

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

YASIR HASSAN ALI

UNIVERSITI TEKNOLOGI MALAYSIA

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

YASIR HASSAN ALI

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

FEBRUARY 2017

## **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.

## ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious and the Most Merciful, and Peace be upon the Holy Prophet Mohammad S.A.W.I am grateful to my main supervisor, ***Professor Ir. Dr. Roslan bin Abdul Rahman*** for his support, guidance, criticism and honesty throughout this study. My thanks also go to my co-supervisor ***Assoc. Professor Dr. Raja Ishak bin Raja Hamzah*** for his wise advice and valuable observation. The high standards set by them have not only greatly contributed to the quality of this research but also helped me become more knowledgeable.

My gratitude is also extended to Universiti Teknologi Malaysia for providing the facilities throughout my research. The author would also like to thank the staff of Noise and Vibration lab for their assistance throughout the duration of this project.

Most of all, I am thankful to my wife and my kids whose have been a continuous source of strength and motivation for success.

## 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 ( $\lambda$ ) of spur gear by Artificial Neural Network (ANN) and Regression models. Parameters such as acoustic emission (AE), temperature and specific film thickness ( $\lambda$ ) data were extracted from works of other researchers. The acoustic emission signals and temperature were used as input to ANN and Regression models, while ( $\lambda$ ) 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 ( $\lambda$ ) gear taji dengan Rangkaian Neural Buatan (ANN) dan Model Regresi. Parameter seperti pengeluaran akustik (AE), suhu dan data ketebalan saput tertentu ( $\lambda$ ) disaring daripada hasil kajian penyelidik lain. Isyarat pengeluaran akustik dan suhu digunakan sebagai input bagi ANN dan model Regresi manakala ( $\lambda$ ) 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. Isyarat 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 bahawa 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 diagnosis. 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.

## TABLE OF CONTENTS

CHAPTER	TITLE	PAGE
	<b>DECLARATION</b>	ii
	<b>DEDICATION</b>	iii
	<b>ACKNOWLEDGEMENT</b>	iv
	<b>ABSTRACT</b>	v
	<b>ABSTRAK</b>	vi
	<b>TABLE OF CONTENTS</b>	vii
	<b>LIST OF TABLES</b>	xii
	<b>LIST OF FIGURES</b>	xiv
	<b>LIST OF ABBREVIATIONS</b>	xviii
	<b>LIST OF SYMBOLS</b>	xix
	<b>LIST OF APPENDICES</b>	xx
<b>1</b>	<b>INTRODUCTION</b>	<b>1</b>
	1.1 Problem Statement	4
	1.2 Research Objective	5
	1.3 Scope of Study	6
	1.4 Significance of Study	6
	1.5 Thesis Outline	7
<b>2</b>	<b>LITERATURE REVIEW</b>	<b>8</b>
	2.1 Introduction	8

2.2	Gear Faults Monitoring Using Acoustic Emission	8
2.3	Acoustic Emission (AE) and lubricant	11
2.4	Artificial Intelligence (AI)	12
2.4.1	Artificial Neural Networks (ANN) Based Fault Diagnosis	13
2.4.2	Genetic Algorithms (GA) Based Fault Diagnosis	17
2.4.3	Fuzzy logic (FL) Based Fault Diagnosis	18
2.4.4	Support Vector Machine (SVM)	20
2.5	Regression Model in Condition Monitoring	22
2.6	Evaluation of Literature Review	26
<b>3</b>	<b>THEORETICAL BACKGROUND</b>	<b>28</b>
3.1	Introduction	28
3.2	Acoustic Emission (AE) Sources Technology	28
3.2.1	Acoustic Emission Sensors	30
3.2.2	AE Measuring	32
3.3	Artificial Neural Network (ANN)	33
3.3.1	Architecture of networks	37
3.3.2	Multi-layer Perceptron	37
3.3.3	Dynamic networks and recurrent neural Network	38
3.3.4	Mathematical statement of recurrent neural Network	39
3.3.5	Back propagation in recurrent networks	41
3.3.6	Function approximation	42
3.3.7	Optimization by ANN	43
3.4	Features Extraction	44
3.4.1	Time domain analysis	44
3.4.2	Frequency domain analysis	45
3.4.3	Time-frequency domain analysis	45
3.5	Features Selection	45
3.6	Regression	46



<b>4</b>	<b>RESEARCH METHODOLOGY AND EXPERIMENTAL SETUP</b>	<b>48</b>
4.1	Introduction	48
4.2	Research Methodology on Oil Film Thickness Prediction and Classification	51
4.2.1	Experimental Data from Hamza	52
4.2.2	Experimental Setup and Data Acquisition System	52
4.2.3	Specific Oil Film Thickness ( $\lambda$ )	56
4.2.4	Artificial Neural Network (ANN) Models Based on Acoustic Emission (AE) and Temperature	58
4.2.4.1	Architecture of ANN model	59
4.2.4.2	Feed Forward Back Propagation Neural Networks (FFBP)	60
4.2.4.3	Elman Network (EN)	61
4.2.4.4	Training and Testing Strategies.	62
4.2.4.5	Data Preparation and Simulation	63
4.2.5	Multiple Linear Regression Model (MLRM) Based on Acoustic Emission (AE) and Temperature	64
4.2.6	Artificial Neural Network (ANN) Models Based on Acoustic Emission (AE) only	66
4.2.6.1	Feed Forward Back Propagation Neural Networks (FFBP)	66
4.2.6.2	Linear Regression Model Based on Acoustic Emission (AE) only	67
4.2.7	Statistical Error Analysis.	68
4.2.7.1	Mean Squared Error (MSE).	68
4.2.7.2	Mean Absolute Percentage Error (MAPE)	69
4.2.7.3	Mean Absolute Error (MAE)	69
4.3	Research Methodology on Gear Fault Diagnoses and Classification	70
4.3.1	Acoustic Emission (AE)	70
4.3.2	Pre-processing Stage	71

