APPLICATION OF VARIATIONAL MODE DECOMPOSITION IN VIBRATION ANALYSIS OF MACHINE COMPONENTS

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DEDICATION

This thesis are dedicated to my parents, whose affection, love, encouragement, support and prays of day and night which make me able to get such success.

This thesis also dedicated to my siblings and my wife, whose had been great sources of motivation and inspiration.

This thesis also dedicated to my supervisor and co-supervisor, whose had been guided me and shared their knowledge in order to help me to achieve the objective of my PhD study.

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ABSTRACT

Monitoring and diagnosis of machinery in maintenance are often undertaken using vibration analysis. The machine vibration signal is invariably complex and diverse, and thus useful information and features are difficult to extract. Variational mode decomposition (VMD) is a recent signal processing method that able to extract some of important features from machine vibration signal. The performance of the VMD method depends on the selection of its input parameters, especially the mode number and balancing parameter (also known as quadratic penalty term). However, the current VMD method is still using a manual effort to extract the input parameters where it subjects to interpretation of experienced experts. Hence, machine diagnosis becomes time consuming and prone to error. The aim of this research was to propose an automated parameter selection method for selecting the VMD input parameters. The proposed method consisted of two-stage selections where the first stage selection was used to select the initial mode number and the second stage selection was used to select the optimized mode number and balancing parameter. A new machine diagnosis approach was developed, named as VMD Differential Evolution Algorithm (VMDEA)-Extreme Learning Machine (ELM). Vibration signal datasets were then reconstructed using VMDEA and the multi-domain features consisted of time-domain, frequency-domain and multi-scale fuzzy entropy were extracted. It was demonstrated that the VMDEA method was able to reduce the computational time about 14% to 53% as compared to VMD-Genetic Algorithm (GA), VMD-Particle Swarm Optimization (PSO) and VMD-Differential Evolution (DE) approaches for bearing, shaft and gear. It also exhibited a better convergence with about two to nine less iterations as compared to VMD-GA, VMD-PSO and VMD-DE for bearing, shaft and gear. The VMDEA-ELM was able to illustrate higher classification accuracy about 11% to 20% than Empirical Mode Decomposition (EMD)-ELM, Ensemble EMD (EEMD)-ELM and Complimentary EEMD (CEEMD)-ELM for bearing shaft and gear. The bearing datasets from Case Western Reserve University were tested with VMDEA-ELM model and compared with Support Vector Machine (SVM)-Dempster-Shafer (DS), EEMD Optimal Mode Multi-scale Fuzzy Entropy Fault Diagnosis (EOMSMFD), Wavelet Packet Transform (WPT)-Local Characteristic-scale Decomposition (LCD)-ELM, and Arctangent S-shaped PSO least square support vector machine (ATSWPLM) models in term of its classification accuracy. The VMDEA-ELM model demonstrates better diagnosis accuracy with small differences between 2% to 4% as compared to EOMSMFD and WPT-LCD-ELM but less diagnosis accuracy in the range of 4% to 5% as compared to SVM-DS and ATSWPLM. The diagnosis approach VMDEA-ELM was also able to provide faster classification performance about 6 – 40 times faster than Back Propagation Neural Network (BPNN) and Support Vector Machine (SVM). This study provides an improved solution in determining an optimized VMD parameters by using VMDEA. It also demonstrates a more accurate and effective diagnostic approach for machine maintenance using VMDEA-ELM.

