FAULT DETECTION AND DIAGNOSIS METHOD FOR THREE-PHASE INDUCTION MOTOR

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To my beloved wife, Elham

To my beloved father and mother

To my beloved brother

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I would like to thank my principal supervisor, Prof. Datin Dr. Rubiyah bt. Yusof for her guidance during my research and study. Her perpetual energy and enthusiasm in research had motivated me.

ABSTRACT

Induction motors (IM) are critical components in many industrial processes. There is a continually increasing interest in the IMs' fault diagnosis. The scope of this thesis involves condition monitoring and fault detection of three phase IMs. Different monitoring techniques have been used for fault detection on IMs. Vibration and stator current monitoring have gained privilege in literature and in the industry for fault diagnosis. The performance of the vibration and stator current setups was compared and evaluated. In that perspective, a number of data were captured from different faulty and healthy IMs by vibration and current sensors. The Principal Component Analysis (PCA) was utilized for feature extraction to monitor and classify collected data for finding the faults in IMs. A new method was proposed with the combined use of vibration and current setups for fault detection. It consists of two steps: firstly, the training part with the aim of giving acceleration property (nature of vibration data) to the current features, and secondly the testing part with the aim of excluding the vibration setup from the fault detection algorithm, while the output data have the property of vibration features. The 0-1 loss function was applied to show the accuracy of vibration, current and proposed fault detection method. The PCA classified results showed mixed and unseparated features for the current setup. The vibration setup and the proposed method resulted in substantial classified features. The 0-1 loss function results showed that the vibration setup and the developed method can provide a good level of accuracy. The vibration setup attained the highest accuracy of 98.2% in training and 92% in testing. The proposed method performed well with accuracies of 96.5% in training and 84% in testing. The current setup, however, attained the lowest level of accuracy (66.7% in training and 52% in testing). To assess the performance of the proposed method, the Confusion matrix of classification in NN was utilized. The Confusion matrix showed an accuracy of 95.1% of accuracy and negligible incorrect responses (4.9%), meaning that the proposed fault detection method is reliable with minimum possible errors. These vibration, current and proposed fault detection methods were also evaluated in terms of cost. The proposed method provided an affordable fault detection technique with a high accuracy applicable in various industrial fields.

ABSTRAK

Induction motor (IM) adalah komponen kritikal dalam banyak proses perindustrian. Terdapat minat yang semakin meningkat dalam diagnosis IMs. Skop tesis ini melibatkan pemantauan keadaan dan pengesanan kesalahan tiga fasa IMs.Teknik pemantauan yang berbeza telah digunakan untuk pengesanan kesalahan pada IM. Getaran dan stator pemantauan semasa telah mendapat keistimewaan dalam banyak kajian dan dalam industri untuk diagnosis kesilapan. Prestasi getaran dan tetapan semasa stator telah dibandingkan dan dinilai. Dalam perspektif itu, beberapadata telah diambil dari pelbagai IM yang elok dengan getaran dan penderia semasa. Analisis Komponen Utama (PCA) digunakan untuk pengekstrakan ciri untuk memantau dan mengklasifikasikan data yang dikumpul untuk mencari kesalahan dalam IM. Kaedah baru dicadangkan menggunakan gabungan getaran dan tetapan semasa untuk pengesanan kesalahan terdiri daripada dua langkah: bahagian latihan dengan tujuan memberikan pecutan harta (sifat data getaran) kepada ciri-ciri semasa, dan sebahagian ujian dengan tujuan pengecualian persedian ediaan getaran dari algoritma pengesanan kesalahan, sementara data output mempunyai sifat ciri getaran. Fungsi kerugian 0-1 digunakan untuk menunjukkan ketepatan getaran, kaedah pengesanan kesalahan semasa dan cadangan yang dicadangkan. Hasil pengklasifikasian PCA menunjukkan ciri bercampur dan tidak terpakai untuk persediaan semasa. Persediaan getaran dan kaedah yang dicadangkan menghasilkan ciri-ciri terkelas yang besar. Hasil fungsi kehilangan 0-1 menunjukkan bahawa persediaan getaran dan kaedah yang dibangunkan dapat memberikan ketepatan yang baik. Persediaan getaran mengakibatkan ketepatan tertinggi 98.2% dalam latihan dan 92% dalam ujian. Kaedah yang dicadangkan dijalankan dengan baik dengan ketepatan 96.5% dalam latihan dan 84% dalam ujian. Walau bagaimanapun, persediaan semasa mengakibatkan tahap ketepatan minimum (66.7% dalam latihan dan 52% dalam ujian). Untuk menilai prestasi kaedah yang dicadangkan, klasifikasi kekeliruan klasifikasi dalam NN digunakan. Matriks kekeliruan menunjukkan 95.1% ketepatan dan tindak balas yang tidak dapat diabaikan (4.9%), yang bermaksud bahawa kaedah pengesanan kesalahan yang dicadangkan boleh dipercayai dengan ralat minimum yang mungkin. Kaedah getaran, semasa dan cadangan pengesanan kesalahan ini juga dinilai dari segi kos. Kaedah yang dicadangkan menyediakan teknik pengesanan kesalahan berpatutan dengan ketepatan tinggi yang digunakan dalam pelbagai bidang perindustrian.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
AR	-	Autoregressive
ARMA	-	Autoregressive Moving Average
CMD	-	Compact Matrix Decomposition
COR	-	Correlation
EEG	-	Electro Encephalogram
ES	-	Expert System
FEA	-	Finite Element Analysis
GA	-	Genetic Algorithms
ICA	-	Independent Component Analysis
IM	-	Induction Motor
KBS	-	Knowledge-Based Systems
LDA	-	Linear Discriminate Analysis
LH	-	Local Homogeneity