	4.3.2.1 Slantlet Transform (SLT)	71
	4.3.3 Features Extraction	73
	4.3.4 Features Selection	75
	4.3.4.1 Information Gain (IG)	75
	4.3.5 Fault Diagnosis Method	76
	4.3.5.1 Spiking Neural Network (SNN)	76
	4.3.5.2 Graphical User Interface of Spur Gear Failure (GUI).	78
4.4	Experimental Setup and Procedure	81
	4.4.1 Test Rig	81
	4.4.1.1 Gears	82
	4.4.1.2 Load Control	83
	4.4.1.3 Voltage regulator	84
	4.4.1.4 Electrical Motor	84
	4.4.1.5 Speed control	84
	4.4.2 Acoustic Emission (AE) System	84
	4.4.2.1 AE Sensors	85
	4.4.2.2 AE Data Acquisition (DAQ)	86
	4.4.2.3 AE-win software	87
	4.4.3 Experimental Procedure	87
	4.4.3.1 Hsu-Nielsen Test	88
	4.4.3.2 Noise Measurement	90
	4.4.3.3 Seeded Defect Tests	90
<b>5</b>	<b>RESULT AND DISCUSSION</b>	<b>95</b>
	5.1 Introduction	95
	5.2 Result and Discussion Based on Acoustic Emission signal and Temperature	95
	5.2.1 Neural network	95
	5.2.1.1 FFBP Result	96
	5.2.1.2 Elman Network Result	100
	5.2.1.3 Comparison between FFBP and Elman Networks	104
	5.2.2 Multiple Regression Model	107

5.2.3	Comparison between artificial neural network (ANN) and multiple regression	115
5.3	Result and Discussion Based on Acoustic Emission Signal	117
5.3.1	Artificial Neural Network (ANN)	117
5.3.2	Regression Model	125
5.3.3	Comparison between artificial neural network (ANN) and regression	132
5.4	Models Performance and Classification Accuracy in Predicating the Specific Film Thickness.	134
5.5	Fault Diagnostics and Classification Result and Discussion	135
<b>6</b>	<b>CONCLUSIONS AND RECOMMENDATIONS</b>	<b>142</b>
6.1	Introduction	142
6.2	Conclusions	142
6.3	Contributions	144
6.4	Future Work	145
	<b>REFERENCES</b>	<b>146</b>
	Appendices A - D	161-200

## LIST OF TABLES

<b>TABLE NO.</b>	<b>TITLE</b>	<b>PAGE</b>
2.1	Literature review summary	25
4.1	Speed and Load conditions Abbreviations	52
4.2	Test gears specifications	53
4.3	Lubricant properties	54
4.4	Various ANN structures were carried out to find appropriate model.	59
4.5	Multiple regression analysis model	65
4.6	Regression analysis model	67
4.7	Features extraction from time domain	74
4.8	Features extraction from frequency domain	75
4.9	Experimental test gears specifications	83
4.10	Seeded fault	91
5.1	Statistical error value in training and testing	96
5.2	FFBP performance	97
5.3	Elman network performance	101
5.4	Best validation performance for FFBP and Elman networks during training	104
5.5	Networks classification success results	106
5.6	ANOVA table	108
5.7	Multiple regression models summary	111
5.8	Multiple Regression model performance and classification success results	115
5.9	FFBP neural network and multiple regression performance	116

5.10	Networks and multiple Regression model classification success results	116
5.11	Network validation performance, number of iteration and regression performance	117
5.12	FFBP performance in training and testing	118
5.13	FFBP Network classification success results	119
5.14	ANOVA table	125
5.15	Simple regression models summary	128
5.16	Simple regression model performance and classification success results	131
5.17	FFBP neural network and simple regression performance	132
5.18	Networks and simple regression model classification success results	133
5.19	Performance of SNN error in order to select threshold value	136
5.20	SNN Performance and accuracy classification	138

## LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
2.1	Branches of Artificial Intelligence (AI)	13
2.2	Genetic algorithm cycle [36]	17
3.1	Schematic of the Acoustic Emission principle [93]	29
3.2	Example of Kaiser Effect [94]	30
3.3	Schematic diagram of a typical acoustic emission PZT sensor mounted on a test object [96]	31
3.4	Different AE signal types [22]	32
3.5	The typical AE signal features [95]	33
3.6	(a) Schematic of biological neuron. (b) Mechanism of signal transfer between two biological neurons [99]	35
3.7	Representation of McCulloch-Pitts neuron $y$ with threshold $\theta$	36
3.8	Diagram of a neuron using the sigmoid function	37
3.9	Multi-layer perceptron	38
3.10	Recurrent neural network	40
4.1	Research methodology flowchart	50
4.2	Back-to-back test gearbox arrangement [118].	53
4.3	AE sensor and thermocouple location on test pinion gear [118]	55
4.4	The Stribeck curve and specific film thickness [121]	57
4.5	ANN structure and transfer function types of FFBP	61
4.6	ANN structure and transfer function types of Elman network	62
4.7	Multiple regression model schematic [90]	66
4.8	Simple regression model schematic [90]	68
4.9	(a) Two-scale iterated filter bank DWT. (b) Equivalent form using the SLT [137].	72

4.10	Spiking neural network [140]	77
4.11	GUI of spur gear failure front window, raw data reading	79
4.12	GUI feature extraction	80
4.13	GUI feature selection by Information Gain	80
4.14	GUI fault diagnoses by SNN	81
4.15	Test rig arrangement	82
4.16	Load mechanism	83
4.17	AE sensor location on spur test pinions	85
4.18	Calibration certificate for AE sensor	86
4.19	Waveform and frequency spectrum for natural frequency of the test rig and gear- bearing assembly	88
4.20	Hsu-Nielsen source test	88
4.21	Pencil break and sensor location during Hsu-Nielsen test	89
4.22	Comparison between electrical and surrounding noise level from one of the tests	90
4.23	Partial tooth breakage.	92
4.24	Pitting fault.	92
4.25	Full missing tooth.	93
4.26	Half missing tooth	93
4.27	Crack on the root.	94
5.1	FFBP network training output and the target	97
5.2	FFBP network testing output and the target	98
5.3	Validation performance for FFBP Network (a) S1L3 (b) S2L3	99
5.4	FFBP network regression performance on its targets and outputs	100
5.5	Elman network training output and the target	101
5.6	Elman network testing output and the target	102
5.7	Validation performance for Elman Network (a) S1L1 (b) S2L1	103
5.8	Comparison between Elman and FFBP network testing Error (A)S1L1, (B)S1L2, (C)S1L3, (D)S2L1, (E)S2L2, (F)S2L3	105