ABSTRAK

Pemantauan dan diagnosis dalam penyelenggaraan mesin sering dijalankan dengan menggunakan analisis getaran. Isyarat getaran mesin sentiasa kompleks dan pelbagai, dan oleh itu, maklumat dan ciri berguna sukar diperoleh. *Variational Mode Decomposition* (VMD) adalah kaedah pemprosesan isyarat terkini yang dapat mengekstrak beberapa ciri penting dari isyarat getaran mesin. Prestasi kaedah VMD bergantung pada pemilihan parameter awalnya, terutamanya nombor mod dan parameter pengimbangan (dikenali sebagai istilah penalti kuadrat). Walau bagaimanapun, kaedah VMD semasa masih menggunakan usaha manual untuk mengekstrak parameter awal yang mana ia tertakluk kepada tafsiran pakar yang berpengalaman. Oleh itu, diagnosis mesin memerlukan masa yang lama dan terdedah kepada kesilapan. Tujuan penyelidikan ini adalah untuk mencadangkan kaedah pemilihan parameter automatik untuk memilih parameter awal VMD. Kaedah yang dicadangkan terdiri daripada dua peringkat yang mana pemilihan tahap pertama untuk memilih nombor mod awal dan pemilihan tahap kedua untuk memilih nombor mod dan parameter pengimbangan yang optimum. Satu pendekatan diagnosis mesin baru telah dibangunkan, dinamakan VMD *Differential Evolution Algorithm* (VMDEA)-*Extreme Learning Machine* (ELM). Set data isyarat getaran kemudiannya dibina semula menggunakan VMDEA dan ciri-ciri pelbagai domain yang terdiri daripada domain masa, domain frekuensi dan *multi-fuzzy entropy* domain telah diekstrak. Didapati bahawa kaedah VMDEA dapat mengurangkan masa pengiraan sekitar 14% hingga 53% berbanding dengan VMD-*Genetic Algorithm* (GA), VMD-*Particle Swarm Optimization* (PSO) dan VMD-*Differential Evolution* (DE) untuk galas, aci dan gear. Ia juga mempamerkan konvergensi yang lebih baik kira-kira dua hingga sembilan kali kurang lelaran berbanding dengan VMD-GA, VMD-PSO dan VMD-DE untuk galas, aci dan gear. VMDEA-ELM dapat menunjukkan ketepatan klasifikasi yang lebih tinggi sekitar 11% hingga 20% berbanding *Empirical Mode Decomposition* (EMD)-ELM, *Ensemble* EMD (EEMD)-ELM dan *Complimentary* EEMD (CEEMD)-ELM untuk galas, aci dan gear. Dataset galas dari Case Western Reserve University telah diuji dengan model VMDEA-ELM dan dibandingkan dengan model *Support Vector Machine* (SVM)-*Dempster Shafer* (DS), EEMD *Optimal Mode Multi-scale Fuzzy Entropy Fault Diagnosis* (EOMSMFD), *Wavelet Packet Transform* (WPT)-*Local Characteristic-scale Decomposition* (LCD)-ELM, and *Arctangent S-shaped PSO least square support vector machine* (ATSWPLM) dari segi ketepatan klasifikasinya. Model VMDEA-ELM menunjukkan ketepatan diagnosis yang lebih baik dengan perbezaan kecil antara 2% hingga 4% berbanding dengan EOMSMFD dan WPT-LCD-ELM tetapi ketepatan diagnosis berkurang dalam julat 4% hingga 5% berbanding dengan SVM-DS dan ATSWPLM. Pendekatan diagnosis VMDEA-ELM juga dapat memberikan prestasi klasifikasi sekitar 6 - 40 kali lebih cepat berbanding dengan *Back Propagation Neural Network* (BPNN) dan *Support Vector Machine* (SVM). Kajian ini memberikan penyelesaian yang lebih baik dalam menentukan parameter VMD yang optima dengan menggunakan VMDEA. Ia juga menunjukkan pendekatan diagnostik yang lebih tepat dan berkesan untuk penyelenggaraan mesin menggunakan VMDEA-ELM.

