x direction
y	y direction

Superscripts

T	Transpose
\widehat	Estimate

List of acronyms

ACF	Autocorrelation function
AIC	Akaike information criterion
ARMC	Autoregressive model coefficient
AR	Autoregressive
ARC	Autoregressive coefficient
ARMA	Autoregressive moving average
DOF	Degree of freedom
DSF	Damage sensitive feature
EMD	Empirical mode decomposition
FE	Finite element
GA	Genetic algorithm
HHT	Hilbert–Huang transform
IMF	Intrinsic mode function
LE	Leading edge
MA	Moving average
MAC	Moving average coefficient
NBI	Next-Best-In
NREL	National Renewable Energy Laboratory
NWO	Next-Worst-Out
PAC	Partial autocorrelation
SDD	Structural damage detection
SHM	Structural health monitoring
SNL	Sandia National Laboratory
TE	Trailing edge
WT	Wind turbine; wavelet transform
WTB	Wind turbine blade