5.9	Relation between specific film thickness, acoustic emission signal and oil temperature [118 ]	107
5.10	Testing of Regression – Histogram	109
5.11	Testing of Regression - P-P Plot	109
5.12	Multiple Regression model output and the target Lambda (a) S1L1, (b) S1L2, (c) S1L3, (d) S2L1, (e) S2L2, and (f) S2L3.	112
5.13	Comparison between multiple regression errors.S1L1, S1L2, and S1L3	113
5.14	Comparison between multiple regression errors.S2L1, S2L2, and S2L3	114
5.15	S1L1 FFBP network training output and the target	120
5.16	S2L3 FFBP network training output and the target	120
5.17	S1L1 FFBP network testing output and the target	121
5.18	S2L3 FFBP network testing output and the target	121
5.19	Validation performance for FFBP Network (a) S1L1Tr (b) S2L3Tr	122
5.20	Network regression performance on its targets and outputs Network (a) S1L1Tr (b) S2L3Tr	123
5.21	Comparison between network training and testing error. (a) S1L1, (b) S1L2, (c) S1L3, (d) S2L1, (e) S2L2, and (f) S2L3.	124
5.22	Testing of Regression – Histogram	126
5.23	Testing of Regression - P-P Plot	127
5.24	Regression model output and the target Lambda (a) S1L1, (b) S1L2, (c) S1L3, (d) S2L1, (e) S2L2, and (f) S2L3 .	129
5.25	Comparison between regression errors.S1L1, S1L2, and S1L3	130
5.26	Comparison between regression errors.S2L1, S2L2 and S2L3	130
5.27	Models performance	134
5.28	Models classification accuracy	135
5.29	Information Gain (IG) technique result	136
5.30	Scatter plots of extracted Features	137
5.31	SNN accuracy for S1L1condition	138



5.32	SNN performance: mean square error for S1L1condition	139
5.33	Performance of SNN training for spur gear fault diagnoses and classification for S1L1condition with (1) Healthy, (2) Partial tooth breakage, (3) Pitting fault, (4) Missing tooth, (5) Half missing tooth and (6) Root crack.	140
5.34	Performance of SNN testing for spur gear fault diagnoses and classification for S1L1condition with (1) Healthy, (2) Partial tooth breakage, (3) Pitting fault, (4) Missing tooth, (5) Half missing tooth and (6) Root crack.	140

**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

$\lambda$	-	Specific Film Thickness
$\eta$	-	Dynamic Viscosity of the Lubricating oil
$\mu$	-	Coefficient of Friction
$v$	-	Rotational Velocity
$R$	-	Surface Roughness
$h$	-	Film Viscosity
$\sigma_{rms}$	-	Composite Surface Roughness
$\eta_o$	-	Dynamic Viscosity
$\mu$	-	Entraining Velocity
$R$	-	Equivalent Radius
$w$	-	Load Applied Along the Line of Contact
$\alpha$	-	Pressure Viscosity Coefficient
$E$	-	Modulus of Elasticity
$\alpha$	-	Constant
$\beta$	-	Coefficient of RMS and Temp
$\mu$	-	Stochastic Error

**LIST OF APPENDICES**

<b>APPENDIX</b>	<b>TITLE</b>	<b>PAGE</b>
A	GEAR	161
B	SLT Properties and Equations	181
C	Oil Film Thickness Prediction and Classification by ANN	185
D	Spur Gear Fault Diagnostics and Classification by SNN	192

## **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 between 1997-2004. 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 took 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 from 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 ( $\lambda$ ):
  - a. Predicting the specific film thickness ( $\lambda$ ) regime.
  - b. Establishing relationship between spur gear specific film thickness ( $\lambda$ ) and temperature and AE activity during spur gear mesh.
  - c. Establishing relationship between spur gear specific film thickness ( $\lambda$ ) and AE activity during spur gear mesh.
  - d. Establishing a program to identify specific film thickness ( $\lambda$ ) 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 ( $\lambda$ ) (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 ( $\lambda$ ) 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 ( $\lambda$ ).
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.

## REFERENCES

1. Igba, J., et al., Performance assessment of wind turbine gearboxes using in-service data: Current approaches and future trends. *Renewable and Sustainable Energy Reviews*, 2015. 50: p. 144-159.
2. Hamel, M., A. Addali, and D. Mba, Investigation of the influence of oil film thickness on helical gear defect detection using Acoustic Emission. *Applied acoustics*, 2014. 79: p. 42-46.
3. Alrabady, L.A.Y., An online-integrated condition monitoring and prognostics framework for rotating equipment. 2014.
4. Tan, C.K., P. Irving, and D. Mba, A comparative experimental study on the diagnostic and prognostic capabilities of acoustics emission, vibration and spectrometric oil analysis for spur gears. *Mechanical Systems and Signal Processing*, 2007. 21(1): p. 208-233.
5. Ribrant, J. and L. Bertling. Survey of failures in wind power systems with focus on Swedish wind power plants during 1997-2005. in *Power Engineering Society General Meeting, 2007. IEEE. 2007. IEEE.*
6. Spinato, F., et al., Reliability of wind turbine subassemblies. *IET Renewable Power Generation*, 2009. 3(4): p. 387-401.
7. Tan, C.K. and D. Mba, Limitation of acoustic emission for identifying seeded defects in gearboxes. *Journal of Nondestructive Evaluation*, 2005. 24(1): p. 11-28.
8. Sharma, V. and A. Parey, A Review of Gear Fault Diagnosis Using Various Condition Indicators. *Procedia Engineering*, 2016. 144: p. 253-263.
9. Karacay, T. and N. Akturk, Experimental diagnostics of ball bearings using statistical and spectral methods. *Tribology International*, 2009. 42(6): p. 836-843.