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LIST OF ABBREVIATIONS

ABC	-	Artificial Bee Colony
ACO	-	Ant Colony Optimization
ADMM	-	Alternate Direction Method of Multipliers
AFSA	-	Artificial Fish Swarm Algorithm
AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
AOF	-	All Objective Function
AWT	-	Analytic Wavelet Transform
BLCD	-	B-spline Local Characteristic-scale Decomposition
BPFI	-	Ball Pass Frequency Inner
BPFO	-	Ball Pass Frequency Outer
BPNN	-	Back Propagation Neural Network
BS-EMD	-	B-Spline Empirical Mode Decomposition
BSF	-	Ball Spin Frequency
CEEMD	-	Complementary Ensemble Empirical Mode Decomposition
CMFD	-	Condition Monitoring and Fault Diagnosis
CR	-	Crossover Rate
CSA	-	Cuckoo Search Algorithm
DEA	-	Differential Evolution Algorithm
DWT	-	Discrete Wavelet Transform
EEMD	-	Ensemble Empirical Mode Decomposition
ELCD	-	Ensemble Local Characteristic-scale Decomposition
ELM	-	Extreme Machine Learning
EMD	-	Empirical Mode Decomposition
EWT	-	Empirical Wavelet Transform
FDA	-	Frequency Domain Averaging
FFT	-	Fast Fourier Transform
GA	-	Genetic Algorithm
GMF	-	Gear Mesh Frequency
GOA	-	Grasshopper Optimization Algorithm

GSO	-	Glowworm Swarm Optimization
HASA	-	Hybrid Artificial Sheep Algorithm
HSD	-	Hilbert Square Demodulation
IAGA	-	Improved Adaptive Genetic Algorithm
ICD	-	Intrinsic Characteristic-scale Decomposition
IFSR	-	Interest Frequency Spectrum Range
IMF	-	Intrinsic Mode Functions
ISC	-	Intrinsic Scale Components
ITD	-	Intrinsic Time-scale Decomposition
IVMD	-	Improved Variational Mode Decomposition
LCD	-	Local Characteristic-scale Decomposition
LMD	-	Local Mode Decomposition
LOWESS	-	Locally Weighted Scatterplot Smoothing Method
MAE	-	Mean Absolute Error
MESEV	-	Minimum Envelope Spectrum Entropy Value
MEVAR	-	Mean Variance Ratio
MFE	-	Multi-scale Fuzzy Entropy
MFS-RDS	-	Machinery Fault and Rotor Dynamics Simulator
MI	-	Mutual Information
OF	-	Objective Function
OS	-	Original Signal
OSF	-	Order Statistical Filters
OVMD	-	Optimal Variational Mode Decomposition
PEEMD	-	Partly Ensemble Empirical Mode Decomposition
PELCD	-	Partly Ensemble Local Characteristic-scale Decomposition
PF	-	Product Functions
PRC	-	Proper Rotating Components
PSO	-	Particle Swarm Optimization
SC	-	Signal Similarity Characteristic
SDA	-	Signal Difference Average
SF-EMD	-	Succinct and Fast Empirical Mode Decomposition
SI	-	Statistical Index
SLFN	-	Single-hidden Layer Feedforward Neural Network

SNR	-	Signal-to-Noise Ratio
SPR	-	Statistical Parameter Ratio
SST	-	Synchro-squeezing Transform
STFT	-	Short-time Fourier Transform
SVD	-	Singular Value Decomposition
SVM	-	Support Vector Machine
TFE	-	Time Frequency Energy
UWT	-	Undecimated Wavelet Transform
VMD	-	Variational Mode Decomposition
VMF	-	Variational Mode Functions
WOA	-	Whale Optimization Algorithm
WPT	-	Wavelet Packet Transform
WT	-	Wavelet Transform
WVD	-	Wigner-Ville Distribution

LIST OF SYMBOLS

α	-	Balancing Penalty Term
τ, λ	-	Dual Ascent
k	-	Number of Mode
DC	-	First Mode
ω	-	Initial Frequency
ε	-	Convergence Tolerance
E	-	Energy
H	-	Entropy
x	-	Signal Data
s	-	Frequency Spectrum Data
u	-	Sub-signals / population position
v	-	Population position
β	-	Output weight
r	-	Ratio

