PREDICTION, CLASSIFICATION AND DIAGNOSIS OF SPUR GEAR CONDITIONS USING ARTIFICIAL NEURAL NETWORK AND ACOUSTIC EMISSION

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DEDICATION

To My mother and father soul,
My wife who has always encouraged me throughout my journey of education and
My children who have given me hope when I feel weak.

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ABSTRACT

The gear system is a critical component in the machinery and predicting the performance of a gear system is an important function. Unpredictable failures of a gear system can cause serious threats to human life, and have large scale economic effects. It is necessary to inspect gear teeth periodically to identify crack propagation and, other damages at the earliest. This study has two main objectives. Firstly, the research predicted and classified specific film thickness (λ) of spur gear by Artificial Neural Network (ANN) and Regression models. Parameters such as acoustic emission (AE), temperature and specific film thickness (λ) data were extracted from works of other researchers. The acoustic emission signals and temperature were used as input to ANN and Regression models, while (λ) was the output of the models. Second objective is to use the third generation ANN (Spiking Neural Network) for fault diagnosis and classification of spur gear based on AE signal. For this purpose, a test rig was built with several gear faults. The AE signal was processed through pre-processing, features extraction and selection methods before the developed ANN diagnosis and classification model were built. These processes were meant to improve the accuracy of diagnosis system based on information or features fed into the model. This research investigated the possibility of improving accuracy of spur gear condition monitoring and fault diagnoses by using Feed-Forward Back-Propagation Neural Networks (FFBP), Elman Network (EN), Regression Model and Spiking Neural Network (SNN). The findings showed that use of specific film thickness has resulted in the FFBP network being able to provide 99.9% classification accuracy, while regression and multiple regression models attained 73.3 % and 81.2% classification accuracy respectively. For gear fault diagnosis, the SNN achieved nearly 97% accuracy in its diagnosis. Finally, the methods use in the study have proven to have high accuracy and can be used as tools for prediction, classification and fault diagnosis in spur gear.

ABSTRAK

Sistem gear ialah komponen penting dalam sesebuah jentera manakala meramal prestasi sistem gear merupakan fungsi utama. Kegagalan sistem gear yang tidak diduga boleh menyebabkan ancaman berat kepada kehidupan manusia dan membawa kesan ekonomi skala besar. Adalah perlu untuk memeriksa gigi gear secara berkala bagi mengenal pasti perambatan retak dan kegagalan lain pada peringkat awal. Kajian ini mempunyai dua objektif utama. Pertama sekali kajian ini meramal dan mengelaskan ketebalan saput tertentu (λ) gear taji dengan Rangkaian Neural Buatan (ANN) dan Model Regresi. Parameter seperti pengeluaran akustik (AE), suhu dan data ketebalan saput tertentu (λ) disaring daripada hasil kajian penyelidik lain. lsyarat pengeluaran akustik dan suhu digunakan sebagai input bagi ANN dan model Regresi manakala (λ) merupakan output model tersebut. Objektif kedua adalah untuk menggunakan generasi ketiga ANN (Rangkaian Neural Berpaku) bagi mendiagnosis kegagalan dan pengelasan gear taji berdasarkan isyarat AE. Rig ujian dibina dengan beberapa kegagalan gear bagi tujuan ini. lsyarat AE diproses melalui pra-pemprosesan, penyarian sifat dan pemilihan kaedah sebelum diagnosis ANN dan pengelasan model dibangunkan. Proses-proses tersebut bertujuan untuk meningkatkan ketepatan sistem diagnosis berdasarkan maklumat atau sifat yang dibekalkan ke dalam model. Kajian ini mengkaji kemungkinan untuk meningkatkan ketepatan pemantauan keadaan gear taji dan diagnosis kegagalan dengan menggunakan Suapan-Depan ke Belakang- Rangkaian Neural Perambatan (FFBP), Rangkaian Elman (EN), Model Regresi dan Rangkaian Neural Berpaku (SNN). Dapatan kajian ini menunjukkan bahwa penggunaan ketebalan saput tertentu menghasilkan rangkaian FFBP yang mampu memberikan ketepatan pengelasan sebanyak 99.9% manakala ketepatan pengelasan bagi model regresi dan regresi berganda masing-masing hanya mencapai 73.3% dan 81.2%. Bagi diagnosis kegagalan gear pula SNN mencapai ketepatan hampir 97% dalam diagnosisnya. Akhir sekali kaedah yang digunakan dalam kajian ini membuktikan bahawa terdapat ketepatan yang tinggi dan dapat digunakan sebagai alat ramalan, pengelasan dan diagnosis kegagalan gear taji.