MA	-	Moving Average
MSE	-	Mean Square Error
MSCA	-	Motor current Signature Analysis
MMFs	-	Magneto Motive Forces
NN	-	Neural Network
PCA	-	Principal Component Analysis
RMS	-	Root Mean Square
SCSA	-	Stator Current-Signature Analysis
SVM	-	Support Vector Machines
SVD	-	Singular Value Decomposition
VSI	-	Voltage Source Inverter
VDI	-	Verein Deutscher Ingenieure

LIST OF SYMBOLS

f_s	-	Input stator frequency
V_s	-	Input stator phase voltage
N_s	-	Number of stator winding turns
p	-	Number of pole pairs
L_{ls}	-	Stator winding leakage inductance
R_s	-	Stator winding electrical resistance
n	-	Number of rotor bars
r_{ag}	-	Air-gap average radius
l_{ag}	-	Air-gap length
l_r	-	Rotor length
L_{rb}	-	Rotor bar self inductance
R_{rb}	-	Rotor bar resistance

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CHAPTER 1

INTRODUCTION

1.1 Faults in Induction Motors

Induction motors (IM) are most commonly used electrical machines in industry because of their low cost, reasonably small size, ruggedness, low maintenance, and operation with an easily available power supply (El Hachemi Benbouzid, 2000). However, they are subjected to different modes of faults leading to failures. These faults can be inherent to the machine itself or may be created by operating conditions. The inherent faults could be caused by the mechanical or electrical forces acting on the machine enclosure. If a fault is not detected or if it is allowed to be developed further, it may lead to a failure (El Hachemi Benbouzid, 2000; Yamamura, 1979).

The main faults of IMs can generally be classified as 1) stator faults resulting in the opening or shorting of one or more of the stator phase winding 2) abnormal connection of the stator windings 3) broken rotor bar or cracked rotor end rings 4) static and dynamic air gap irregularities 5) bent shaft 6) shorted rotor field winding 7) bearing & gearbox failures (Bonett & Soukup, 1992; Shashidhara & Raju, 2013; J.-W.Zhang, Zhu, Li, Qi, & Qing, 2007; Cusidó et al., 2011). The squirrel cage of an induction machine consists of rotor bars and end rings. Motor with broken bar fault has one or more of the cracked or broken bars. Broken rotor bar can be caused by manufacturing defects, thermal stresses or frequent starts of the motor at rated voltage (Siddiqui, Sahay, & Giri, 2014). Winding fault is due to catastrophe of insulation of the stator winding. This fault can be caused by mechanical stresses due to movement of stator coil and rotor striking the stator, electrical stresses due to the supply voltage transient or thermal stresses due to thermal overloading (Siddiqui, Sahay, & Giri, 2014). Whereas faulty IMs must normally be removed from the application in order to be fixed and repaired, a suitable fault diagnosis and monitoring system can reduce the financial loss, drastically (Zarei, 2012; P. Zhang, Du, Habetler, & Lu, 2011).

Early detection of incipient faults is a very important issue in preventive and predictive maintenance of electrical equipment. Since in modern industries, the majority of the equipment is driven by three-phase induction motors (IMs), the condition monitoring of such machines constitutes an essential concern in any industrial section (Butler, 1996; Cusidó, Romeral, Ortega, Garcia, & Riba, 2011).

1.2 Maintenance Strategies

Traditional machinery maintenance practice in industry can be categorized broadly into three methods:

a) Run-to-failure maintenance
b) Scheduled maintenance
c) Condition based maintenance

Run-to-failure maintenance, which reacts to the equipment failure after it happens. This maintenance approach is a corrective management method that has no special maintenance plan in place. Due to the nature of the industry sectors, the failure of one piece of equipment may stop production in a significant portion. For example, the failure of a main haulage belt motor in mining industry may idle an entire mine. In this case, the run-to-failure maintenance will be too costly. This type of maintenance method is not an acceptable maintenance method because there might be a high risk of secondary failure, overtime labor and high cost of spare parts (Palem, 2013; Yam, Tse, Li, & Tu, 2001).

Scheduled maintenance, which is the practice of replacing components in fixed time intervals. This maintenance takes preventive actions to check, repair, or replace the equipment at a prearranged schedule before machine faults. Such maintenance policy benefits in terms of maintenance cost reduction as it minimizes the unscheduled downtime and labor costs in comparison to the run-and-failure maintenance strategy. However, this strategy does not consider the condition of the equipment in that it scheduled the maintenance activity at a fixed time interval without considering the condition of the equipment or component (Palem, 2013; Yam, Tse, Li, & Tu, 2001). In addition, machines may be repaired when there are no failures (Kwitowski, Lewis, & Mayercheck, 1989). Condition based monitoring is a maintenance procedure that uses sensors to evaluate the health of the system. Condition monitoring and fault diagnostics are useful for early detection of mechanical and electrical failures to prevent main component faults (Jardine, Lin, & Banjevic, 2006). One of the key elements to condition based maintenance is the understanding of the actual condition or health of a machine, then using this information to schedule and perform maintenance when it is most needed. If performed correctly, condition based maintenance can bring out many advantages such as increasing machinery availability and performance, reducing consequential damage, increasing machine life, reducing spare parts inventories, and reducing breakdown maintenance (Siddiqui, Sahay, & Giri, 2014). Figure 1.1 presents three main maintenance strategies.