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CHAPTER 1

INTRODUCTION

1.1 Overview and Research Background

Condition monitoring and fault diagnosis (CMFD) are widely used in maintaining engineering facilities and assets. CMFD helps to improve machine reliability and avoid catastrophic failures. Advancement of technology has led to an automated or autonomous diagnosis approach, also known as intelligent diagnosis integrating artificial intelligence (AI) in CMFD. The intelligent diagnosis approach mainly consists of vibration-based analysis (1), oil-based analysis (2), acoustic emission-based analysis (3,4), temperature-based analysis (5), ultrasonic-based analysis (6), etc. Among these analyses, vibration-based analysis is the most popular and commonly used in most intelligent diagnosis analysis. This is due to its simplicity, being more sensitive, with low implementation cost and able to provide the most intrinsic information of the equipment or machine (7–9). In general, the monitoring and diagnosis identifies an abnormal condition and to access the fault type, location, and severity of the equipment or machine. In current literature, numerous intelligent diagnosis methodologies have been proposed for rotating machinery applications (10–14). The basic vibration-based intelligent diagnosis consists of five main tasks as illustrated in Figure 1.1.

Signal processing is one of the most important tasks in the intelligent diagnosis approach. Signal processing can be defined as an analysis and modifying process of a signal in order to enhance its efficiency, quality and physical meaning which involve mathematical and computational algorithms. For instance, windowing, filtering, enveloping, converting the time-domain signal to frequency-domain, frequency-domain to time-domain and decomposing a signal into its sub-signals. An efficient and accurate signal processing method enabled an optimum information to be extracted from the raw signals. Hence, it is important in order to produce a robust diagnosis model. The vibration signals of rotating machinery applications are mainly subjected to non-linearity, non-stationary, and multi-frequency characteristic which required good signal processing methods in order to enhance its physical meaning and quality (15,16).

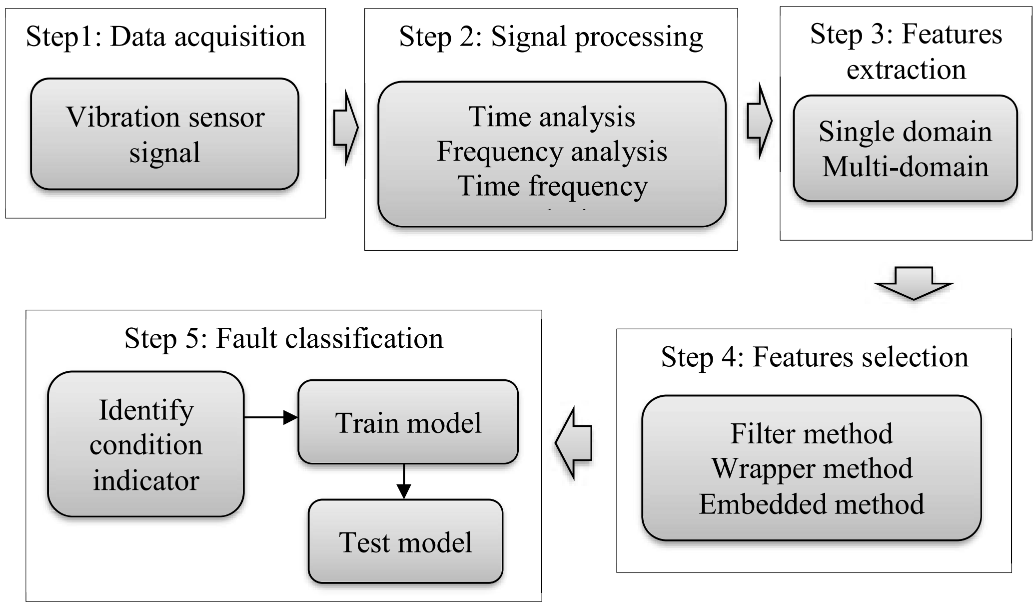

Figure 1.1 Basic intelligent diagnosis methodology

The capability and superiority of signal processing are crucial in order to extract the most important information from the raw vibration signal. There are numerous signal processing methods that have been developed such as Fast Fourier Transform (FFT), Short-time Fourier Transform (STFT), Wigner-Ville distribution (WVD), wavelet analysis, etc. Recent research showed that most researchers have moved to a more complex signal characteristic approach in their studies which renders the extraction of useful information from the raw vibration signals becoming more challenging. These signals require more advanced signal processing methods such as empirical mode decomposition (EMD), local mean decomposition (LMD), intrinsic time-scale decomposition (ITD), variational mode decomposition (VMD), etc.