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LIST OF ABBREVIATIONS

AE	-	Acoustic Emission
CM	-	Condition Monitoring
RMS	-	Root Mean Square AE signal
ANN	-	Artificial Neural Network
GUI	-	Graphical User Interface
SLT	-	Slantlet Transform
SNN	-	Spiking Neural Network
BL	-	Boundary Lubrication
EHL	-	Elastohydrodynamic Lubrication
HL	-	Hydrodynamic Lubrication
AI	-	Artificial Intelligence
TEMP	-	Temperature
ANOVA	-	Analysis of Variance
MSE	-	Mean Squared Error
MAE	-	Mean Absolute Error
MAPE	-	Mean Absolute Percentage Error
S	-	Speed
L	-	Load
WD	-	Wideband
ADC	-	Analogue-to-Digital Converter.
FFBP	-	Feed-Forward Back-Propagation Neural Networks
EN	-	Elman Network
LM	-	Levenberg and Marquardt
Tr	-	Training
Ts	-	Testing
IG	-	Information Gain
DAQ	-	Data Acquisition

LIST OF SYMBOLS

λ	-	Specific Film Thickness
η	-	Dynamic Viscosity of the Lubricating oil
μ	-	Coefficient of Friction
v	-	Rotational Velocity
R	-	Surface Roughness
h	-	Film Viscosity
σ_{rms}	-	Composite Surface Roughness
η_o	-	Dynamic Viscosity
μ	-	Entraining Velocity
R	-	Equivalent Radius
w	-	Load Applied Along the Line of Contact
α	-	Pressure Viscosity Coefficient
E	-	Modulus of Elasticity
α	-	Constant
β	-	Coefficient of RMS and Temp
μ	-	Stochastic Error

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CHAPTER 1

INTRODUCTION

The gearboxes are very important part of any rotating machine. It is a type of transmission mechanism which provides the torque and the speed conversions from the rotating power source (e.g., electric motor) to the devices with respect to their gear ratio. A lot of research has been conducted on the field performance of the gearbox, which is characterized by its availability, reliability, and its maintainability, due to the numerous challenged faced by the industry regarding the design of the gearbox and its operation and maintenance [1].

In the current commercial production industries, there is an increasing trend towards the need for a higher availability equipment that can work nonstop which means 24/7. Thus, any type of failure, even minor, cannot be accepted as it can greatly affect the cost and the production. Hence, a very accurate monitoring of the machine condition and a proper fault diagnosis of the machine failure is necessary. The machine fault diagnosis has seen a vast improvement since the time when the maintenance was provided only after the machine had developed a fault and affected the production. Thereafter it developed into preventive maintenance in the past few years before all the industries started using the condition-based maintenance, and still used. Preventive maintenance can be defined as providing maintenance before the machinery faces any faults. On the other hand, condition-based maintenance can be defined as providing maintenance depending on the data obtained from target measurements. The efficacy of this technique is measured depending on the accurate diagnostic tactics which are fulfilled.

For surviving in the current competitive market, the industries need to improve their product reliability and also reduce their production costs. The product reliability is more important for certain industries like the aviation, nuclear and the petrochemical industries where any failure can lead to very serious environmental disasters. For instance, the typical lifespan of a wind turbine is approximately 23 years [2], however, there is a lot of commercial pressure to increase the lifespan and the productivity of the machine which can greatly require a better monitoring of its gearbox. Currently, industries have shifted from using the condition-based (predictive) approach to the maintenance-based approach depending on the trending and the data analysis from one or more parameters that indicate the development or the presence of known failures or faults. This can be managed by gathering information regarding the process parameters (pressure, temperature, power consumption, flow rate, etc.), along with other indicators like the Acoustic emission (AE), Noise, Vibration, and Current signature [3].