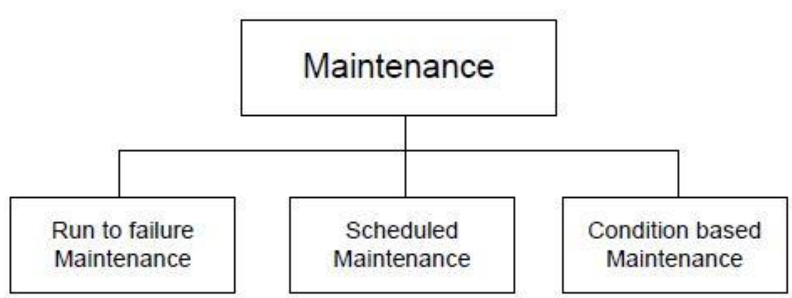

Figure 1.1 Three main maintenance strategies

1.2.1 Condition Monitoring for Fault Diagnosis Prediction

Condition monitoring leading to fault detection of IMs has been an attractive research area in the last few years because of its significant effect in many industrial processes. Correct detection and early prediction of incipient faults consequence in fast unscheduled maintenance and short downtime for the process under consideration. Destructive consequences can be avoided by condition monitoring. Financial loss also is reduced. An ideal diagnostic technique should provide the minimum essential measurements from a motor (Jin, Zhao, Chow, & Pecht, 2014; Toliyat, Nandi, Choi, & Meshgin-Kelk, 2012).

In the scope of industry, most of the occurred faults are not predictable or even visible with the naked eye. Therefore, it is very critical to identify and diagnose these faults at early stages to prevent any corruption or damages in electrical instruments. For example, since the air gap between rotor and stator is very small, any imbalance in barriers or mis-positioning of rotor may cause serious physical damages to the rotor and stator of the IM (Bellini, Filippetti, Tassoni, & Capolino, 2008).

Different monitoring procedures have been utilized for fault detection on IMs. Vibration analysis, stray flux, and stator current-signature analysis (SCSA) are the most popular ones (A Bellini, Concari, Franceschini, Tassoni, & Toscani, 2006). Stator faults result in the open or short circuits on one or more stator windings (V Spyropoulos & D Mitronikas, 2013). Extreme heating, transient over voltages, winding movement, or contamination are the factors providing the winding-insulation damage. This fault causes in high currents and winding overheating, which result in severe phase-to-phase, turn-to-turn, or turn-to-ground faults. All these may lead to an irreversible damage in the windings or in the stator core. Hence, affordable and reliable diagnosis of incipient faults between turns during motor operation is vital (El Hachemi Benbouzid, 2000; Nandi, Toliyat, & Li, 2005; Tallam et al., 2007; Torkaman).

1.3 Methods for Fault Diagnosis of IMs

The existing methods for the fault diagnosis of IMs can be generally categorized into three groups, namely: model-based, signal-based, and data-based (Alberto Bellini, Filippetti, Tassoni, & Capolino, 2008). Most of the diagnostic techniques for IMs can be extended easily to other types of rotating electrical machines.

1.3.1 Model-Based Fault Detection Method

Model-based fault detection method depends in light of a theoretical analysis of the asymmetrical motor whose model is utilized to anticipate fault signatures (Alberto Bellini et al., 2008; Isermann, 2005; Siddiqui et al., 2014). The difference between measured and simulated signatures is used as a fault detector as shown in Figure 1.2.

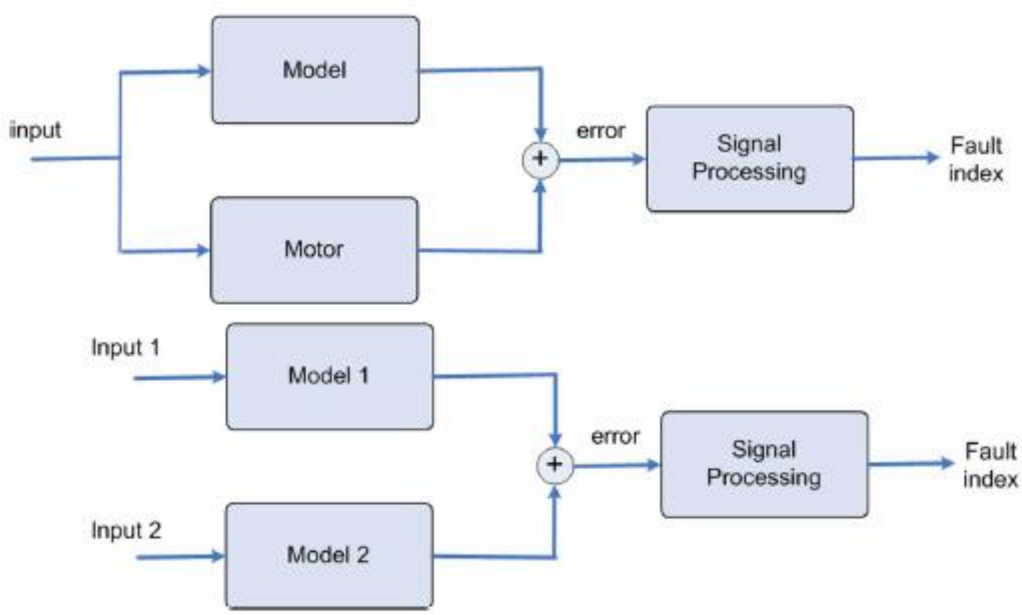

Figure 1.2 Model-based diagnostic technique. Two techniques are possible according to the same basic structure (Bellini et al., 2008)

In order to express a fault index, residual analysis and proper signal processing are usually utilized (Bellini et al., 2008). Some left-overs are generated by model-based fault detection and diagnosis methods which is indication of variations between measurement and prediction. Theoretically, System faults only affect these left-over signals and the deviations in the system inputs and predicted disturbances faced in normal operating conditions have almost no effect on them. Power supply imbalances and load variations are two critical parameters for electric motors. Hence, for normal condition and operating without any faults the left-overs must be almost zero-mean white noise while in the case of any faults they must deviate from this behavior. Model-based fault detection method has not been prevalent and popular to be applied in the industry due to complications in obtaining accurate and suitable models while modeling uncertainties resulting from system nonlinearities, parameter uncertainties, disturbances and other measurement noise exist (Combastel et al., 2002). Moreover, modeling of electromechanical systems is not practical due to their complex construction and the requirement of extensive approximations, which makes model-based analysis methods an inappropriate choice (Combastel, Lesecq, Petropol, & Gentil, 2002; Kim & Parlos, 2002).

