BLADE FAULT DIAGNOSIS USING ARTIFICIAL INTELLIGENCE TECHNIQUE

NGUI WAI KENG

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Mechanical Engineering)

Faculty of Mechanical Engineering
Universiti Teknologi Malaysia

NOVEMBER 2016

ACKNOWLEDGEMENT

First and foremost, I would like to express my gratitude to my supervisor, Prof. Dr. Mohd Salman Leong and my co-supervisor Ir. Dr. Lim Meng Hee for their support, guidance and encouragement. I also thank Dr. Mohd Ibrahim Bin Shapiai for his valuable help and suggestions. I thank all the staffs in the Institute of Noise and Vibration for their help, assistance and cooperation.

I would also like to thank Institute of Noise and Vibration, University Malaysia Pahang, and Malaysian Government for their financial support.

Finally, I thank my family members and all my friends for their support and encouragement.

ABSTRACT

Blade fault diagnosis is conventionally based on interpretation of vibration spectrum and wavelet map. These methods are however found to be difficult and subjective as it requires visual interpretation of chart and wavelet color map. To overcome this problem, important features for blade fault diagnosis in a multi row of rotor blade system was selected to develop a novel blade fault diagnosis method based on artificial intelligence techniques to reduce subjective interpretation. Three artificial neural network models were developed to detect blade fault, classify the type of blade fault, and locate the blade fault location. An experimental study was conducted to simulate different types of blade faults involving blade rubbing, loss of blade part, and twisted blade. Vibration signals for all blade fault conditions were measured with a sampling rate of 5 kHz under steady-state conditions at a constant rotating speed. Continuous wavelet transform was used to analyse the vibration signals and its results were used subsequently for feature extraction. Statistical features were extracted from the continuous wavelet coefficients of the rotor operating frequency and its corresponding blade passing frequencies. The extracted statistical features were grouped into three different feature sets. In addition, two new feature sets were proposed: blade statistical curve area and blade statistical summation. The effectiveness of the five different feature sets for blade fault detection, classification, and localisation was investigated. Classification results showed that the statistical features extracted from the operating frequency to be more effective for blade fault detection, classification, and localisation than the statistical features from blade passing frequencies. Feature sets of blade statistical curve area was found to be more effective for blade fault classification, while feature sets of blade statistical summation were more effective for blade fault localisation. The application of feature selection using genetic algorithm showed good accuracy performance with fewer features achieved. The neural network developed for blade fault detection, classification, and localisation achieved accuracy of 100%, 98.15% and 83.47% respectively. With the developed blade fault diagnosis methods, manual interpretation solely dependent on knowledge and the experience of individuals can be reduced. The novel methods can therefore be used as an alternative method for blade fault diagnosis.

ABSTRAK

Diagnosis kecacatan bilah adalah lazimnya berdasarkan interpretasi ke atas spektrum getaran dan peta gelombang kecil. Kaedah ini akan tetapi didapati sukar dan subjektif kerana ia memerlukan interpretasi secara visual ke atas carta dan peta berwarna gelombang kecil. Untuk mengatasi masalah ini, sifat-sifat penting untuk diagnosis kecacatan bilah pada satu sistem rotor bilah yang berbilang baris telah dipilih untuk membangunkan satu kaedah diagnosis kecacatan bilah novel berdasarkan kepada teknik-teknik kecerdasan buatan bagi mengurangkan interpretasi subjektif. Tiga tiruan rangkaian neural model telah dibangunkan bagi mengesan kecacatan bilah, mengelas jenis kecacatan bilah, dan mencari lokasi kecacatan bilah. Satu eksperimen telah dijalankan untuk mensimulasikan beberapa jenis kecacatan bilah yang berbeza termasuk geseran bilah, kehilangan sebahagian bilah, dan bilah terpiuh. Isyarat getaran untuk semua keadaan kecacatan bilah telah diukur pada keadaan mantap dengan kadar pensampelan 5 kHz pada kelajuan tetap. Transformasi gelombang kecil berterusan telah digunakan untuk menganalisa isyarat getaran dan keputusan seterusnya digunakan bagi pengekstrakan sifat. Sifat-sifat statistik telah diekstrak dari pekali gelombang kecil berterusan pada frekuensi operasi pemutar dan frekuensi berlalu bilah yang sepadan. Sifat-sifat statistik yang telah diekstrak telah dikumpulkan kepada tiga set sifat yang berasingan. Di samping itu, dua set sifat baru telah dicadangkan iaitu *blade statistical curve area* dan *blade statistical summation*. Keberkesanan lima set sifat yang berbeza untuk pengesanan kecacatan bilah, pengelasan, dan penyetempatan telah dikaji. Keputusan klasifikasi menunjukkan bahawa sifat-sifat statistik diekstrak dari frekuensi operasi lebih berkesan bagi pengesanan kecacatan bilah, pengelasan, dan penyetempatan berbanding sifat-sifat statistik dari frekuensi berlalu bilah. Set sifat *blade statistical curve area* adalah didapati lebih berkesan bagi pengelasan kecacatan bilah, manakala set sifat *blade statistical summation* adalah lebih berkesan bagi penyetempatan kecacatan bilah. Aplikasi pemilihan sifat menggunakan algoritma genetik menunjukkan prestasi ketepatan yang baik dengan sifat-sifat yang lebih sedikit dicapai. Rangkaian neural yang dibangunkan bagi pengesanan kecacatan bilah, pengelasan, dan penyetempatan masing-masing mencapai ketepatan 100%, 98.15% dan 83.47%. Dengan kaedah diagnosis kecacatan bilah yang dibangunkan, interpretasi secara manual yang semata-matanya bergantung kepada pengetahuan dan pengalaman individu dapat dikurangkan. Dengan ini, kaedah novel ini boleh digunakan sebagai kaedah alternatif bagi diagnosis kecacatan bilah.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
BPF	-	Blade passing frequency
BPF_1_CF_X	-	Crest factor from the first BPF in the horizontal direction
BPF_1_CF_Y	-	Crest factor from the first BPF in the vertical direction
BPF_1_CM_X	-	Central moment from the first BPF in the horizontal direction
BPF_1_CM_Y	-	Central moment from the first BPF in the vertical direction
BPF_1_E_X	-	Energy from the first BPF in the horizontal direction
BPF_1_E_Y	-	Energy from the first BPF in the vertical direction
BPF_1_ESE_X	-	Energy to Shanon entropy ratio from the first BPF in the horizontal direction
BPF_1_ESE_Y	-	Energy to Shanon entropy ratio from the first BPF in the vertical direction
BPF_1_KUR_X	-	Kurtosis from the first BPF in the horizontal direction
BPF_1_KUR_Y	-	Kurtosis from the first BPF in the vertical direction
BPF_1_M_X	-	Mean from the first BPF in the horizontal direction
BPF_1_M_Y	-	Mean from the first BPF in the vertical direction
BPF_1_RMS_X	-	RMS from the first BPF in the horizontal direction
BPF_1_RMS_Y	-	RMS from the first BPF in the vertical direction
BPF_1_SE_X	-	Shanon entropy from the first BPF in the horizontal direction