10. Tian, Z., An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring. *Journal of Intelligent Manufacturing*, 2012. 23(2): p. 227-237.
11. Yang, B.-S. and A.C.C. Tan, Multi-step ahead direct prediction for the machine condition prognosis using regression trees and neuro-fuzzy systems. *Expert Systems with Applications*, 2009. 36(5): p. 9378-9387.
12. Tian, Z., D. Lin, and B. Wu, Condition based maintenance optimization considering multiple objectives. *Journal of Intelligent Manufacturing*, 2012. 23(2): p. 333-340.
13. Wu, J.-D. and C.-C. Hsu, Fault gear identification using vibration signal with discrete wavelet transform technique and fuzzy–logic inference. *Expert Systems with Applications*, 2009. 36(2): p. 3785-3794.
14. Mahamad, A.K., S. Saon, and T. Hiyama, Predicting remaining useful life of rotating machinery based artificial neural network. *Computers & Mathematics with Applications*, 2010. 60(4): p. 1078-1087.
15. Waqar, T.W., M. Demetgul, and C. Kelesoglu, Fault Diagnosis on Bevel Gearbox with Neural Networks and Feature Extraction. *Elektronika ir Elektrotechnika*, 2015. 21(5): p. 69-74.
16. Boness, R. and S. McBride, Adhesive and abrasive wear studies using acoustic emission techniques. *Wear*, 1991. 149(1): p. 41-53.
17. Tan, C.K. and D. Mba, Identification of the acoustic emission source during a comparative study on diagnosis of a spur gearbox. *Tribology International*, 2005. 38(5): p. 469-480.
18. Toutountzakis, T., C.K. Tan, and D. Mba, Application of acoustic emission to seeded gear fault detection. *NDT & E International*, 2005. 38(1): p. 27-36.
19. Dowson, D. and G.R. Higginson, *Elasto-hydrodynamic lubrication: international series on materials science and technology*. Vol. 23. 2014: Elsevier.
20. Hamzah, R.R. and D. Mba, The influence of operating condition on acoustic emission (AE) generation during meshing of helical and spur gear. *Tribology International*, 2009. 42(1): p. 3-14.
21. Mba, D. and R.B. Rao, *Development of Acoustic Emission Technology for Condition Monitoring and Diagnosis of Rotating Machines; Bearings, Pumps, Gearboxes, Engines and Rotating Structures*. 2006.

22. Holroyd, T.J., *The acoustic emission & ultrasonic monitoring handbook*. 2000: Coxmoor Publishing Company.
23. Ulus, S. and S. Erkaya, An Experimental Study on Gear Diagnosis by Using Acoustic Emission Technique. *INTERNATIONAL JOURNAL OF ACOUSTICS AND VIBRATION*, 2016. 21(1): p. 103-111.
24. Li, C., et al., Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibratory signals. *Mechanical Systems and Signal Processing*, 2016. 76: p. 283-293.
25. Li R, Seçkiner SU, He D, Bechhoefer E, Menon P. Gear fault location detection for split torque gearbox using AE sensors. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*. 2012;42(6):1308-17
26. Benabdallah, H. and D. Aguilar, Acoustic emission and its relationship with friction and wear for sliding contact. *Tribology Transactions*, 2008. 51(6): p. 738-747.
27. Zhang, J., B.W. Drinkwater, and R.S. Dwyer-Joyce, Acoustic measurement of lubricant-film thickness distribution in ball bearings. *The Journal of the Acoustical Society of America*, 2006. 119(2): p. 863-871.
28. Toutountzakis, T. and D. Mba, Observations of acoustic emission activity during gear defect diagnosis. *NDT & E International*, 2003. 36(7): p. 471-477.
29. Tan, C.K. and D. Mba, Experimentally established correlation between acoustic emission activity, load, speed, and asperity contact of spur gears under partial elastohydrodynamic lubrication. *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, 2005. 219(6): p. 401-409.
30. Hamzah, R.R. and D. Mba, Acoustic emission and specific film thickness for operating spur gears. *Journal of Tribology*, 2007. 129(4): p. 860-867.
31. Eftekharijad, B. and D. Mba, Acoustic emission signals associated with damaged helical gears. *Insight-Non-Destructive Testing and Condition Monitoring*, 2008. 50(8): p. 450-453.
32. Eftekharijad, B. and D. Mba, Seeded fault detection on helical gears with acoustic emission. *Applied Acoustics*, 2009. 70(4): p. 547-555.
33. Kok, J.N., et al., *ARTIFICIAL INTELLIGENCE: DEFINITION, TRENDS, TECHNIQUES, AND CASES*. *Artificial intelligence*, 2009: p. 1.

34. Pham, D. and P. Pham, Artificial intelligence in engineering. *International Journal of Machine Tools and Manufacture*, 1999. 39(6): p. 937-949.
35. Kouroussis, D., et al., Advances in classification of acoustic emission sources. *Les Journées COFREND*, Reims, 2001.
36. Saxena, A. and A. Saad, Genetic algorithms for artificial neural net-based condition monitoring system design for rotating mechanical systems, in *Applied Soft Computing Technologies: The Challenge of Complexity*. 2006, Springer. p. 135-149.
37. Al-Balushi, K. and B. Samanta. Gear fault diagnostics using wavelets and artificial neural network. in *COMADEM 2000: 13 th International Congress on Condition Monitoring and Diagnostic Engineering Management*. 2000.
38. Mahamad, A.K.B., *Diagnosis, Classification and Prognosis of Rotating Machine using Artificial Intelligence*. 2010, Kumamoto University.
39. Abu-Mahfouz, I., Condition monitoring of a gear box using vibration and acoustic emission based artificial neural network. *SAE transactions*, 2001. 110(6): p. 1771-1781.
40. Menon, S., et al. Wavelet-based acoustic emission detection method with adaptive thresholding. in *SPIE's 7th Annual International Symposium on Smart Structures and Materials*. 2000. International Society for Optics and Photonics.
41. Blahacek, M., M. Chlada, and Z. Prevorovský, Acoustic emission source location based on signal features. *Advanced Materials Research*, 2006. 13: p. 77-82.
42. Fog, T.L., et al., Exhaust valve leakage detection in large marine diesel engines. *Proceedings of Comadem' 98*, 1998.
43. Kouroussis, D., et al., Unsupervised Pattern recognition of acoustic emission from full scale testing of a wind turbine blade. *Journal of Acoustic Emission(USA)*, 2000. 18: p. 217.
44. Wang, J.-Z., et al. Prediction of surface roughness in cylindrical traverse grinding based on ALS algorithm. in *Machine Learning and Cybernetics*, 2005. *Proceedings of 2005 International Conference on*. 2005. IEEE.
45. Wang, Z., et al., Neural network detection of grinding burn from acoustic emission. *International Journal of Machine Tools and Manufacture*, 2001. 41(2): p. 283-309.