1.3.2 Signal-Based Fault Detection Method

Signal-based methods mostly focus on frequency domain data. The known fault signatures in quantities sampled from the actual machine are detected by signal-based diagnosis (Bellini et al., 2008). The signs are examined and observed by a proper signal processing unit as shown in Figure 1.3. Even though advanced methods and/ or decision-making techniques can be used, frequency analysis is normally used. In this method, signal processing has an important role since it can improve signal-to-noise ratio and normalize data to differentiate other faults generated from other sources. It is also able to reduce the sensitivity to operating conditions (Bellini et al., 2008; Kim & Parlos, 2002). The signal-based systems are mostly utilized for the procedures in the steady state. Effectiveness of such fault diagnosis method in dynamic systems is significantly limited.

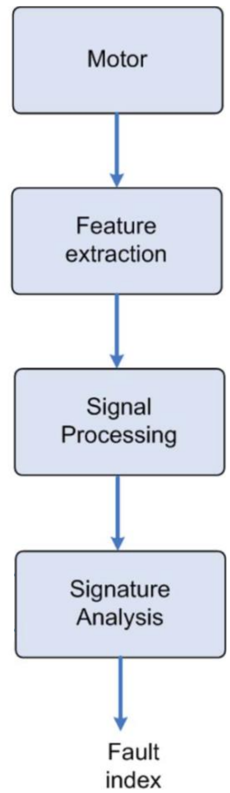

Figure 1.3 Block diagram of signal-based diagnostic procedure (Bellini et al., 2008)

1.3.3 Data-Based Fault Detection Method

Data-based diagnosis relies on signal processing and on classification methods. The data-based techniques are considered more suitable options as a result of any information of machine parameters and model is not required in this type of fault detection technique (Bellini et al., 2008). In that perspective, such fault diagnosis offers a few numbers of mathematical calculations. They are applied on the lines of the supervised learning methods. In the supervised learning, the data are collected from the system in known health conditions and based on the decision rules developed, health conditions of unknown systems are categorized and prognosticated (Kim & Parlos, 2002).

The advantage of using data-based diagnosis is that it does not need any information of machine model and parameters. Signal processing and clustering methods are only requirement in this technique. Sample data are captured from an actual IM and are processed in order to find a set features for classification purpose. Finally, fault index can be achieved by utilizing decision process techniques as shown in Figure 1.4.

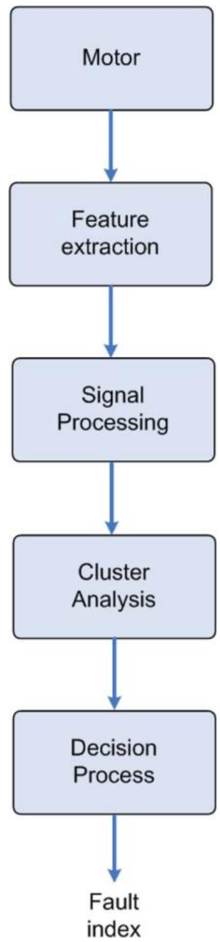

Figure 1.4 Block diagram of data-based diagnostic procedure (Bellini et al., 2008)

Data sampled from the motor are managed to extract a features' set that are classified by classification methods. A fault index is defined by decision process techniques. Artificial intelligence (AI) systems are broadly applied to classify faulty and healthy conditions (Siddique, Yadava, & Singh, 2003).

1.4 AI Techniques for Motor Fault Diagnosis

In recent years, AI technologies have been employed to overcome the difficulties that conventional diagnosis strategies (direct inspection, wear particle analysis and parameter estimation) are facing. Conventional methods are easy to understand. However, they are not always possible in reality because they require in-depth knowledge of the induction motor system or its working mechanisms. In the case of inadequate information false alarms can occur. A brief review of the advantages and disadvantages of these approaches is given in Table 1.1 (Awadallah & Morcos, 2003; Gao & Ovaska, 2001; Laghari, Memon, & Khuwaja, 2004; Tsang, 1995).

Table 1.1: Comparison of methods for motor fault detection and diagnosis

Approach	Advantage	Disadvantage
Direct inspection	Simple & direct	Requires experienced engineers
Wear particle analysis	Analysis theory is mature and suitable for routine check-up	Time consuming and exhaustive examination required
Parameter estimation	Suitable for on-line monitoring and fault diagnosis	Difficult to obtain accurate mathematical model
Expert systems (ES)	Known experience and knowledge. Excellent explanation capability	Expert experience & knowledge is difficult to be transformed & automated
Artificial neural network (ANN)	Without the need of complex and rigorous mathematical models or expert experience	Need training data

In general, expert systems and artificial neural networks (ANN) are one of the most popular methods within AI systems. The effectiveness of the expert systems depends on the precision and completeness of the knowledge base, which is usually very complicated, time consuming and must be constructed manually. The major problem with expert systems is that they cannot adjust their diagnostic rules automatically, and thus cannot acquire knowledge from new data samples (Siddiqui et al., 2014).

ANN based method is rather easy to develop and perform. Unlike parameter estimation and expert systems, ANN strategy can detect and diagnose motor faults based on measurements without the need for complex and rigorous mathematical models or experience. ANN systems can learn fault detection and diagnosis solely based on input-output examples without the need of mathematical models. Therefore, ANN systems have drawn significant attention in the motor fault detection and diagnosis field. No prior knowledge about motor fault detection and diagnosis is needed. Only the training data, including normal and faulty data need to be obtained in advance. Once ANNs are trained appropriately, the networks could contain knowledge needed to perform fault detection and diagnosis (Kumari & Sunita, 2013; Nasira, Kumar, & Kiruba, 2008; Shi, Sun, Li, & Liu, 2007; Siddiqui et al., 2014).