BPF_1_SE_Y	-	Shanon entropy from the first BPF in the vertical direction
BPF_1_SK_X	-	Skewness from the first BPF in the horizontal direction
BPF_1_SK_Y	-	Skewness from the first BPF in the vertical direction
BPF_1_STD_X	-	Standard deviation from the first BPF in the horizontal direction
BPF_1_STD_Y	-	Standard deviation from the first BPF in the vertical direction
BPF_1_V_X	-	Variance from the first BPF in the horizontal direction
BPF_1_V_Y	-	Variance from the first BPF in the vertical direction
BPF_2_CF_X	-	Crest factor from the second BPF in the horizontal direction
BPF_2_CF_Y	-	Crest factor from the second BPF in the vertical direction
BPF_2_CM_X	-	Central moment from the second BPF in the horizontal direction
BPF_2_CM_Y	-	Central moment from the second BPF in the vertical direction
BPF_2_E_X	-	Energy from the second BPF in the horizontal direction
BPF_2_E_Y	-	Energy from the second BPF in the vertical direction
BPF_2_ESE_X	-	Energy to Shanon entropy ratio from the second BPF in the horizontal direction
BPF_2_ESE_Y	-	Energy to Shanon entropy ratio from the second BPF in the vertical direction
BPF_2_KUR_X	-	Kurtosis from the second BPF in the horizontal direction
BPF_2_KUR_Y	-	Kurtosis from the second BPF in the vertical direction
BPF_2_M_X	-	Mean from the second BPF in the horizontal direction

BPF_2_M_Y	-	Mean from the second BPF in the vertical direction
BPF_2_RMS_X	-	RMS from the second BPF in the horizontal direction
BPF_2_RMS_Y	-	RMS from the second BPF in the vertical direction
BPF_2_SE_X	-	Shanon entropy from the second BPF in the horizontal direction
BPF_2_SE_Y	-	Shanon entropy from the second BPF in the vertical direction
BPF_2_SK_X	-	Skewness from the second BPF in the horizontal direction
BPF_2_SK_Y	-	Skewness from the second BPF in the vertical direction
BPF_2_STD_X	-	Standard deviation from the second BPF in the horizontal direction
BPF_2_STD_Y	-	Standard deviation from the second BPF in the vertical direction
BPF_2_V_X	-	Variance from the second BPF in the horizontal direction
BPF_2_V_Y	-	Variance from the second BPF in the vertical direction
BPF_3_CF_X	-	Crest factor from the third BPF in the horizontal direction
BPF_3_CF_Y	-	Crest factor from the third BPF in the vertical direction
BPF_3_CM_X	-	Central moment from the third BPF in the horizontal direction
BPF_3_CM_Y	-	Central moment from the third BPF in the vertical direction
BPF_3_E_X	-	Energy from the third BPF in the horizontal direction
BPF_3_E_Y	-	Energy from the third BPF in the vertical direction
BPF_3_ESE_X		Energy to Shanon entropy ratio from the third BPF in the horizontal direction

BPF_3_ESE_Y	-	Energy to Shanon entropy ratio from the third BPF in the vertical direction
BPF_3_KUR_X		Kurtosis from the third BPF in the horizontal direction
BPF_3_KUR_Y	-	Kurtosis from the third BPF in the vertical direction
BPF_3_M_X	-	Mean from the third BPF in the horizontal direction
BPF_3_M_Y	-	Mean from the third BPF in the vertical direction
BPF_3_RMS_X	-	RMS from the third BPF in the horizontal direction
BPF_3_RMS_Y	-	RMS from the third BPF in the vertical direction
BPF_3_SE_X	-	Shanon entropy from the third BPF in the horizontal direction
BPF_3_SE_Y	-	Shanon entropy from the third BPF in the vertical direction
BPF_3_SK_X	-	Skewness from the third BPF in the horizontal direction
BPF_3_SK_Y	-	Skewness from the third BPF in the vertical direction
BPF_3_STD_X	-	Standard deviation from the third BPF in the horizontal direction
BPF_3_STD_Y	-	Standard deviation from the third BPF in the vertical direction
BPF_3_V_X	-	Variance from the third BPF in the horizontal direction
BPF_3_V_Y	-	Variance from the third BPF in the vertical direction
BSCA	-	Blade statistical curve area
BSCA_CF_X	-	Crest factor from the BSCA in the horizontal direction
BSCA_CF_Y	-	Crest factor from the BSCA in the vertical direction
BSCA_CM_X	-	Central moment from the BSCA in the horizontal direction
BSCA_CM_Y	-	Central moment from the BSCA in the vertical direction
BSCA_E_X	-	Energy from the BSCA in the horizontal direction
BSCA_E_Y	-	Energy from the BSCA in the vertical direction

BSCA_ESE_X	-	Energy to Shanon entropy ratio from the BSCA in the horizontal direction
BSCA_ESE_Y	-	Energy to Shanon entropy ratio from the BSCA in the vertical direction
BSCA_KUR_X	-	Kurtosis from the BSCA in the horizontal direction
BSCA_KUR_Y	-	Kurtosis from the BSCA in the vertical direction
BSCA_M_X	-	Mean from the BSCA in the horizontal direction
BSCA_M_Y	-	Mean from the BSCA in the vertical direction
BSCA_RMS_X	-	RMS from the BSCA in the horizontal direction
BSCA_RMS_Y	-	RMS from the BSCA in the vertical direction
BSCA_SE_X	-	Shanon entropy from the BSCA in the horizontal direction
BSCA_SE_Y	-	Shanon entropy from the BSCA in the vertical direction
BSCA_SK_X	-	Skewness from the BSCA in the horizontal direction
BSCA_SK_Y	-	Skewness from the BSCA in the vertical direction
BSCA_STD_X	-	Standard deviation from the BSCA in the horizontal direction
BSCA_STD_Y	-	Standard deviation from the BSCA in the vertical direction
BSCA_V_X	-	Variance from the BSCA in the horizontal direction
BSCA_V_Y	-	Variance from the BSCA in the vertical direction
BSS	-	Blade statistical summation
BSS_CF_X	-	Crest factor from the BSS in the horizontal direction
BSS_CF_Y	-	Crest factor from the BSS in the vertical direction
BSS_CM_X	-	Central moment from the BSS in the horizontal direction
BSS_CM_Y	-	Central moment from the BSS in the vertical direction
BSS_E_X	-	Energy from the BSS in the horizontal direction
BSS_E_Y	-	Energy from the BSS in the vertical direction
BSS_ESE_X	-	Energy to Shanon entropy ratio from the BSS in the horizontal direction