Variational mode decomposition (VMD) is a recent signal processing method developed in 2014 which decomposed raw vibration signals into sets of sub-signals called variational mode functions (VMFs). The VMD method has been used in many areas of studies such as machine diagnosis (17,18), speech recognition (19), image processing (20), air quality indexing (21), oil price forecasting (22), pipeline monitoring (23), and financial and economic forecasting (24). This method has the ability to provide more accurate and superior diagnosis results, especially in fault visualization. It also has been used in some rotating machinery diagnosis studies. Figure 1.2 shows the recent publication number of the VMD method for rotating machinery studies based on three different literature database. The VMD method has the capability to solve the mode mixing problem in many signal processing method. It also provide an excellent result in filtering the noise from the input signals. The performance of the VMD method is totally depends on the accuracy of its input parameters value. Developing a robust selection method to select accurate input parameters value for the VMD method is therefore important.

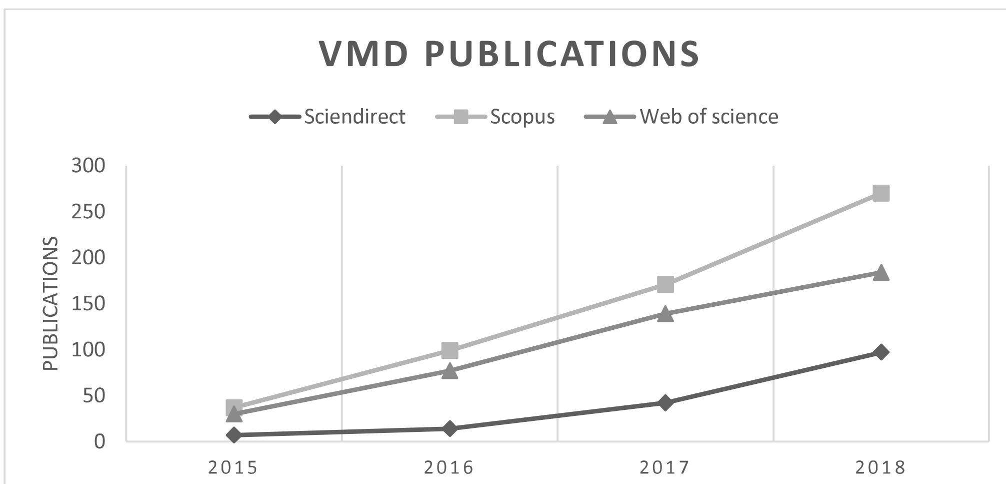

Figure 1.2 VMD publications per year from a different database

This research study was intended to develop an automated and robust method for selecting the optimized input parameters for the VMD method using a meta-heuristic algorithm known as differential evolution algorithm (DEA). An effective minimization fitness function also need to be developed in this study to enhance DEA optimization result and applicable to be used for all rotating machinery vibration signals. A new machine learning algorithm called as extreme learning machine (ELM) was used for fault classification in this research based on multi-scale domain features consists of time-domain statistical features, frequency-domain statistical features, and multi-scale fuzzy entropy features.

1.2 Problem Statement

Numerous signal processing methods have been used for rotating machinery diagnosis to provide more efficient and effective intelligent diagnosis. In recent years, a signal processing method by decomposition has been widely used in fault diagnosis due to its capabilities to deal with complex, non-stationary and non-linear signals. EMD is one of the most popular decomposition methods that has been used in many rotating machinery diagnoses. The EMD method however has an inherent mode mixing problem and it is sensitive to noise (25). This therefore led to the improvised versions of EMD being proposed to solve the EMD problem. The VMD method is one of the methods which can address this major problem in the signal processing method by decomposition (17,25).