46. Dotto, F.R., et al., Automatic system for thermal damage detection in manufacturing process with internet monitoring. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 2006. 28(2): p. 153-160.
47. Kwak, J.-S. and M.-K. Ha, Neural network approach for diagnosis of grinding operation by acoustic emission and power signals. *Journal of Materials Processing Technology*, 2004. 147(1): p. 65-71.
48. Aguiar, P., T. França, and E. Bianchi. Roughness and roundness prediction in grinding. in *Proceedings of the 5th CIRP International Seminar on Intelligent Computation in Manufacturing Engineering (CIRP ICME 06)*. 2006.
49. Aguiar, P.R., et al., *Digital Signal Processing for Acoustic Emission*. 2012.
50. Aguiar, P., et al., Predicting surface roughness in grinding using neural networks. *Robotics. Automation and Control*, 2008. 1: p. 33-44.
51. Goebel, K. and P.K. Wright, *Monitoring and Diagnosing Manufacturing Processes Using a Hybrid Architecture with Neural Networks and Fuzzy Logic*. EUFIT, Proceedings, 1993. 2.
52. Shen, G., et al., Investigation of Artificial Neural Network Pattern Recognition of Acoustic Emission Signals for Pressure Vessels. *NDT*, 2001. 23: p. 144-146.
53. Walker, J.L., et al., Neural network/acoustic emission burst pressure prediction for impact damaged composite pressure vessels. *Materials evaluation*, 1997. 55(8): p. 903-907.
54. Macías, E.J., et al., Neural Networks and Acoustic Emission for Modelling and Characterization of the Friction Stir Welding Process. *Revista Iberoamericana de Automática e Informática Industrial RIAI*, 2013. 10(4): p. 434-440.
55. Tian, Y., et al. Application of acoustic emission techniques and artificial neural networks to partial discharge classification. in *Electrical Insulation*, 2002. Conference Record of the 2002 IEEE International Symposium on. 2002. IEEE.
56. Szyszko, S. and P. Payne. Artificial neural networks for feature extraction from acoustic emission signals. in *Measurements, Modelling and Imaging for Non-Destructive Testing*, IEE Colloquium on. 1991. IET.
57. Ming, Z.X., *Application of Acoustic Emission Technique in Fault Diagnostics of Rolling Bearing*, in *Mechanical Engineering*. 2006, Tsinghua University: Beijing, Haidian.



58. Sibil, A., et al., Optimization of acoustic emission data clustering by a genetic algorithm method. *Journal of nondestructive evaluation*, 2012. 31(2): p. 169-180.
59. Zadeh, L.A., Fuzzy sets. *Information and control*, 1965. 8(3): p. 338-353.
60. Zadeh, L.A., Outline of a new approach to the analysis of complex systems and decision processes. *Systems, Man and Cybernetics, IEEE Transactions on*, 1973(1): p. 28-44.
61. Zadeh, L.A., Fuzzy algorithms. *Information and control*, 1968. 12(2): p. 94-102.
62. Hellmann, M., Fuzzy Logic Introduction” a Laboratoire Antennes Radar Telecom. FRE CNRS. 2272.
63. Cusido, J., et al. EMA fault detection using fuzzy inference tools. in *AUTOTESTCON, 2010 IEEE*. 2010. IEEE.
64. Omkar, S., et al. Acoustic emission signal classification using fuzzy C-means clustering. in *Neural Information Processing, 2002. ICONIP'02. Proceedings of the 9th International Conference on*. 2002. IEEE.
65. de Aguiar, P.R., E.C. Bianchi, and R.C. Canarim, Monitoring of Grinding Burn by Acoustic Emission. 2012: INTECH Open Access Publisher.
66. Ren, Q., L. Baron, and M. Balazinski, Fuzzy identification of cutting acoustic emission with extended subtractive cluster analysis. *Nonlinear Dynamics*, 2012. 67(4): p. 2599-2608.
67. Ren, Q., L. Baron, and M. Balazinski. Application of type-2 fuzzy estimation on uncertainty in machining: an approach on acoustic emission during turning process. in *Fuzzy Information Processing Society, 2009. NAFIPS 2009. Annual Meeting of the North American*. 2009. IEEE.
68. Ren, Q., L. Baron, and M. Balazinski, Type-2 fuzzy modeling for acoustic emission signal in precision manufacturing. *Modelling and Simulation in Engineering*, 2011. 2011: p. 17.
69. Ren, Q., et al., Type-2 fuzzy tool condition monitoring system based on acoustic emission in micromilling. *Information Sciences*, 2014. 255: p. 121-134.
70. Ren, Q., et al. Acoustic emission signal feature analysis using type-2 fuzzy logic system. in *Fuzzy Information Processing Society (NAFIPS), 2010 Annual Meeting of the North American*. 2010. IEEE.