BSS_ESE_Y	-	Energy to Shanon entropy ratio from the BSS in the vertical direction
BSS_KUR_X	-	Kurtosis from the BSS in the horizontal direction
BSS_KUR_Y	-	Kurtosis from the BSS in the vertical direction
BSS_M_X	-	Mean from the BSS in the horizontal direction
BSS_M_Y	-	Mean from the BSS in the vertical direction
BSS_RMS_X	-	RMS from the BSS in the horizontal direction
BSS_RMS_Y	-	RMS from the BSS in the vertical direction
BSS_SE_X	-	Shanon entropy from the BSS in the horizontal direction
BSS_SE_Y	-	Shanon entropy from the BSS in the vertical direction
BSS_SK_X	-	Skewness from the BSS in the horizontal direction
BSS_SK_Y	-	Skewness from the BSS in the vertical direction
BSS_STD_X	-	Standard deviation from the BSS in the horizontal direction
BSS_STD_Y	-	Standard deviation from the BSS in the vertical direction
BSS_V_X	-	Variance from the BSS in the horizontal direction
BSS_V_Y	-	Variance from the BSS in the vertical direction
CF	-	Crest factor
CFD	-	Computational Fluid Dynamics
CM	-	Central moment
CWT	-	Continuous Wavelet Transform
E	-	Energy
EMD	-	Empirical Mode Decomposition
EPRI	-	Electric Power Research Institute
ESE	-	Energy to Shanon entropy ratio
FFT	-	Fast Fourier Transform
GA	-	Genetic Algorithm
KUR	-	Kurtosis
LDA	-	Linear Discriminant Analysis
LLE	-	Locally Linear Embedding

M	-	Mean
MLP	-	Multi-Layer Perceptron
NFS_A1	-	Feature set from the blade statistical curve area
NFS_A2	-	Feature set from the blade statistical summation
OF_CF_X	-	Crest factor from the operating frequency in the horizontal direction
OF_CF_Y	-	Crest factor from the operating frequency in the vertical direction
OF_CM_X	-	Central moment from the operating frequency in the horizontal direction
OF_CM_Y	-	Central moment from the operating frequency in the vertical direction
OF_E_X	-	Energy from the operating frequency in the horizontal direction
OF_E_Y	-	Energy from the operating frequency in the vertical direction
OF_ESE_X	-	Energy to Shanon entropy ratio from the operating frequency in the horizontal direction
OF_ESE_Y	-	Energy to Shanon entropy ratio from the operating frequency in the vertical direction
OF_KUR_X	-	Kurtosis from the operating frequency in the horizontal direction
OF_KUR_Y	-	Kurtosis from the operating frequency in the vertical direction
OF_M_X	-	Mean from the operating frequency in the horizontal direction
OF_M_Y	-	Mean from the operating frequency in the vertical direction
OF_RMS_X	-	RMS from the operating frequency in the horizontal direction
OF_RMS_Y	-	RMS from the operating frequency in the vertical direction

OF_SE_X	-	Shanon entropy from the operating frequency in the horizontal direction
OF_SE_Y	-	Shanon entropy from the operating frequency in the vertical direction
OF_SK_X	-	Skewness from the operating frequency in the horizontal direction
OF_SK_Y	-	Skewness from the operating frequency in the vertical direction
OF_STD_X	-	Standard deviation from the operating frequency in the horizontal direction
OF_STD_Y	-	Standard deviation from the operating frequency in the vertical direction
OF_V_X	-	Variance from the operating frequency in the horizontal direction
OF_V_Y	-	Variance from the operating frequency in the vertical direction
PCA	-	Principle Component Analysis
PNN	-	Probabilistic Neural Network
PSVM	-	Proximal Support Vector Machines
RBF	-	Radial Basis Function
RMS	-	Root mean square
SE	-	Shanon entropy
SFS_A1	-	Feature set from the operating frequency
SFS_A2	-	Feature set from the blade passing frequencies
SFS_A3	-	Feature set from the operating frequency and blade passing frequencies
SK	-	Skewness
SOM	-	Self-Organizing Maps
STA	-	Synchronised Time Averaging
STD	-	Standard deviation
SVM	-	Support Vector Machine
V	-	Variance
WPT	-	Wavelet Packet Transform

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview

Turbine and compressor that utilise blades to extract energy are of importance in power generation, petrochemical plants, and aerospace industries. Over the years, blade related failures have caused significant problems for rotating machinery operators in the industry. Even a single blade failure can lead to significant financial losses, severe damages, and catastrophic failure. The Electric Power Research Institute (EPRI) study on the power generation industry for example reported that failure of blades alone caused over US$1.1 billion of lost power production during the years 1970–1981. Costs for blades, diaphragm, and rotor replacements were reported at US$87 million [1]. Barnard [2] reported that 2 catastrophic failures of a gas turbine totaling more than US$ 25million in production downtime. Marsh, one of the global leader in insurance broking and risk management reported that turbine and turbine-blade failures in 2015 remain the most common form of machinery breakdown experienced by their clients [3]. Some examples of blade failures are shown in Figure 1.1. To reduce the turbine failures caused by blade faults, research on new blade design, new blade fabrication technology, and more accurate blade fault diagnosis methods are of current and on-going interest.

Failed gas turbine engine, [4]

Damaged 4th stage disk, [5]

Compressor rotor blades due to foreign object impact, [6]

Figure 1.1 Example of blade failures

To avoid blade failure and to optimise the use of the blades, it is necessary to have reliable and sensitive condition monitoring and signal processing methods to both measure and extract important information or features for blade fault diagnosis. The health of the blade can be observed by measuring and analysing the vibration, pressure, acoustic, and thermal measurement signals.

1.2 Problem Statement

Over the years, research on the condition monitoring methods and signal processing techniques used to diagnose various types of blade faults (e.g., blade deformation, blade rubbing, loose blade, blade fouling, and blade fatigue failure) have been widely reported in the open literature. Condition monitoring methods;

commonly used for blade faults diagnosis, include but are not limited to temperature analysis, vibration analysis, acoustic analysis, and pressure analysis. Among these, the most widely used for blade faults diagnosis is vibration analysis because it is the most practical method to use under field conditions.

Frequency domain (Fourier Transform) and time-frequency domain (wavelet analysis) vibration analysis are the most widely deployed techniques for both blade faults detection and diagnosis. The application of Fourier analysis and wavelet analysis has been successful in blade fault detection and diagnosis, comparing the amplitude or pattern of the vibration spectrum or the wavelet map for a faulty condition to a healthy condition [7][8]. Changes in the operating frequency and blade passing frequencies, however, require individuals to detect and diagnose blade faults. Previous studies showed that wavelet analysis is more reliable and sensitive for blade fault diagnosis [8][9]. Interpretation of vibration spectrum and wavelet results is however difficult and challenging. Blade faults diagnosis becomes difficult when the interpretation of vibration spectrum or wavelet results is not possible. Furthermore, the accuracy of these methods is affected by the knowledge and the experience of individuals in interpreting vibration spectrum and wavelet results.