1.5 Problem Statement

Electrical and mechanical data are commonly used in data-based diagnosis (Kano & Nakagawa, 2008). The electrical current waveform of the IM can potentially reveal whether the machine is working properly or not. It is notable that there are specific characteristic behaviors in the current signals (provided by inverters) or vibration signals (provided by accelerometer sensors placed on the machine) for each kind of main motor faults. Therefore, it is feasible to detect the faults based on current and vibration measurements (Garcia-Ramirez, Osornio-Rios, Granados-Lieberman, Garcia-Perez, & Romero-Troncoso, 2012).

Motor current signature analysis (MCSA) is known as an effective technique for fault diagnosis in three-phase IMs. This method is associated to various faults such as broken rotor bars and windings faults. Numerous technical works have been recently studied the benefits of this method in detecting the IM faults (El Hachemi Benbouzid, 2000; Penman et al., 1994; Radhika et al., 2010; Sadri, 2004; J.-W. Zhang et al., 2007; Z. Zhang et al., 2003). Current sensors are mostly cheap and could be used and maintained easily. Tandon et.al (2007) reported that stator current monitoring requires minimum instruments and can be considered as an affordable fault detection technique (Tandon, Yadava, & Ramakrishna, 2007). However, it has some limitations that reduce the performance and accuracy of motor diagnosis. Bellini et.al (2008) proposed that stator current monitoring is not a reliable fault detection system because the current signal analysis is effective for the faults whose critical frequency rate is lower than the supply frequency. The current signal can be utilized as a reliable approach only in dedicated operating conditions (Bellini, Immovilli, Rubini, & Tassoni, 2008).

Vibration monitoring technique is a powerful approach for fault diagnosis in IMs. It has been widely used due to its significant results. Fault diagnosis based on mechanical features such as vibration of the stator furnishes the operator with high accuracy of results (Dorrell, Thomson, & Roach, 1997). The dark side of such technique is the high cost of accelerometers and associated wiring, which also require expensive software and technical assistant to be utilized as reported by Nandi et.al (2005). They stated that vibration transducers are expensive and require special installation conditions to avoid harm owing to shock and vibration (Nandi, Toliyat, & Li, 2005). Thus, its use in several applications may be limited. Subsequently, this method cannot utilize for large machines fault diagnostics purpose because it is expensive (Siddiqui, Sahay, & Giri, 2014). The vibration sensors could be damaged easily as well, which makes them improper for being used in rough industrial environments (Gritli, Filippetti, Miceli, Rossi, & Chatti, 2012).

In a research done by Bellini et.al, use of vibration and current signal was compared, in order to show advantages and disadvantages of this two condition monitoring systems. They utilized the frequency domain to analyze capturing data. Signal processing methods including Hilbert transformation and Envelope analysis were used for machines with healthy and faulty bearings to demonstrate which monitoring system is the best suited to the bearing failures. They found out that current signal cannot be considered as a reliable fault detection system because of the current signal analysis is effective for the faults whose critical frequency rate is lower than the supply frequency. Vibration monitoring technique, however, showed that can be a reliable but expensive indicator for bearing faults in low and high frequency. Though, vibration needs a structural model with mass, damping and stiffness parameters. On the other hand, frequency domain analysis requires different types of signal processing methods with complex mathematical equations (Bellini, Immovilli, Rubini, & Tassoni, 2008).

Rodenas and Daviu proposed a twofold method for detection of broken rotor bars, cooling system problems and bearing faults in IMs. The first stage utilized current monitoring technique using steady state and transient methods. They used infrared cameras to take thermography images to find failure places in a second stage. Although, each of these approaches provided useful information to detect extensive ranges of faults, but they were applicable for large and expensive motors. The infrared technique was sensitive to failures located near the machine frame surface rather than to internal faults. Furthermore, infrared cameras are so expensive. Another limitation was the length of the required data due to the long duration of the heating transient. This system also may not be applicable in industrial area with high temperature environment. Therefore, an insensitive to heat and cost-effective fault diagnosis approach is required to be affordable for all types of motors not only large and expensive ones. Besides, an ideal fault detection technique should diagnose failures at inner and outer parts of machines (Picazo-Ródenas, Antonino-Daviu, Climente-Alarcon, Royo-Pastor, & Mota-Villar, 2015).

There is almost no single fault diagnosis method capable to detect all probable faults taking place in IMs with a reasonable price and high accuracy. Although stator current and vibration monitoring are the most commonly used monitoring procedures in the industry, but each of these techniques alone have some limitations. Consequently, a single fault detection technique cannot be considered as a reliable and general diagnosis system. While current monitoring technique is an inexpensive method, but it is less accurate. Vibration monitoring on the other hand has higher price and accuracy compared to the current monitoring. It must be noted that systems required high accuracy and lower cost. Therefore, a new method for fault detection is deeply needed to meet these requirements. This thesis presented a cost-effective and reliable method for detection of faults in three-phase IMs by combination of the two aforementioned monitoring techniques (vibration and current) with great prospect for application in industrial scale.

1.6 Objectives of the Study

The objectives of this thesis are as follows:

(1) To develop an affordable installation and maintenance setup for fault diagnosis in IMs.

(2) To develop an intelligent fault detection strategy based on vibration and electrical current signals.

(3) To evaluate the performance of vibration and current setup in term of accuracy and cost.

1.7 Scope of the Study

This investigation was conducted to determine the stator winding and broken rotor bar faults in three phase induction machines with a squirrel cage rotor. Two faulty IMs with broken rotor and winding faults and one healthy IM have been investigated in the

Center for Artificial Intelligent and Robotics (CAIRO) laboratory at University Teknologi Malaysia (UTM). Data were captured by two different setups in time domain:

i) Vibration setup contains NI PCI- 4474 DAQ card and accelerometers

ii) Current setup included NI 9234 and NI 9174 CDAQ cards, and current clipping sensor.