The effective machine condition monitoring technique must be able to determine the onset of any fault in its early stages and also provide an accurate diagnosis regarding the type of the fault and its location. Ideally, the condition monitoring technique must give an overall and a detailed accurate health assessment of the equipment. This technique usually applies advanced technology, however conventionally, it would include the aural and the visual inspection (applying all the human senses), temperature monitoring, oil analysis (known as the wear debris analysis), airborne sounds and the AE analysis, measurement of the vibrations and its analysis, and the motor current signature analysis. This also included the non-destructive testing.

The oil analysis can be very effective for using with many types of machinery like the bearings and the gear boxes of the wind turbines. A measurement of the amounts of the ferrous and the non-ferrous particles present in the lubricant provides useful information regarding the equipment condition. Also, trending helps in predicting the faults before the machine fails completely [4]. Using a correct type of lubricant helps in the smooth-running and a longer lifespan of the gear boxes. A gear box is a very vital component of the wind turbine and it is noted that using a proper lubricant helps in saving costs to the tune of $5,000 annually for every turbine that is used. In one report, the author observed that experts who were working on different plants noted that an average of around 23 % of the gear box failures could be accredited to either a lack of any lubricant or using a wrong type of lubricant [2].

Furthermore, Ribrant and Bertling surveyed the failures in the wind power plants in Sweden for 8 years ranging between1997-2004. They collected a huge amount of data which indicated that the gear boxes caused several of the breakdowns of the wind turbines. Generally, 20% of the wind turbine downtime was because of the gearbox failure, and the gearbox repairs tool on an average around 256 h [5]. All the different surveys published in the public domain have stated that a gearbox consists of the highest downtime for every failure for the onshore wind turbine sub-assemblies [6]. Furthermore, state that the gearbox faults are responsible for around 30% of the lost available onshore wind turbines.

Since the past few years, use of AE has been increased for the monitoring of the gearbox condition. It has been seen to be very effective in the detection and the diagnosis of the fault formation at the rolling contact. This technique has a very high-frequency content, which is higher than the background signals it is insensitive to background noise and is also very sensitive to any change in the machine conditions [7]. The condition indicators provide a very accurate data with respect to the different components at various damage levels (i.e., either initial, heavy or growing) [8].

Many researchers are still exploring the various techniques and their strengths, several of the researchers and scientists are not satisfied with only diagnosing the problem but also provide a prognosis regarding the remaining life span of the machine [9-10]. All these techniques help in creating new dimensions for the diagnosis of the machine faults for improving the reliability of the rotary machines. For detecting the failure of these machines, the technique of vibration monitoring is generally used [11-13]. It is seen that the acoustic emission level magnitude increases proportionally to the degradation of the machine. The acoustic emission signal is then analyzed using the signal processing. All the features of the acoustic emission signal are extracted through the time, frequency and the time-frequency domains. Several of the parameters can be extracted by the processes like the maximum, minimum, kurtosis, Root Mean Square (RMS), variance, skewness, and the crest factor [14]. Nevertheless, it is seen that not all the features are significant for representing the machine failure and machine degradation information. Hence, it is imperative to choose only the essential features and disregard the others. This is known as the feature selection process.

1.1 Problem Statement

The gear system is a crucial component for most of machine. Unpredictable failures to the gear system often produce terrible circumstance that could be the source of large disaster in financial and human losses. The modern machines are very complex and therefore they are known to produce several vibrations along with other noises [15]. It is necessary to identify the correct signals above the background noise for detecting the faults early, also lacking knowledge of neural networks and huge number of data and weak features lead to inaccurate fault diagnosis.