Recently, a number of researchers have shown an increased interest in developing artificial intelligence-based pattern recognition techniques for rotating machinery fault diagnosis, especially for bearings and gears [10][11]. In-depth interpretation of vibration spectrum and wavelet map requires human intervention, which can be minimised by an artificial intelligence-based classification system. The artificial intelligence method has also been employed by many previous researchers for blade fault detection and diagnosis. Features extracted from frequency domain analysis are usually used as input to the classifier. The application of features extracted using time-frequency domain analysis for blade fault diagnosis is, however, still lacking.

1.3 Research Questions

This study addressed the following research questions:

1. Do features extracted via time-frequency analysis contain useful information that can assist in developing a novel blade fault diagnosis method?
2. Is a genetic algorithm capable of selecting important features and enhancing the network performance?
3. Do artificial intelligence techniques have the capability to detect, classify, and locate both single blade faults in a single row and single blade faults in multiple rows?
4. What method can be used to address the above issues?

1.4 Objectives

The objectives of this study were:

1. Formulation of important features for blade fault diagnosis in a multi row of rotor blade system.
2. Development of a novel blade fault diagnosis method based on artificial intelligence techniques using the extracted and the selected features.

1.5 Scope of the Study

Typical rotating machinery has a number of sub-components which upon mechanical or physical failure can lead to severe machinery damage and economic losses. This study was for rotor blade related failures, consisting of blade rubbing, loss of blade part and twisted blade. Laboratory testing was undertaken for faults simulation in a multi row rotor blade system. Faults investigated included single blade fault in a single row and single blade fault in multiple rows. Multiple blade faults in a single row or multiple rows were not considered in this study. The condition monitoring employed vibration measurement. The study was for constant speed condition. The effectiveness of Fast Fourier Transform (FFT) and wavelet analysis for blade fault diagnosis were examined using experimental data. This study involved use of an artificial intelligence-based classification system to detect, classify and locate different blade fault conditions. Effectiveness of the proposed blade fault diagnosis method using testing data was undertaken.

1.6 Thesis Outline

This thesis consists of eight chapters. The second chapter in this thesis presents a literature review on the state-of-the-art approaches employed in blade fault diagnosis. The review discusses the types of blade faults, as well as the strategies used in blade fault monitoring and diagnostics. Applications of artificial intelligence techniques used in rotating machinery fault diagnosis are also included in this chapter. Chapter 3 focuses on the theoretical backgrounds of wavelet analysis and explains Artificial Neural Network (ANN), Genetic Algorithm (GA), and cross-validation techniques. Chapter 4 presents the details of the blade fault test rig, the experimental work, and the experiment setup. The effectiveness of FFT and wavelet analysis for blade fault diagnosis in a multi row rotor blade system is examined and the results are discussed in Chapter 5. In Chapter 6, the novel blade fault diagnosis methods are presented. This chapter first describes the proposed feature extraction technique and the newly proposed features for blade fault diagnosis. The feature selection method using GA is also explained. Finally, Chapter 7 presents the three ANN networks developed for blade fault detection, classification, and localisation. The effectiveness of the extracted features, the newly proposed features, and the feature selection technique are summarized. This chapter also discusses the performance of ANNs on experimental data. Chapter 8 summarises the findings, as well as the contributions of the study. The recommendations for future research are also presented in this chapter.

REFERENCES

1. Dewey, R. P., and Rieger, N. F. *Survey of Steam Turbine Blade Failures*. EPRI. 1985.
2. Barnard, I. Asset Management, An Insurance Perspective. *1st World Congress on Engineering Asset Management*. July 11-14, 2006. Australia. 2006.
3. Marsh. *Power and Utilities Market Update*. MARSH. 2016.
4. Qu, S., Fu, C. M., Dong, C., Tian, J. F., and Zhang, Z. F. Failure Analysis of the 1st Stage Blades in Gas Turbine Engine. *Eng Fail Anal*. 2013. 32: 292–303.
5. Lourenco, N. J., Graca, M. L. A., Franco, L. A. L., and Silva, O. M. M. Fatigue Failure of a Compressor Blade. *Eng Fail Anal*. 2008. 15(8): 1150–1154.
6. Mishra, R. K., Srivastav, D. K., Srinivasan, K., Nandi, V., and Bhat, R. R. Impact of Foreign Object Damage on an Aero Gas Turbine Engine. *J Fail Anal Prev*. 2015. 15(1): 25–32.
7. Simmons, H. A Non-intrusive Method for Detecting HP Turbine Blade Resonance. *ASME Paper No. 86-JPGC-Pwr-36, 1986 Joint ASME/IEEE Power Generation Conference*. October 19-23, 1986. Portland, USA. 1986.
8. Aretakis, N., and Mathioudakis, K. Wavelet analysis for gas turbine fault diagnostics. *J Eng Gas Turbines Power*. 1997. 119(4): 870–876.
9. Lim, M. H., and Leong, M. S. Diagnosis for Loose Blades in Gas Turbines Using Wavelet Analysis. *J Eng Gas Turbines Power*. 2005. 127(2): 314–322.
10. Yang, H., Mathew, J., and Ma, L. Intelligent Diagnosis of Rotating Machinery Faults-A Review. *3rd Asia-Pacific Conference on Systems Integrity and Maintenance (ACSIM 2002)*. September 25-27, 2002. Cairns, Australia. 2002.
11. Lei, Y., He, Z., and Zi, Y. Application of an Intelligent Classification Method to Mechanical Fault Diagnosis. *Expert Syst Appl*. 2009. 36(6): 9941–9948.

12. Ma, H., Yin, F., Guo, Y., Tai, X., and Wen, B. A Review on Dynamic Characteristics of Blade–Casing Rubbing. *Nonlinear Dyn*. 2016. 84(2): 437–472.
13. Kurz, R., and Brun, K. Fouling Mechanisms in Axial Compressors. *J Eng Gas Turbines Power*. 2012. 134(3).
14. Morini, M., Pinelli, M., Spina, P. R., and Venturini, M. Numerical Analysis of the Effects of Nonuniform Surface Roughness on Compressor Stage Performance. *J Eng Gas Turbines Power*. 2011. 133(7).
15. Bammert, K., and Woelk, G. U. The Influence of the Blading Surface Roughness on the Aerodynamic Behawior and Characteristic of an Axial Compressor. *J Eng Power*. 1980. 102(2): 283–287.
16. Naeem, M. T., Jazayeri, S. A., and Rezamahdi, N. Failure Analysis of Gas Turbine Blades. *Proceddings of The 2008 IAJC-IJME International Conference*. November 17-19, 2008. USA. 2008.
17. Stamatis, A. G., and Papailiou, K. D. Using HPC in Gas Turbines Blade Fault Diagnosis. In Hertzberger, B. Sloot, P. ed. *HPCN*. Springer Berlin Heidelberg. 11-20; 1997.
18. Aretakis, N., Mathioudakis, K., and Dedoussis, V. Derivation of Signatures for Faults in Gas Turbine Compressor Blading. *Control Eng Pract*. 1998. 6(8): 969–974.
19. Dedoussis, V., Mathioudakis, K., and Papailiou, K. D. Numerical Simulation of Blade Fault Signatures From Unsteady Wall Pressure Signals. *J Eng Gas Turbines Power*. 1997. 119(2): 362–369.
20. Forbes, G. L., and Randall, R. B. Simulated Gas Turbine Casing Response to Rotor Blade Pressure Excitation. *5th Australasian Congress on Applied Mechanics, ACAM 2007*. December 10-12, 2007. Brisbane, Australia. 2007.
21. Koubogiannis, D. G., Iliadis, V. P., and Giannakoglou, K. C. A Parallel CFD Tool to Produce Faulty Blade Signatures for Diagnostic Purposes. *ASME 1998 International Gas Turbine and Aeroengine Congress and Exhibition*. June 2–5, 1998. Stockholm, Sweden: The American Society of Mechanical Engineers. 1998.
22. Hameed, M. S., and Manarvi, I. A. Using FEM and CFD for Engine Turbine Blades to Localize Critical Areas for Non Destructive Inspections. *Int J Multidiscip Sci Eng*. 2011. 2(3): 29–37.