Each of these two setups alone have some limitations for fault diagnosis in IMs. Vibration setup is expensive, whilst current setup is cheap but with low detection reliability. This research work assumes to develop a reliable and cost-effective fault detection method with the joint use of vibration and current setups. In addition, ANN was used for classification and nonlinear regression system. PCA technique also utilized for reduction of features dimensions.

1.8 Thesis Organization

This thesis is organized into five chapters. A brief outline of the thesis's contents is as follows:

Chapter 1 presents an introduction to the research problem. It involves the background of the study, problem statement and hypothesis of the thesis. The logical flow and structure of the thesis are also outlined in this chapter.

A complete literature review on faulty IMs with various types of faults, condition monitoring techniques, different methods for fault detection and their advantages and disadvantages are presented in **chapter 2**.

Chapter 3 focuses on the proposed methodology contained data acquisition, feature extraction, method development including testing set to train the algorithm and

REFERENCES

Arthur, N., & Penman, J. (2000). Induction machine condition monitoring with higher order spectra. *Industrial Electronics, IEEE Transactions on, 47*(5), 1031-1041.

Awadallah, M., & Morcos, M. M. (2003). Application of AI tools in fault diagnosis of electrical machines and drives-an overview. *Energy Conversion, IEEE Transactions on, 18*(2), 245-251.

Ayaz, E. (2014). A Review Study on Mathematical Methods for Fault Detection Problems in Induction Motors. *Balkan Journal of Electrical and Computer Engineering, 2*(3).

Beguenane, R., & Benbouzid, M. E. H. (2000). Induction motors thermal monitoring by means of rotor resistance identification. *IEEE transactions on energy conversion*, 14(3), 566-570.

Bellini, A., Concari, C., Franceschini, G., Tassoni, C., & Toscani, A. (2006). *Vibrations, currents and stray flux signals to asses induction motors rotor conditions.* Paper presented at the IEEE Industrial Electronics, IECON 2006-32nd Annual Conference on.

Bellini, A., Filippetti, F., Franceschini, G., Tassoni, C., & Kliman, G. B. (2001). Quantitative evaluation of induction motor broken bars by means of electrical signature analysis. *Industry Applications, IEEE Transactions on, 37*(5), 1248-1255.

Bellini, A., Filippetti, F., Tassoni, C., & Capolino, G.-A. (2008). Advances in diagnostic techniques for induction machines. *IEEE Transactions on Industrial Electronics, 12*(55), 4109-4126.

Blödt, M., Chabert, M., Regnier, J., & Faucher, J. (2006). Mechanical load fault detection in induction motors by stator current time-frequency analysis. *Industry Applications, IEEE Transactions on, 42*(6), 1454-1463.

Borras, D., Castilla, M., Moreno, N., & Montano, J. (2001). Wavelet and neural structure: a new tool for diagnostic of power system disturbances. *Industry Applications, IEEE Transactions on, 37*(1), 184-190.

Butler, K. L. (1996). *An expert system based framework for an incipient failure detection and predictive maintenance system.* Paper presented at the Intelligent Systems Applications to Power Systems, 1996. Proceedings, ISAP'96., International Conference on.

Cabanas, M., Melero, M., Orcajo, G., Faya, F. R., & Sariego, J. S. (1998). *Experimental application of axial leakage flux to the detection of rotor asymmetries, mechanical anomalies and interturn short circuits in working induction motors.* Paper presented at the Proc ICEM'98.

Cao, L., Chua, K., Chong, W., Lee, H., & Gu, Q. (2003). A comparison of PCA, KPCA and ICA for dimensionality reduction in support vector machine. *Neurocomputing, 55*(1), 321-336.

Combastel, C., Lesecq, S., Petropol, S., & Gentil, S. (2002). Model-based and wavelet approaches to induction motor on-line fault detection. *Control Engineering Practice, 10*(5), 493-509.

Corres, J. M., Bravo, J., Arregui, F. J., & Matias, I. R. (2006). Vibration monitoring in electrical engines using an in-line fiber etalon. *Sensors and Actuators A: Physical, 132*(2), 506-515.

Cusidó, J., Romeral, L., Ortega, J. A., Garcia, A., & Riba, J. (2011). Signal injection as a fault detection technique. *Sensors, 11*(3), 3356-3380.

Da Silva, A. M. (2006). *Induction motor fault diagnostic and monitoring methods.* Faculty Of the Graduate School, Marquette University.

Da Silva, A. M., Povinelli, R. J., & Demerdash, N. A. (2013). Rotor bar fault monitoring method based on analysis of air-gap torques of induction motors. *IEEE Transactions on Industrial Informatics,* 9(4), 2274-2283.

Delgado Prieto, M., Cusido Roura, J., & Romeral Martínez, J. L. (2011). *Bearings fault detection using inference tools*: In-Tech.

Dorrell, D. G., Thomson, W. T., & Roach, S. (1997). Analysis of airgap flux, current, and vibration signals as a function of the combination of static and dynamic airgap eccentricity in 3-phase induction motors. *Industry Applications, IEEE Transactions on, 33*(1), 24-34.

Douglas, H., Pillay, P., & Ziarani, A. K. (2004). A new algorithm for transient motor current signature analysis using wavelets. *Industry Applications, IEEE Transactions on, 40*(5), 1361-1368.

Dowding, C. H. (1985). *Blast vibration monitoring and control* (Vol. 297): Prentice-Hall Englewood Cliffs.

Drucker, H., Wu, D., & Vapnik, V. N. (1999). Support vector machines for spam categorization. *Neural Networks, IEEE Transactions on, 10*(5), 1048-1054.

Dutta, H., Giannella, C., Borne, K. D., & Kargupta, H. (2007). *Distributed Top-K Outlier Detection from Astronomy Catalogs using the DEMAC System.* Paper presented at the SDM.