71. Blahacek, M., et al., Neural network localization of noisy AE events in dispersive media. *Journal of Acoustic Emission(USA)*, 2000. 18: p. 279.
72. Khalifa, S. and M.H. Komarizadeh, An intelligent approach based on adaptive neuro-fuzzy inference systems (ANFIS) for walnut sorting. *Australian Journal of Crop Science*, 2012. 6(2).
73. Vapnik, V., *Statistical learning theory* new york. NY: Wiley, 1998.
74. Burges, C.J., A tutorial on support vector machines for pattern recognition. *Data mining and knowledge discovery*, 1998. 2(2): p. 121-167.
75. Saravanan, N., V. Kumar Siddabattuni, and K. Ramachandran, A comparative study on classification of features by SVM and PSVM extracted using Morlet wavelet for fault diagnosis of spur bevel gear box. *Expert systems with applications*, 2008. 35(3): p. 1351-1366.
76. Widodo, A., et al., Fault diagnosis of low speed bearing based on acoustic emission signal and multi-class relevance vector machine. *Nondestructive Testing and Evaluation*, 2009. 24(4): p. 313-328.
77. Widodo, A., et al., Fault diagnosis of low speed bearing based on relevance vector machine and support vector machine. *Expert Systems with Applications*, 2009. 36(3): p. 7252-7261.
78. Yu, Y. and L. Zhou, Acoustic emission signal classification based on support vector machine. *TELKOMNIKA Indonesian Journal of Electrical Engineering*, 2012. 10(5): p. 1027-1032.
79. Chu-Shu, K., A machine learning approach for locating acoustic emission. *EURASIP Journal on Advances in Signal Processing*, 2010. 2010.
80. Yang, Z. and Z. Yu, Grinding wheel wear monitoring based on wavelet analysis and support vector machine. *The International Journal of Advanced Manufacturing Technology*, 2012. 62(1-4): p. 107-121.
81. Yu, Y. and L. Zhou, Acoustic emission signal classification based on support vector machine, in *Computer Engineering and Technology (ICCET), 2010 2nd International Conference*. 2010: Chengdu. p. 300-304.
82. Razi, M.A. and K. Athappilly, A comparative predictive analysis of neural networks (NNs), nonlinear regression and classification and regression tree (CART) models. *Expert Systems with Applications*, 2005. 29(1): p. 65-74.

83. Usynin, A., Model-Fitting Approaches to Reliability Assessment and Prognostic Problems. *Journal of Pattern Recognition Research*, 2006. 1(1): p. 32-36.
84. Timofeev, R., Classification and regression trees (CART) theory and applications. 2004, Humboldt University, Berlin.
85. AlThobiani, F. and A. Ball, An approach to fault diagnosis of reciprocating compressor valves using Teager–Kaiser energy operator and deep belief networks. *Expert Systems with Applications*, 2014. 41(9): p. 4113-4122.
86. Chen, J.C. and J.C. Chen, A Multiple-Regression Model for Monitoring Tool Wear with a Dynamometer in Milling Operations. *Journal of Technology Studies*, 2004. 30(4): p. 71-77.
87. Henneberg, M., B. Jørgensen, and R.L. Eriksen, Oil condition monitoring of gears onboard ships using a regression approach for multivariate T<sup>2</sup> control charts. *Journal of Process Control*, 2016. 46: p. 1-10.
88. Phillips, J., et al., Classifying machinery condition using oil samples and binary logistic regression. *Mechanical Systems and Signal Processing*, 2015. 60: p. 316-325.
89. Li, H., et al., Cutting tool operational reliability prediction based on acoustic emission and logistic regression model. *Journal of Intelligent Manufacturing*, 2015. 26(5): p. 923-931.
90. Schlechtingen, M. and I.F. Santos, Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection. *Mechanical systems and signal processing*, 2011. 25(5): p. 1849-1875.
91. Abdusamad, K.B., D.W. Gao, and E. Muljadi. A condition monitoring system for wind turbine generator temperature by applying multiple linear regression model. in *North American Power Symposium (NAPS)*, 2013. 2013. IEEE.
92. Miller, R.K. and P. McIntire, *Nondestructive Testing Handbook. Vol. 5: Acoustic Emission Testing*. American Society for Nondestructive Testing, 4153 Arlingate Plaza, Caller# 28518, Columbus, Ohio 43228, USA, 1987. 603, 1987.
93. Hamel, M.A., *Condition Monitoring of Helical Gears Using Acoustic Emission (AE) Technology*. 2013.
94. NDT, E.R.C., *Theory - AE Sources*. 2016.

95. Co., P.A., PAC PCI-DSP 4 Multi-channel Acoustic Emission System. 2009.
96. Svečko, R., et al., Acoustic emission detection of macro-cracks on engraving tool steel inserts during the injection molding cycle using PZT sensors. *Sensors*, 2013. 13(5): p. 6365-6379.
97. Hecht-Nielsen, R., *Neurocomputing*. 1990. Reading: Addison-Wesley Google Scholar.
98. Schalkoff, R.J., *Artificial neural networks*. 1997: McGraw-Hill Higher Education.
99. Basheer, I. and M. Hajmeer, *Artificial neural networks: fundamentals, computing, design, and application*. *Journal of microbiological methods*, 2000. 43(1): p. 3-31.
100. McCulloch, W.S. and W. Pitts, A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, 1943. 5(4): p. 115-133.
101. Haykin, S.S., *Blind deconvolution*. 1994: Prentice Hall.
102. Rumelhart, D.E., et al., *Sequential thought processes in PDP models*. V, 1986. 2: p. 3-57.
103. Pham, X.H. and R. Betts, Congestion control for intelligent networks. *Computer Networks and ISDN Systems*, 1994. 26(5): p. 511-524.
104. Hassoun, M.H., *Fundamentals of artificial neural networks*. 1995: MIT press.
105. Jain, A.K., J. Mao, and K.M. Mohiuddin, *Artificial neural networks: A tutorial*. *IEEE computer*, 1996. 29(3): p. 31-44.
106. Mahamad, A.K. and T. Hiyama. Development of artificial neural network based fault diagnosis of induction motor dearing. in *Power and Energy Conference, 2008. PECon 2008. IEEE 2nd International*. 2008. IEEE.
107. Lei, Y., Z. He, and Y. Zi, A new approach to intelligent fault diagnosis of rotating machinery. *Expert Systems with Applications*, 2008. 35(4): p. 1593-1600.
108. Xu, Z., et al., A novel fault diagnosis method of bearing based on improved fuzzy ARTMAP and modified distance discriminant technique. *Expert Systems with Applications*, 2009. 36(9): p. 11801-11807.
109. Xu, Z., et al., Application of a modified fuzzy ARTMAP with feature-weight learning for the fault diagnosis of bearing. *Expert Systems with Applications*, 2009. 36(6): p. 9961-9968.