23. Rodriguez, J. A., Hamzaoui, Y. El, Hernandez, J. A., Garcia, J. C., Flores, J. E., and Tejeda, A. L. The Use of Artificial Neural Network (ANN) for Modeling the Useful Life of the Failure Assessment in Blades of Steam Turbines. *Eng Fail Anal*. 2013. 35: 562–575.

24. Hee, L. M., Leong, M. S., and Hui, K. H. Blade Faults Classification and Detection Methods: Review. *Adv Mater Res*. 2014. 845: 123–127.

25. Abdelrhman, A. M., Hee, L. M., Leong, M. S., and Al-Obaidi, S. Condition Monitoring of Blade in Turbomachinery: A Review. *Adv Mech Eng*. 2014. 6.

26. Mathioudakis, K., Papathanasiou, A., Loukis, E., and Papailiou, K. Fast Response Wall Pressure Measurement as A Means of Gas Turbine Blade Fault Identification. *J Eng Gas Turbines Power*. 1991. 113(2): 269–275.

27. Hilger, A. W., Herwart, H., and Heinz, E. G. *Process for Detecting Fouling of an Axial Compressor*. US 5479818 A. 1996.

28. Millsaps, K. T., Baker, J., and Patterson, J. S. Detection and Localization of Fouling in a Gas Turbine Compressor From Aerothermodynamic Measurements. *ASME Turbo Expo 2004: Power for Land, Sea, and Air*. June 14–17, 2004. Vienna, Austria: The American Society of Mechanical Engineers. 2004. 1867–1876.

29. Barschdorff, D., and Korthauer, R. Aspects of Failure Diagnosis on Rotating Parts of Turbomachinerys Using Computer Simulation and Pattern Recognition Methods. *International Conference On Condition Monitoring*. Brighton, United Kingdom. 1986.

30. Annerfeldt, M., Shukin, S., Björkman, M., Karlsson, A., Jönsson, A., and Svistounova, E. GTX 100 Turbine Section Measurement using a Temperature Sensitive Crystal Technique. A Comparison with 3D Thermal and Aerodynamic Analyses. *Power-Gen Europe*. May 25–27, 2004. Barcelona, Spain. 2004.

31. Kim, K. M., Park, J. S., Lee, D. H., Lee, T. W., and Cho, H. H. Analysis of Conjugated Heat Transfer, Stress and Failure in a Gas Turbine Blade with Circular Cooling Passages. *Eng Fail Anal*. 2011. 18(4): 1212–1222.

32. LeMieux, D. H. *On-Line Thermal Barrier Coating Monitoring for Real-Time Failure Protection and Life Maximization*. Technical report prepared for U.S Department of Energy, National Energy Technology Laboratory. 2005.

33. Al-Ghamd, A. M., and Mba, D. A Comparative Experimental Study on the Use of Acoustic Emission and Vibration Analysis for Bearing Defect Identification and Estimation of Defect Size. *Mech Syst Signal Process*. 2006. 20(7): 1537–1571.
34. Leon, R. L., and Trainor, K. Monitoring Systems for Steam Turbine Blade Faults. *Sound Vib*. 1990. 24: 12–15.
35. Momeni, S., Koduru, J. P., Gonzalez, M., Zarate, B., and Godinez, V. Online Acoustic Emission Monitoring of Combustion Turbines for Compressor Stator Vane Crack Detection. *Proc. SPIE 8690, Industrial and Commercial Applications of Smart Structures Technologies 2013*. March 10, 2013. San Diego, California, USA. 2013.
36. Mba, D., and Hall, L. D. The Transmission of Acoustic Emission Across Large-Scale Turbine Rotors. *NDT E Int*. 2002. 35(8): 529–539.
37. Hall, L. D., and Mba, D. Acoustic Emissions Diagnosis of Rotor-Stator Rubs using the KS Statistic. *Mech Syst Signal Process*. 2004. 18(4): 849–868.
38. Hall, L. D., and Mba, D. Diagnosis of Continuous Rotor-Stator Rubbing in Large Scale Turbine Units using Acoustic Emissions. *Ultrasonics*. 2004. 41(9): 765–773.
39. Randall, R. L., Hong, C., and Graham, L. J. Acoustic emission monitoring of steam turbines. 1986 .
40. Douglas, R. M., Beugné, S., Jenkins, M. D., et al. Monitoring of Gas Turbine Operating Parameters using Acoustic Emission. *Proceedings of the EWGAE 2004*. September 15-17, 2004. Berlin, Germany. 2004. 389–396.
41. Urbach, A., Banov, M., Turko, V., and Feshchuk, Y. Diagnostics of Fatigue Damage of Gas Turbine Engine Blades by Acoustic Emission Method. *World Acad Sci Eng Technol Int Sci Index 59, Int J Mech Aerospace, Ind Mechatron Manuf Eng*. 2011. 5(11): 2165–2170.
42. Iwatsubo, T., Tsujiuchi, Y., and Inoue, T. Vibration of Asymmetric Rotor Supported by Oil Film Bearings. *Ingenieur-Archiv*. 1986. 56(1): 1–15.
43. Patel, T. H., and Darpe, A. K. Vibration Response of A Cracked Rotor in Presence of Rotor-Stator Rub. *J Sound Vib*. 2008. 317(3-5): 841–865.
44. Randall, R. B. *Vibration-based Condition Monitoring Industrial, Aerospace and Automotive Applications*. Wiley. 2011.