Ekici, S., Yildirim, S., & Poyraz, M. (2008). Energy and entropy-based feature extraction for locating fault on transmission lines by using neural network and wavelet packet decomposition. *Expert Systems with Applications, 34*(4), 2937-2944.

El Hachemi Benbouzid, M. (2000). A review of induction motors signature analysis as a medium for faults detection. *Industrial Electronics, IEEE Transactions on, 47*(5), 984-993.

Ellison, A., & Yang, S. (1971). *Effects of rotor eccentricity on acoustic noise from induction machines.* Paper presented at the Proceedings of the Institution of Electrical Engineers.

Filippetti, F., Franceschini, G., Tassoni, C., & Vas, P. (1998). AI techniques in induction machines diagnosis including the speed ripple effect. *Industry Applications, IEEE Transactions on, 34*(1), 98-108.

Filippetti, F., Franceschini, G., Tassoni, C., & Vas, P. (2000). Recent developments of induction motor drives fault diagnosis using AI techniques. *Industrial Electronics, IEEE Transactions on, 47*(5), 994-1004.

Filippetti, F., Martelli, M., Franceschini, G., & Tassoni, C. (1992). *Development of expert system knowledge base to on-line diagnosis of rotor electrical faults of induction motors.* Paper presented at the Industry Applications Society Annual Meeting, 1992., Conference Record of the 1992 IEEE.

Finley, W. R., Hodowanec, M. M., & Holter, W. G. (1999). *An analytical approach to solving motor vibration problems.* Paper presented at the Petroleum and Chemical Industry Conference, 1999. Industry Applications Society 46th Annual.

Fujimaki, R., Yairi, T., & Machida, K. (2005). *An approach to spacecraft anomaly detection problem using kernel feature space.* Paper presented at the Proceedings of the eleventh ACM SIGKDD international conference on Knowledge discovery in data mining.

Fukuyama, Y., & Ueki, Y. (1992). *Hybrid fault analysis system using neural networks and artificial intelligence.* Paper presented at the Circuits and Systems, 1992. ISCAS'92. Proceedings., 1992 IEEE International Symposium on.

Gao, X. Z., & Ovaska, S. J. (2001). Soft computing methods in motor fault diagnosis. *Applied soft computing, 1*(1), 73-81.

Garcia-Ramirez, A. G., Osornio-Rios, R. A., Granados-Lieberman, D., Garcia-Perez, A., & Romero-Troncoso, R. J. (2012). Smart sensor for online detection of multiple-combined faults in VSD-fed induction motors. *Sensors, 12*(9), 11989-12005.

Ghate, V. N., & Dudul, S. V. (2009). *Fault diagnosis of three phase induction motor using neural network techniques.* Paper presented at the Emerging Trends in Engineering and Technology (ICETET), 2009 2nd International Conference on.

Godoy, W. F., da Silva, I. N., Goedtel, A., Palácios, R. H., Bazan, G. H., & Morííñigo-Sotelo, D. (2016). *An application of artificial neural networks and PCA for stator fault diagnosis in inverter-fed induction motors*. Paper presented at the Electrical Machines (ICEM), 2016 XXII International Conference on.

Goode, P. V., & Chow, M.-Y. (1994). A hybrid fuzzy/neural system used to extract heuristic knowledge from a fault detection problem. Paper presented at the Fuzzy Systems, 1994. IEEE World Congress on Computational Intelligence., Proceedings of the Third IEEE Conference on.

Gritli, Y., Filippetti, F., Miceli, R., Rossi, C., & Chatti, A. (2012). *Investigation of motor current signature and vibration analysis for diagnosing rotor broken bars in double cage induction motors.* Paper presented at the Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM), 2012 International Symposium on.

Günter, S., Schraudolph, N., & Vishwanathan, S. (2007). Fast iterative kernel principal component analysis. *Made available in DSpace on 2010-12-20T06: 02: 43Z (GMT). No. of bitstreams: 1 Guenter_Fast2007. pdf: 3186111 bytes, checksum: 068a6868a41936f686cc8c5e9412eaaa (MD5) Previous issue date: 2009-05-21T05: 19: 22Z.*

Han, T., Yang, B.-S., Choi, W.-H., & Kim, J.-S. (2006). Fault diagnosis system of induction motors based on neural network and genetic algorithm using stator current signals. *International Journal of Rotating Machinery, 2006*.

Hawkins, D. M. (1974). The detection of errors in multivariate data using principal components. *Journal of the American Statistical Association*, *69*(346), 340-344.

Horvath, G. (2003). CMAC neural network as an SVM with B-Spline kernel functions. Paper presented at the Instrumentation and Measurement Technology Conference, 2003. IMTC'03. Proceedings of the 20th IEEE.

Huang, Z., Chen, H., Hsu, C.-J., Chen, W.-H., & Wu, S. (2004). Credit rating analysis with support vector machines and neural networks: a market comparative study. *Decision support systems*, 37(4), 543-558.

Hsu, J. S. (1995). Monitoring of defects in induction motors through air-gap torque observation. *Industry Applications, IEEE Transactions on, 31*(5), 1016-1021.

Ide, T., & Kashima, H. (2004). *Eigenspace-based anomaly detection in computer systems.* Paper presented at the Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining.

Isermann, R. (2005). Model-based fault-detection and diagnosis–status and applications. *Annual Reviews in control, 29*(1), 71-85.

Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, 20(7), 1483-1510.

Jia, F., Lei, Y., Lin, J., Zhou, X., & Lu, N. (2016). Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. Mechanical systems and signal processing, 72, 303-315.

Jin, X., Zhao, M., Chow, T. W., & Pecht, M. (2014). Motor bearing fault diagnosis using trace ratio linear discriminant analysis. Industrial Electronics, *IEEE Transactions on*, 61(5), 2441-2451.

Jolliffe, I. (2002). *Principal component analysis*: Wiley Online Library.

Kano, M., & Nakagawa, Y. (2008). Data-based process monitoring, process control, and quality improvement: Recent developments and applications in steel industry. *Computers & Chemical Engineering, 32*(1), 12-24.