110. Lei, Y., et al., Fault diagnosis of rotating machinery based on multiple ANFIS combination with GAs. *Mechanical Systems and Signal Processing*, 2007. 21(5): p. 2280-2294.
111. Matsuura, T., An application of neural network for selecting feature parameters in machinery diagnosis. *Journal of materials processing technology*, 2004. 157: p. 203-207.
112. Saravanan, N., V.K. Siddabattuni, and K. Ramachandran, Fault diagnosis of spur bevel gear box using artificial neural network (ANN), and proximal support vector machine (PSVM). *Applied Soft Computing*, 2010. 10(1): p. 344-360.
113. Saravanan, N. and K. Ramachandran, Incipient gear box fault diagnosis using discrete wavelet transform (DWT) for feature extraction and classification using artificial neural network (ANN). *Expert Systems with Applications*, 2010. 37(6): p. 4168-4181.
114. Sakthivel, N., V. Sugumaran, and S. Babudevasenapati, Vibration based fault diagnosis of monoblock centrifugal pump using decision tree. *Expert Systems with Applications*, 2010. 37(6): p. 4040-4049.
115. Duhaney, J., T.M. Khoshgoftaar, and R. Wald. Applying feature selection to short time wavelet transformed vibration data for reliability analysis of an ocean turbine. in *Machine Learning and Applications (ICMLA), 2012 11th International Conference on*. 2012. IEEE.
116. ZHANG, J. and H. NIE, Experimental study and logistic regression modeling for machine condition monitoring through microcontroller-based data acquisition system. *Journal of Advanced Manufacturing Systems*, 2009. 8(02): p. 177-192.
117. Subasi, A., EEG signal classification using wavelet feature extraction and a mixture of expert model. *Expert Systems with Applications*, 2007. 32(4): p. 1084-1093.
118. Hamzah, R.R., Condition Monitoring of Spur and Helical Gears Using Acoustic Emission (AE) [PhD Thesis], School of Engineering. 2008: Cranfield University.
119. Höhn, B.-R. and K. Michaelis, Influence of oil temperature on gear failures. *Tribology International*, 2004. 37(2): p. 103-109.

120. Hamzah, R.R., K.R. Al-Balushi, and D. Mba, Observations of acoustic emission under conditions of varying specific film thickness for meshing spur and helical gears. *Journal of Tribology*, 2008. 130(2): p. 021506.
121. Hamel, M., A. Addali, and D. Mba, Monitoring oil film regimes with acoustic emission. *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, 2014. 228(2): p. 223-231.
122. Sreepradha, C., et al., Neural network model for condition monitoring of wear and film thickness in a gearbox. *Neural Computing and Applications*, 2014. 24(7-8): p. 1943-1952.
123. Krishnakumari A, Perumal AE, Panda R. PREDICTION FOR CONDITION MONITORING OF WEAR AND FILM THICKNESS IN A GEAR BOX. *Engineering MECHANICS*. 2012;19(6):393-405.
124. Fernandes, C.M., et al., Film thickness and traction curves of wind turbine gear oils. *Tribology International*, 2015. 86: p. 1-9.
125. Ferentinos, K.P., Biological engineering applications of feedforward neural networks designed and parameterized by genetic algorithms. *Neural networks*, 2005. 18(7): p. 934-950.
126. Sheela, K.G. and S. Deepa, Review on methods to fix number of hidden neurons in neural networks. *Mathematical Problems in Engineering*, 2013. 2013.
127. Rafiee, J., et al., Intelligent condition monitoring of a gearbox using artificial neural network. *Mechanical systems and signal processing*, 2007. 21(4): p. 1746-1754.
128. Snijders, T.A., *Multilevel analysis*. 2011: Springer.
129. Baird, G.L. and S.L. Bieber, The Goldilocks Dilemma: Impacts of Multicollinearity--A Comparison of Simple Linear Regression, Multiple Regression, and Ordered Variable Regression Models. *Journal of Modern Applied Statistical Methods*, 2016. 15(1): p. 18.
130. Li, S., et al., Comparative analysis of regression and artificial neural network models for wind turbine power curve estimation. *Journal of Solar Energy Engineering*, 2001. 123(4): p. 327-332.
131. Rajakarunakaran, S., et al., Artificial neural network approach for fault detection in rotary system. *Applied Soft Computing*, 2008. 8(1): p. 740-748.

132. Samanta, B. and K. Al-Balushi, Artificial neural network based fault diagnostics of rolling element bearings using time-domain features. *Mechanical systems and signal processing*, 2003. 17(2): p. 317-328.
133. Li, B., et al., Neural-network-based motor rolling bearing fault diagnosis. *IEEE transactions on industrial electronics*, 2000. 47(5): p. 1060-1069.
134. Filippetti, F., et al., Recent developments of induction motor drives fault diagnosis using AI techniques. *IEEE transactions on industrial electronics*, 2000. 47(5): p. 994-1004.
135. Gebraeel, N., et al., Residual life predictions from vibration-based degradation signals: a neural network approach. *IEEE Transactions on industrial electronics*, 2004. 51(3): p. 694-700.
136. Selesnick, I.W., The slantlet transform. *IEEE transactions on signal processing*, 1999. 47(5): p. 1304-1313.
137. Harsha, M. and T. Sudha. Slantlet Transform Based MC-CDMA Transceiver System for Wireless Communication. in *International Journal of Engineering Research and Technology*. 2013. ESRSA Publications.
138. Mitchell, T.M., *Machine learning*. WCB. 1997, McGraw-Hill Boston, MA:.
139. Irani, K.B., et al., Applying machine learning to semiconductor manufacturing. *IEEE Expert*, 1993. 8(1): p. 41-47.
140. Ahmed, F.Y., B. Yusob, and H.N.A. Hamed, Computing with Spiking Neuron Networks A Review. *International Journal of Advances in Soft Computing & Its Applications*, 2014. 6(1).
141. Kasabov, N., To spike or not to spike: A probabilistic spiking neuron model. *Neural Networks*, 2010. 23(1): p. 16-19.
142. Kasabov, N., Integrative connectionist learning systems inspired by nature: current models, future trends and challenges. *Natural Computing*, 2009. 8(2): p. 199-218.
143. Kojima, H. and S. Katsumata. An analysis of synaptic transmission and its plasticity by glutamate receptor channel kinetics models and 2-photon laser photolysis. in *International Conference on Neural Information Processing*. 2008. Springer.
144. Ikegaya, Y., et al., Statistical significance of precisely repeated intracellular synaptic patterns. *PloS one*, 2008. 3(12): p. e3983.