45. Jardine, A. K. S., Lin, D., and Banjevic, D. A Review on Machinery Diagnostics and Prognostics Implementing Condition-based Maintenance. *Mech Syst Signal Process*. 2006. 20(7): 1483–1510.
46. Mitchell, J. S. Examination of Pump Cavitation, Gear Mesh and Blade Performance Using External Vibration Characteristics. *Proceedings of the Fourth Turbomachinery Symposium*. Texas A & M University. 1975.
47. Simmons, H. Non-intrusive detection of turbine blade resonance. *3rd EPRI Conference on Incipient Failure Detection in Power Plants*. Philadelphia, USA. 1987.
48. Parge, P., Trevillion, B., and Carle, P. Non-intrusive Vibration Monitoring for Turbine Blade Reliability. *Proceedings of the 2nd International Machinery Monitoring and Diagnostic Conference*. Los Angeles, USA. 1990. 435–446.
49. Rao, A. R., and Atomic, B. Non Intrusive Method of Detecting Turbine Blade Vibration in an Operating Power Plant. *Proceedings of ISMA 2010*. September 20-22, 2010. Belgium. 2010. 2937–2948.
50. Forbes, G. L., and Randall, R. B. Gas Turbine Casing Vibrations under Blade Pressure Excitation. *MFPT 2009 Failure Prevention: Implementation, Success Stories and Lessons Learned*. Dayton, USA: Society for Machinery Failure Prevention Technology. 2009. 1–11.
51. Forbes, G. L. *Non-Contact Gas Turbine Blade Vibration Monitoring using Internal Pressure and Casing Response Measurements*. Ph.D. Thesis. University of New South Wales; 2010.
52. Mathioudakis, K., Loukis, E., and Papailiou, K. D. Casing Vibration and Gas Turbine Operating Conditions. *J Eng Gas Turbines Power*. 1990. 112(4): 478–485.
53. Forbes, G. L., and Randall, R. B. Estimation of Turbine Blade Natural Frequencies from Casing Pressure and Vibration Measurements. *Mech Syst Signal Process*. 2013. 36(2): 549–561.
54. Maynard, K. P., and Trethewey, M. W. Blade and Shaft Crack Detection using Torsional Vibration Measurements Part 1: Feasibility Studies. *Noise Vib Worldw*. 2000. 31(11): 9–15.
55. Maynard, K. P., and Trethewey, M. Blade and Shaft Crack Detection using Torsional Vibration Measurements Part 2: Resampling to Improve Effective Dynamic Range. *Noise Vib Worldw*. 2001. 32(2): 23–26.

56. Maynard, K. P., and Trethewey, M. Blade and Shaft Crack Detection using Torsional Vibration Measurements Part 3: Field Application Demonstrations. *Noise Vib Worldw*. 2001. 32(11): 16–23.
57. Lim, M. H., Leong, M. S., and Ngui, W. K. Vibration Analysis of Rub in Rotating Machinery. *Appl Mech Mater*. 2013. 390: 215–219.
58. Abdelrhman, A. M., Leong, M. S., Hee, L. M., and Hui, K. H. Vibration Analysis of Multi Stages Rotor for Blade Faults Diagnosis. *Adv Mater Res*. 2013. 845: 133–137.
59. Loukis, E., Mathioudakis, K., and Papailiou, K. A Procedure for Automated Gas Turbine Blade Fault Identification Based on Spectral Pattern Analysis. *J Eng Gas Turbines Power*. 1992. 114(2): 201–208.
60. Aretakis, N., Mathioudakis, K., and Dedoussis, V. Derivation of Signatures For Faults in Gas Turbine Compressor Blading. *Control Eng Pract*. 1998. 6(8): 969–974.
61. Kuo, R. J. Intelligent Diagnosis for Turbine Blade Faults using Artificial Neural Networks and Fuzzy Logic. *Eng Appl Artif Intell*. 1995. 8(1): 25–34.
62. Angelakis, C., Loukis, E. N., Pouliezos, A. D., and Stavrakakis, G. S. A Neural Network-Based Method for Gas Turbine Blading Fault Diagnosis. *Int J Model Simul*. 2001. 21(1): 51–60.
63. Kyriazis, A., Aretakis, N., and Mathioudakis, K. Gas Turbine Fault Diagnosis from Fast Response Data using Probabilistic Methods and Information Fusion. *ASME Turbo Expo 2006: Power for Land, Sea, and Air*. May 8–11, 2006. Barcelona, Spain: The American Society of Mechanical Engineers. 2006. 571–579.
64. Peng, Z., Chu, F., and He, Y. Vibration Signal Analysis and Feature Extraction Based on Reassigned Wavelet Scalogram. *J Sound Vib*. 2002. 253(5): 1087–1100.
65. Lim, M. H., and Leong, M. S. Improved Blade Fault Diagnosis Using Discrete Blade Passing Energy Packet and Rotor Dynamics Wavelet Analysis. *ASME Turbo Expo 2010: Power for Land, Sea, and Air*. June 14–18, 2010. Glasgow, UK: The American Society of Mechanical Engineers. 2010. 31–37.
66. Lim, M. H., and Leong, M. S. Detection of Early Faults in Rotating Machinery Based on Wavelet Analysis. *Adv Mech Eng*. 2013. 5.

67. Abdelrhman, A. M., Leong, M. S., Hee, L. M., and Ngui, W. K. Application of Wavelet Analysis in Blade Faults Diagnosis for Multi-Stages Rotor System. *Appl Mech Mater*. 2013. 393: 959–964.
68. Abdelrhman, A. M., Leong, M. S., Hee, L. M., and Hui, K. H. Vibration Analysis of Multi Stages Rotor for Blade Faults Diagnosis. *Adv Mater Res*. 2014. 845: 133–137.
69. Ahmed, A. M. A. *Blade faults diagnosis in multi stage rotor system by means of wavelet analysis*. Ph.D. Thesis. Universiti Teknologi Malaysia; 2014.
70. Lim, M. H., and Ngui, W. K. Diagnosis of Twisted Blade in Rotor System. *22nd International Congress on Sound and Vibration*. July 12-16, 2015. Florence, Italy: International Institute of Acoustics and Vibrations. 2015.
71. Wang, Q., and Chu, F. Experimental Determination of the Rubbing Location By Means of Acoustic Emission and Wavelet Transform. *J Sound Vib*. 2001. 248(1): 91–103.
72. Chang, C. C., and Chen, L. W. Damage Detection of Cracked Thick Rotating Blades by a Spatial Wavelet Based Approach. *Appl Acoust*. 2004. 65(11): 1095–1111.
73. Al-Badour, F., Sunar, M., and Cheded, L. Vibration Analysis of Rotating Machinery using Time-Frequency Analysis and Wavelet Techniques. *Mech Syst Signal Process*. 2011. 25(6): 2083–2101.
74. Baillie, D. C., and Mathew, J. A Comparison of Autoregressive Modeling Techniques for Fault Diagnosis of Rolling Element Bearings. *Mech Syst Signal Process*. 1996. 10(1): 1–17.
75. Wang, W. J., and McFadden, P. D. Application of Orthogonal Wavelets to Early Gear Damage Detection. *Mech Syst Signal Process*. 1995. 9(5): 497–507.
76. Mori, K., Kasashima, N., Yoshioka, T., and Ueno, Y. Prediction of Spalling on a Ball Bearing by Applying the Discrete Wavelet Transform to Vibration Signals. *Wear*. 1996. 195(1-2): 162–168.
77. Prabhakar, S., Mohanty, A. R., and Sekhar, A. S. Application of Discrete Wavelet Transform for Detection of Ball Bearing Race Faults. *Tribol Int*. 2002. 35(12): 793–800.
78. Tondon, N., and Choudhury, A. A Review of Vibration and Acoustics Measurement Methods for the Detection of Defects in Rolling Element Bearing. *Tribol Int*. 1999. 32(8): 469–480.