The VMD method has merits over other signal processing methods due to its capability to provide more accurate and efficient decomposition results (25). It is also capable to decompose a non-stationary, non-linear and multi-component signals into sets of VMFs which make this method is suitable to deal with the complex raw vibration signals (25). The major issues of the VMD method requiring attention relates to the selection method of its input parameters in particular the number of mode, k and the balancing parameter, α. The accuracy of selecting these parameters for the VMD method is important in order to have a good decomposition result and also to provide a better physical meaning of a signal. Inaccurate sets of these input parameters may lead to an under-decomposed problem, over-decomposed problem and signal information losses. Developing a technique to select the optimized input parameters value for the VMD method is therefore an important research direction which has been considered as an open research problem by researchers (17,25). The technique is basically a selection technique to select an optimized the input parameters value for the VMD method which are k and α. This selection technique would provide an accurate number of sub-signals from the VMD method.

There are currently three different approaches to solve this problem, i.e. frequency spectrum approach, iteration approach, and optimization approach. The automatic selection method for the VMD input parameters using meta-heuristic or optimization algorithm is one of the most recent approaches proposed and considered as the best solution to the problem. This is due to its capability to do a selection for k and α simultaneously and automatically. There are however two limitations rise when using this optimization approach which is a long computational time and the suitability of fitness function. The implementation of a meta-heuristic algorithm will increase the computational time due to its process to find the global optimum solution that requires the VMD method to be decomposed repeatedly. Generally, the VMD decomposition would only run for 15 to 20 times in iterative approach whereas the VMD decomposition would run for more than 20 times and up to hundreds times which is based on the generation number of meta-heuristic algorithms in optimization approach (26). The suitability of fitness function would also become a problem as some fitness functions may work for some signals and it may not work for other signals (27). For example, a fitness function used in optimizing VMD input parameters for bearing vibration signals would not work for gear vibration signals or vice versa (27). This study therefore aims to address these issues and proposed a robust parameter selection method for the VMD method.

1.3 Research objectives

In this research, the main purpose was to formulate an intelligent diagnostic models based on VMD, DEA, and ELM using vibration signals. To achieve this target, the objectives of this research were:

1. To establish an automated selection method for selecting the optimized input parameters value for the VMD method.
2. To formulate an effective fitness function for the meta-heuristic algorithm for selecting the optimized VMD input parameters value for rotating machinery vibration signals.
3. To establish an intelligent diagnosis approach for rotating machinery diagnosis based on VMD, DEA, and ELM.

1.4 Significance of the study

The research contribution of this work was in the field of vibration signal processing and rotating machinery diagnosis as follows:

1. Provide an improvement of the recent signal processing method which was the VMD method that would enhance its performance and capability to be used for rotating machinery signals in the diagnostic approach.

2. Provide an effective fitness function to be used in the meta-heuristic algorithm for optimizing the VMD input parameters.

3. The features extracted from the reconstructed signal of the proposed method was able to provide higher sensitivity and accuracy in fault classification with an improvement of about 10 % higher classification accuracy result.

4. Provide an accurate and effective intelligent diagnosis approach for rotating machinery applications based on proposed method and ELM.