The efficient, accurate condition monitoring (CM) and diagnosis of faults that are responsible for degrading the performance of gearbox are highly significant tools to guarantee good productivity and safe machine functionality. This mechanism possibly saves human and industries form catastrophic failures. Recently, there is a rising interest and need for high quality condition monitoring and speedy fault diagnosis in the gears for decreasing the downtime required for the production machines that can be due to failures. Hence, several studies have been conducted for condition monitoring and detecting the faults as soon as possible by analyzing their vibrational and acoustic emission signals.

In this thesis, AE signals used the for prognosis, condition monitoring and fault diagnosis of the spur gear only appropriate feature sets that improve the reliability and the accuracy of the condition monitoring and the fault diagnosis used. Several models were applied for prediction, monitoring and fault diagnoses purposes ranging from statistical and artificial neural network models.

1.2 Research Objective

This research program objectives is to identify the feasibility of Artificial Neural Network (ANN), Regression models and Acoustic Emission (AE) for spur gear condition monitoring and fault diagnosis. A two main objectives have been outlined for this research program which includes:

1. Creating a monitoring models for spur gear specific film thickness (λ):
   a. Predicting the specific film thickness (λ) regime.
   b. Establishing relationship between spur gear specific film thickness (λ) and temperature and AE activity during spur gear mesh.
   c. Establishing relationship between spur gear specific film thickness (λ) and AE activity during spur gear mesh.
   d. Establishing a program to identify specific film thickness (λ) regime.

2. Development of diagnosis and classification methods for spur gear faults.
   a. Development of Slantlet Transform (SLT) method for converting the AE signal from time to frequency domain.
   b. Development of effective features selection method.
      In order to offer effective features, it is required to create many features through feature extraction. Then the most significant thing is providing the useful features through features selection, for that reason a new signal pre-processing technique and feature selection methods is used.
   c. Development of diagnosis and classification methods based on new third generation ANN techniques for spur gear fault.
   d. Design user friendly Graphical User Interface for fault diagnoses and classification in spur gear.

1.3 Scope of Study

Although the proposed methods is applicable to any type of rotating machine, this work implements the proposed models on spur gear only. Within the condition monitoring and fault diagnoses framework, this work covers four main parts:

1. Monitoring lubricant regime to indicate the spur gear operating conditions.
2. Predict the future progress of the specific film thickness (λ) (prognostics) using two methods: ANN and Regression.
3. Identification of the most effective AE features.
4. Diagnose the fault developed in spur gear through an ANN diagnostics system.

1.4 Significance of Study

The significance of this research can be described as follow;

1. The methods to predict the specific film thickness (λ) regime of spur gear reliability can improve the machine safety and reliability and therefore adding value to the maintenance performs.

2. The ANN and regression methods establishing a correlation between ANN, AE technology and the lubrication regimes to monitor where the gear is running with respect to its specific film thickness (λ).

3. The suggested Slantlet transform (SLT) can improve the features extraction technique.

4. The influential features selection will improve the optimization of ANN input data. The Information Gain supported with ANN can be used to choice the very important features to diagnose and classify the spur gear failure.

5. The proposed third generation of ANN (Spiking neural network method) can improve the spur gear failure diagnosis.

6. The designed program to prognoses, diagnoses and classify spur gear failure can contribute to easy monitoring and low maintenance cost.

1.5 Thesis Outline

This thesis is constructed into 6 chapters. Chapter 1 presents general literatures review, research topic, objectives and significance of the research. Reviewing the most important literature on the spur gear condition monitoring and fault diagnoses, AI and AE. A comprehensive survey of experimental and theoretical findings pertaining to spur gear condition monitoring and fault diagnoses as a whole can be found in Chapter 2. Brief explanation of AE Technology, artificial neural network modeling, regression model, Slantlet transform (SLT), feature extraction and feature selection methods can be cited in chapter 3. The research methodology, experimental setup and experimental procedure in chapter 4. Whole the result and discussion is in chapter 5. Lastly chapter 6 the conclusion.

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