79. Liu, T. I., and Mengel, J. M. Intelligent Monitoring of Ball Bearing Conditions. *Mech Syst Signal Process*. 1992. 6(5): 419–431.
80. Widodo, A., Kim, E. Y., Son, J.-D., et al. Fault Diagnosis of Low Speed Bearing Based on Relevance Vector Machine and Support Vector Machine. *Expert Syst Appl*. 2009. 36(3): 7252–7261.
81. Yiakopoulos, C. T., Gryllias, K. C., and Antoniadis, I. A. Rolling Element Bearing Fault Detection in Industrial Environments Based on a K-Means Clustering Approach. *Expert Syst Appl*. 2011. 38(3): 2888–2911.
82. Thanagasundram, S., and Schlindwein, F. S. Autoregressive Based Diagnostics Scheme for Detection of Bearing Faults. *Proceedings of ISMA2006 Noise and Vibration Engineering Conference*. September 18-20, 2006. Belgium: Katholieke Universiteit Leuven. 2006. 3531–3546.
83. Zhao, L. Y., Yu, W., and Yan, R. Q. Rolling Bearing Fault Diagnosis Based on CEEMD and Time Series Modeling. *Math Probl Eng*. 2014. 2014.
84. Sun, Q., Chen, P., Zhang, D., and Xi, F. Pattern Recognition for Automatic Machinery Fault Diagnosis. *J Vib Acoust*. 2004. 126(2): 307–316.
85. Wang, Y., and Liang, M. An Adaptive SK Technique and its Application for Fault Detection of Rolling Element Bearings. *Mech Syst Signal Process*. 2011. 25(5): 1750–1764.
86. Sawalhi, N., and Randall, R. B. The Application of Spectral Kurtosis to Bearing Diagnostics. *Proceedings of Acoustics 2004*. November 3-5, 2004. Gold Coast, Australia: Australian Acoustical Society. 2004. 393–398.
87. Zheng, H., Li, Z., and Chen, X. Gear Fault Diagnosis Based on Continuous Wavelet Transform. *Mech Syst Signal Process*. 2002. 16(2-3): 447–457.
88. Zarei, J., and Poshtan, J. Bearing Fault Detection using Wavelet Packet Transform of Induction Motor Stator Current. *Tribol Int*. 2007. 40(5): 763–769.
89. Wang, X., Makis, V., and Yang, M. A Wavelet Approach to Fault Diagnosis of a Gearbox under Varying Load Conditions. *J Sound Vib*. Elsevier. 2010 Apr. 329(9): 1570–1585.
90. Lee, S. M., and Choi, Y. S. Fault Diagnosis of Partial Rub and Looseness in Rotating Machinery using Hilbert-Huang Transform. *J Mech Sci Technol*. 2008. 22(11): 2151–2162.

91. Yu, Y., and Lang, H. Fault Diagnosis of Rotor Rub based on Ensemble EMD. *ICEMI 2009 - Proceedings of 9th International Conference on Electronic Measurement and Instruments*. August 16-19, 2009. Beijing: The Institute of Electrical and Electronics Engineers. 2009.

92. Georgoulas, G., Loutas, T., Stylios, C. D., and Kostopoulos, V. Bearing Fault Detection Based on Hybrid Ensemble Detector and Empirical Mode Decomposition. *Mech Syst Signal Process*. 2013. 41(1-2): 510–525.

93. Feng, Z., Liang, M., Zhang, Y., and Hou, S. Fault Diagnosis for Wind Turbine Planetary Gearboxes via Demodulation Analysis Based on Ensemble Empirical Mode Decomposition and Energy Separation. *Renew Energy*. 2012. 47: 112–126.

94. Zhang, X., and Zhou, J. Multi-Fault Diagnosis for Rolling Element Bearings Based on Ensemble Empirical Mode Decomposition and Optimized Support Vector Machines. *Mech Syst Signal Process*. 2013. 41(1-2): 127–140.

95. Bhavaraju, K., Kankar, P., Sharma, S., and Harsha, S. A Comparative Study on Bearings Faults Classification by Artificial Neural Networks and Self-Organizing Maps using Wavelets. *Int J Eng Sci Technol*. 2010. 2(5): 1001–1008.

96. Pandya, D. H., Upadhyay, S. H., and Harsha, S. P. ANN Based Fault Diagnosis of Rolling Element Bearing Using Time-Frequency Domain Feature. *Int J Comput Eng Sci*. 2012. 4(6): 2878–2886.

97. Farrar, C. R., and Worden, K. *Structural Health Monitoring: A Machine Learning Perspective*. Wiley. 2013.

98. Sreejith, B., Verma, A. K., and Srividya, A. Fault Diagnosis of Rolling Element Bearing using Time-Domain Features and Neural Networks. *2008 IEEE Region 10 Colloquium and the Third international Conference on Industrial and Information Systems*. December 8-10, 2008. Kharagpur, India: The Institute of Electrical and Electronics Engineers. 2008.

99. Al-Raheem, K. F., and Abdul-Karem, W. Rolling Bearing Fault Diagnostics using Artificial Neural Networks based on Laplace Wavelet Analysis. *Int J Eng Sci Technol*. 2010. 2(6): 278–290.

100. Zheng, H., and Zhou, L. Rolling element bearing fault diagnosis based on support vector machine. *2012 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet)*. April 21-23,

2012.Yichang, China: The Institute of Electrical and Electronics Engineers. 2012. 544–547.

101. Wang, W. Q., Golnaraghi, M. F., and Ismail, F. Prognosis of Machine Health Condition using Neuro-Fuzzy Systems. *Mech Syst Signal Process*. 2004. 18(4): 813–831.

102. Chen, C., Zhang, B., and Vachtsevanos, G. Prediction of Machine Health Condition Using Neuro-Fuzzy and Bayesian Algorithms. *IEEE Trans Instrum Meas*. 2012. 61(2): 297–306.

103. Hall, D. L., Hansen, R. J., and Lang, D. C. The Negative Information Problem in Mechanical Diagnostics. *J Eng Gas Turbines Power*. 1997. 119(2): 370–377.

104. Shao, Y., and Nezu, K. An On-Line Monitoring and Diagnostic Method of Rolling EIement Bearing with AI. *Proceedings of the 34th SICE Annual Conference*. July 26-28, 1995. Hokkaido: The Institute of Electrical and Electronics Engineers. 1995. 1543–1548.

105. Chen, D., and Wang, W. J. Classification of Wavelet Map Pattern using Multi-Layer Neural Networks for Gear Fault Detection. *Mech Syst Signal Process*. 2002. 16(4): 695–704.