1.5 Scope of the study

This research study covered the intelligent diagnosis steps in data acquisition, signal processing, feature extraction, and fault classification, excluding the feature selection procedure, based on vibration signals. The signal processing methods used was VMD. EMD, EEMD, and CEEMD that compared the sensitivity of the feature in this study. Multi-domain features consist of time-domain features, frequency-domain features, and multi-scale fuzzy entropy features were used. The machine learning used here was the extreme learning machine (ELM). The backpropagation neural network (BPNN) and support vector machine (SVM) were used for comparison. For experimental work, a test rig with bearing and shaft applications were used. Bearing consisted of healthy, inner race with 1.5mm defect, outer race with 1.5mm defect and ball with 1.5mm defect were used. Shaft with healthy, slit crack fault and v-notch fault were used. Datasets for gearbox consists of healthy and faulty data from the online database were also used for gearbox application in this study. A constant operation speed was used in all experiments. All experiments were conducted under controlled room condition. Signal samples were extracted from each shaft, bearing and gearbox datasets. VMDEA was applied to all signal samples to select optimized parameter for VMD decomposition and VMDEA-ELM applied for fault classification for each application.

1.6 Thesis structure

Chapter 1 presents the background of the study, objectives and significance of the research. Chapter 2 presents a literature review on the conventional and current signal processing methods, advantages and limitations of the VMD method, current solution to the VMD limitation, research progress on rotating machinery CMFD and research gap. Chapter 3 presents theoretical background for the VMD, DEA and ELM, construction of the objective function, proposed VMDEA method, proposed VMDEA-ELM method and the experimental setup. Chapter 4 presents the VMDEA performance and its comparison with other methods. Chapter 5 presents the diagnosis performance of the VMDEA-ELM and its comparison with other methods. Finally, the research conclusion and the recommendations for future research work are summarized in Chapter 6.

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LIST OF PUBLICATIONS

Journal with Impact Factor

1. **M. Firdaus Isham**, M. Salman Leong, M. H. Lim, & Z. A. B. Ahmad (2019). Intelligent wind turbine gearbox diagnosis using VMDEA and ELM. *Wind Energy*, 22(6), 813-833. https://doi.org/10.1002/we.2323. **(Q1, IF: 2.938)**

Indexed Journal

1. **M. Firdaus Isham**, M. Salman Leong, M. H. Lim, & Z. A. B. Ahmad (2017). Empirical mode decomposition: A review on mode selection method for rotating machinery diagnosis. *International Journal of Mechanical Engineering and Technology*, 8(6), 16-26. **(Indexed by SCOPUS)**

2. **M. Firdaus Isham**, M. Salman Leong, M. H. Lim, & Z. A. B. Ahmad (2018). Variational mode decomposition for rotating machinery condition monitoring using vibration signals. *Transactions of Nanjing University of Aeronautics & Astronautics*, 35(1), 38-50. https://doi.org/10.16356/j.1005-1120.2018.01.038. **(Indexed by SCOPUS)**

3. **M. Firdaus Isham**, M. Salman Leong, M. H. Lim, & Z. A. B. Ahmad (2018). Variational mode decomposition: mode determination method for rotating machinery diagnosis. *Journal of Vibroengineering*, 20(7), 2604-2621. https://doi.org/10.21595/jve.2018.19479. **(Indexed by SCOPUS)**

4. **M. Firdaus Isham**, M. Salman Leong, M. H. Lim, & Z. A. B. Ahmad (2019). Iterative variational mode decomposition and extreme learning machine for gearbox diagnosis based on vibration signals. *Journal of Mechanical Engineering and Sciences*, 13(1), 4477-4492. https://doi.org/10.15282/jmes.13.1.2019.10.0380. **(Indexed by SCOPUS)**

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1. **M. Firdaus Isham**, M. Salman Leong, M. H. Lim, & Z. A. B. Ahmad (2019). Optimized ELM based on Whale Optimization Algorithm for gearbox diagnosis. *MATEC Web of Conferences*, 255, 02003. https://doi.org/10.1051/matecconf/201925502003. **(Indexed by SCOPUS)**

2. **M. Firdaus Isham**, M. Salman Leong, M. H. Lim, & M. K. Zakaria (2019). A Review on Variational Mode Decomposition for Rotating Machinery Diagnosis. *MATEC Web of Conferences*, 255, 02017. https://doi.org/10.1051/matecconf/201925502017. **(Indexed by SCOPUS)**