145. Ahmed, F.Y., S.M. Shamsuddin, and S.Z.M. Hashim, Improved SpikeProp for using particle swarm optimization. *Mathematical Problems in Engineering*, 2013. 2013.
146. Izhikevich, E., *Dynamical Systems in Neuroscience: The Geometry of Excitability and Bursting (Computational Neuroscience)* The MIT Press. 2006.
147. Izhikevich, E.M. and G.M. Edelman, Large-scale model of mammalian thalamocortical systems. *Proceedings of the national academy of sciences*, 2008. 105(9): p. 3593-3598.
148. Kasabov, N. Evolving spiking neural networks and neurogenetic systems for spatio-and spectro-temporal data modelling and pattern recognition. in *IEEE World Congress on Computational Intelligence*. 2012. Springer.
149. Silva, R.G., Condition monitoring of the cutting process using a self-organizing spiking neural network map. *Journal of Intelligent Manufacturing*, 2010. 21(6): p. 823-829.
150. Silva, R.G., S. Wilcox, and A.A. Araújo. Multi-sensor condition monitoring using spiking neuron networks. in *IADIS international conference applied computing 2007*. 2007.
151. Hu, Q., et al., Fault diagnosis of rotating machinery based on improved wavelet package transform and SVMs ensemble. *Mechanical Systems and Signal Processing*, 2007. 21(2): p. 688-705.
152. Davis, J.R., *Gear materials, properties, and manufacture*. 2005: ASM International.
153. Olver, A., Gear lubrication—a review. *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, 2002. 216(5): p. 255-267.
154. Townsend, D.P. and J. Shimski, *Evaluation of the EHL film thickness and extreme pressure additives on gear surface fatigue life*. 1994.
155. Seireg, A., Thermal stress effects on the surface durability of gear teeth. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 2001. 215(8): p. 973-979.
156. Handschuh, R.F. and C.J. Kilmain, *Preliminary investigation of the thermal behavior of high-speed helical gear trains*. 2002, DTIC Document.



157. Yi, J. and P. Quinonez, Gear surface temperature monitoring. Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology, 2005. 219(2): p. 99-105.
158. MacConochie, I.O. and W.H. Newman, The effect of lubricant viscosity on the lubrication of gear teeth. Wear, 1961. 4(1): p. 10-21.
159. Booser, E.R., CRC Handbook of Lubrication and Tribology, Volume III: Monitoring, materials, synthetic lubricants, and applications. Vol. 3. 1993: CRC Press.
160. Glaeser, W., Materials for tribology. Vol. 20. 1992: Elsevier.
161. Stribeck, Die Wesentlichen Eigenschaften der Gleit- und Rollenlager--the key qualities of sliding and roller bearings. Zeitschrift des Vereines Seutscher Ingenieure. Zeitschrift des Vereines Seutscher Ingenieure, 1902. 46(38): p. 1342-1348.
162. Hamrock, B.J., S.R. Schmid, and B.O. Jacobson, Fundamentals of fluid film lubrication. 2004: CRC press.
163. Lynwander, P., Gear drive systems: design and application. Vol. 20. 1983: CRC Press.
164. Stokes, A., Gear handbook: design and calculations. 1992: Society of Automotive Engineers.
165. Walton, D. and A. Goodwin, The wear of unlubricated metallic spur gears. Wear, 1998. 222(2): p. 103-113.
166. Dalpiaz, G. and U. Meneghetti, Monitoring fatigue cracks in gears. NDT & E International, 1991. 24(6): p. 303-306.
167. Reeves, C.W., Machine & Systems Condition Monitoring Series. 1998, Oxford: Coxmoor.
168. Neale, M.J., The tribology handbook. 1995: Butterworth-Heinemann.
169. Rao, B., Handbook of condition monitoring. 1996: Elsevier.
170. Collacott, R., Mechanical fault diagnosis and condition monitoring. 2012: Springer Science & Business Media.
171. Thomas, R., The thermography monitoring handbook. Machine & systems condition monitoring series. 1999, Oxford, UK: Coxmoor Pub.
172. Eftekharijad, B., Condition monitoring of gearboxes using acoustic emission. 2010.

173. Elforjani, M.A., Condition monitoring of slow speed rotating machinery using acoustic emission technology. 2010.
174. Amezcuita-Sanchez, J.P. and H. Adeli, Signal processing techniques for vibration-based health monitoring of smart structures. *Archives of Computational Methods in Engineering*, 2016. 23(1): p. 1-15.
175. Samuel, P.D. and D.J. Pines, A review of vibration-based techniques for helicopter transmission diagnostics. *Journal of sound and vibration*, 2005. 282(1): p. 475-508.
176. Sikorska, J. and D. Mba, Challenges and obstacles in the application of acoustic emission to process machinery. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, 2008. 222(1): p. 1-19.
177. Morhain, A. and D. Mba, Bearing defect diagnosis and acoustic emission. *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, 2003. 217(4): p. 257-272.
178. Al-Dossary, S., R.R. Hamzah, and D. Mba, Observations of changes in acoustic emission waveform for varying seeded defect sizes in a rolling element bearing. *Applied acoustics*, 2009. 70(1): p. 58-81.
179. Al-Ghamd, A.M. and D. Mba, A comparative experimental study on the use of acoustic emission and vibration analysis for bearing defect identification and estimation of defect size. *Mechanical systems and signal processing*, 2006. 20(7): p. 1537-1571.
180. Pollock, A., *Practical guide to acoustic emission testing*. Physical Acoustics Corporation Publication, 1988.