106. Samanta, B., Al-Balushi, K. R., and Al-Araimi, S. A. Artificial Neural Networks and Genetic Algorithm for Bearing Fault Detection. *Soft Comput*. 2006. 10(3): 264–271.

107. Paya, B. A., Esat, I. I., and Badi, M. N. M. Artificial Neural Network Based Fault Diagnostics of Rotating Machinery Using Wavelet Transforms As a Preprocessor. *Mech Syst Signal Process*. 1997. 11(5): 751–765.

108. Kankar, P. K., Sharma, S. C., and Harsha, S. P. Fault Diagnosis of Ball Bearings using Continuous Wavelet Transform. *Appl Soft Comput J*. 2011. 11(2): 2300–2312.

109. Saravanan, N., and Ramachandran, K. I. A Comparative Study on Classification of Features by Fast Single-Shot Multiclass PSVM using Morlet Wavelet for Fault Diagnosis of Spur Bevel Gear Box. *Expert Syst Appl*. 2009. 36(8): 10854–10862.

110. Ali, J. Ben, Fnaiech, N., Saidi, L., Chebel-Morello, B., and Fnaiech, F. Application of Empirical Mode Decomposition and Artificial Neural Network for Automatic Bearing Fault Diagnosis based on Vibration Signals. *Appl*

Acoust. 2015. 89: 16–27.

111. Lei, Y., He, Z., and Zi, Y. Application of an Intelligent Classification Method to Mechanical Fault Diagnosis. *Expert Syst Appl*. 2009. 36(6): 9941–9948.
112. Duan, Z. W., Gao, B. K., Song, J. B., and Liu, X. Fault Diagnosis for Rolling Bearing Based on the (SVM) Combined with (EMD) Instantaneous Power Spectral Entropy. *IOSR J Eng*. 2015. 5(12): 32–38.
113. Peng, Z. K., and Chu, F. L. Application of the Wavelet Transform in Machine Condition Monitoring and Fault Diagnostics: A Review with Bibliography. *Mech Syst Signal Process*. 2004. 18(2): 199–221.
114. Ngui, W. K., Leong, M. S., Hee, L. M., and Abdelrhman, A. M. Wavelet Analysis: Mother Wavelet Selection Methods. *Appl Mech Mater*. 2013. 393: 953–958.
115. Sheen, Y. T. On the Study of Applying Morlet Wavelet to the Hilbert Transform for the Envelope Detection of Bearing Vibrations. *Mech Syst Signal Process*. 2009. 23(5): 1518–1527.
116. Lin, J., and Qu, L. S. Feature Extraction Based on Morlet Wavelet and its Application for Mechanical Fault Diagnosis. *J Sound Vib*. 2000. 234(1): 135–148.
117. Jain, A. K., Mao, J., and Mohiuddin, K. M. Artificial Neural Networks: A Tutorial. *Computer (Long Beach Calif)*. 1996. 29(3): 31–44.
118. Kohavi, R. A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *Proceedings of the 14th international joint conference on Artificial intelligence - Volume 2 (IJCAI'95)*. August 20-25, 1995. Canada: Morgan Kaufmann Publishers Inc. 1995. 1137–1143.
119. Bruzzone, L., and Persello, C. A Novel Approach to the Selection of Spatially Invariant Features for the Classification of Hyperspectral Images with Improved Generalization Capability. *IEEE Trans Geosci Remote Sens*. 2009. 47(9): 3180–3191.
120. Miller, B. L., and Goldberg, D. E. Genetic Algorithms, Tournament Selection, and the Effects of Noise. *Complex Syst*. 1995. 9(3): 193–212.
121. Yesilyurt, I. The Application of the Conditional Moments Analysis to Gearbox Fault Detection - A Comparative Study using the Spectrogram and Scalogram. *NDT E Int*. 2004. 37(4): 309–320.
122. Wang, S. Bin, Zhu, Z. K., and Wang, A. Z. Gearbox Fault Feature Detection

based on Adaptive Parameter Identification with Morlet Wavelet. *2010 International Conference on Wavelet Analysis and Pattern Recognition*. July 11-14, 2010. Qingdao, China: The Institute of Electrical and Electronics Engineers. 2010. 409–414.

123. Erguzel, T. T., Ozekes, S., Tan, O., and Gultekin, S. Feature Selection and Classification of Electroencephalographic Signals: An Artificial Neural Network and Genetic Algorithm based Approach. *Clin EEG Neurosci*. 2014. 46(4).

124. Ahmad, F., Mat Isa, N. A., Hussain, Z., Osman, M. K., and Sulaiman, S. N. A GA-based Feature Selection and Parameter Optimization of an ANN in Diagnosing Breast Cancer. *Pattern Anal Appl*. 2015. 18(4): 861–870.

125. Yacci, P. *Feature Selection of Microarray Data Using Genetic Algorithms and Artificial Neural Networks*. Master thesis. Rochester Institute of Technology; 2009.

126. Hajnayeb, A., Ghasemloonia, A., Khadem, S. E., and Moradi, M. H. Application and Comparison of an ANN-Based Feature Selection Method and the Genetic Algorithm in Gearbox Fault Diagnosis. *Expert Syst Appl*. 2011. 38(8): 10205–10209.

127. Alajmi, A., and Wright, J. Selecting the most efficient genetic algorithm sets in solving unconstrained building optimization problem. *Int J Sustain Built Environ*. The Gulf Organisation for Research and Development. 2014. 3(1): 18–26.

128. Subrahmanyam, M., and Sujatha, C. Using Neural Networks for the Diagnosis of Localized Defects in Ball Bearings. *Tribol Int*. 1997. 30(10): 739–752.

129. Samanta, B. Gear Fault Detection using Artificial Neural Networks and Support Vector Machines with Genetic Algorithms. *Mech Syst Signal Process*. 2004. 18(3): 625–644.

130. Haykin, S. *Neural Networks and Learning Machines. 3th. ed. New York: Prentice Hall*. 2009.

131. Møller, M. F. A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning. *Neural Networks*. 1993. 6(4): 525–533.

132. Kumar, S. , Kumar, M. Application of Artificial Neural Network in the Investigation of Bearing Defects. *World Acad Sci Eng Technol Int Sci Index 104, Int J Civil, Environ Struct Constr Archit Eng*. 2015. 9(8): 1083–1086.

133. Babatunde, O. H., Armstrong, L. J., Leng, J., and Dean, D. A Genetic Algorithm-Based Feature Selection. *Br J Math Comput Sci*. 2014. 5(4): 899–905.

134. Siriwardene, N. R., and Perera, B. J. C. Selection of genetic algorithm operators for urban drainage model parameter optimisation. *Math Comput Model*. 2006. 44(5-6): 415–429.

135. Loukis, E., Mathioudakis, K., and Papailiou, K. A Procedure for Automated Gas Turbine Blade Fault Identification Based on Spectral Pattern Analysis. *J Eng Gas Turbines Power*. 1992. 114(2): 201–208.