Kim, K., & Parlos, A. G. (2002). Induction motor fault diagnosis based on neuropredictors and wavelet signal processing. *Mechatronics, IEEE/ASME Transactions on, 7*(2), 201-219.

Kumari, N., & Sunita, S. (2013). Comparison of ANNs, Fuzzy Logic and Neuro-Fuzzy Integrated Approach for Diagnosis of Coronary Heart Disease: A Survey.

Kwitowski, A. J., Lewis, W. H., & Mayercheck, W. D. (1989). *Computer-based, teleoperation of a new highwall mining system.* Paper presented at the Robotics and Automation, 1989. Proceedings., 1989 IEEE International Conference on.

Laghari, M. S., Memon, Q. A., & Khuwaja, G. A. (2004). Knowledge based wear particle analysis. *International Journal of Information Technology, 1*(3), 91-95.

Lakhina, A., Crovella, M., & Diot, C. (2005). *Mining anomalies using traffic feature distributions.* Paper presented at the ACM SIGCOMM Computer Communication Review.

Luo, Y., Zhixiang, X., Sun, H., Yuan, S., & Yuan, J. (2015). Research on the induction motor current signature for centrifugal pump at cavitation condition. *Advances in Mechanical Engineering, 7*(11), 1687814015617134.

Malhotra, S., & Soni, M. (2013). Fault diagnosis of induction motor. *European Scientific Journal, 9*(21).

Martins, J. F., Pires, V. F., & Pires, A. (2007). Unsupervised neural-network-based algorithm for an on-line diagnosis of three-phase induction motor stator fault. *IEEE transactions on industrial electronics, 54*(1), 259-264.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). *Imagenet classification with deep convolutional neural networks.* Paper presented at the Advances in neural information processing systems.

Luo, Y., Zhixiang, X., Sun, H., Yuan, S., & Yuan, J. (2015). Research on the induction motor current signature for centrifugal pump at cavitation condition. *Advances in Mechanical Engineering, 7*(11), 1687814015617134.

Masnadi-Shirazi, H., & Vasconcelos, N. (2009). *On the design of loss functions for classification: theory, robustness to outliers, and savageboost.* Paper presented at the Advances in neural information processing systems.

Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*.

Vico, J., Stankovic, D., Voloh, I., Zhang, Z., & Swigost, D. (2010). Enhanced algorithm for motor rotor broken bar detection.

Vitek, O., Janda, M., Hajek, V., & Bauer, P. (2011). *Detection of eccentricity and bearings fault using stray flux monitoring.* Paper presented at the Diagnostics for Electric Machines, Power Electronics & Drives (SDEMPED), 2011 IEEE International Symposium on.

Wan, L., Zeiler, M., Zhang, S., Le Cun, Y., & Fergus, R. (2013). *Regularization of neural networks using dropconnect.* Paper presented at the International Conference on Machine Learning.

McCormick, A. C. (1998). Cyclostationary and higher-order statistical signal processing algorithms for machine condition monitoring. Citeseer.

McFadden, P., & Smith, J. (1984). Vibration monitoring of rolling element bearings by the high-frequency resonance technique—a review. *Tribology international, 17*(1), 3-10.

Mehala, N. (2010). *Condition monitoring and fault diagnosis of induction motor using motor current signature analysis.* National institute of technology kurukshetra, India.

Mellor, P., Roberts, D., & Turner, D. (1991). *Lumped parameter thermal model for electrical machines of TEFC design.* Paper presented at the IEE Proceedings B (Electric Power Applications).

Milanfar, P., & Lang, J. H. (1996). Monitoring the thermal condition of permanent-magnet synchronous motors. *Aerospace and Electronic Systems, IEEE Transactions on, 32*(4), 1421-1429.

Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2012). *Foundations of machine learning*: MIT press.

Moreno, J. F., Hidalgo, F. P., & Martinez, M. (2001). *Realisation of tests to determine the parameters of the thermal model of an induction machine.* Paper presented at the Electric Power Applications, IEE Proceedings.

Nasira, G., Kumar, S. A., & Kiruba, M. S. (2008). A Comparative Study Of Fuzzy Logic With Artificial Neural Networks Algorithms In Clustering. *Journal of Computer Applications, 1*(4), 6.

Okoro, O. (2005). Steady and transient states thermal analysis of a 7.5-kW squirrel-cage induction machine at rated-load operation. *Energy Conversion, IEEE Transactions on, 20*(4), 730-736.

Palem, G. (2013). Condition-based maintenance using sensor arrays and telematics. *arXiv preprint arXiv*:1309.1921.

Paoletti, G., & Golubev, A. (1999). *Partial discharge theory and applications to electrical systems.* Paper presented at the Pulp and Paper, 1999. Industry Technical Conference Record of 1999 Annual.

Parra, L., Deco, G., & Miesbach, S. (1996). Statistical independence and novelty detection with information preserving nonlinear maps. *Neural Computation, 8*(2), 260-269.

Payne, D., Ball, A., & Gu, F. (2002). Detection and diagnosis of induction motor faults using statistical measures. *International Journal of COMADEM, 5*(2), 5-19.

Penman, J., Sedding, H., Lloyd, B., & Fink, W. (1994). Detection and location of interturn short circuits in the stator windings of operating motors. *Energy Conversion, IEEE Transactions on, 9*(4), 652-658.

Pham, D., & Pham, P. (1999). Artificial intelligence in engineering. *International Journal of Machine Tools and Manufacture, 39*(6), 937-949.

Picazo-Ródenas, M. J., Antonino-Daviu, J., Climente-Alarcon, V., Royo-Pastor, R., & Mota-Villar, A. (2015). Combination of noninvasive approaches for general assessment of induction motors. IEEE Transactions on Industry Applications, 51(3), 2172-2180.

Premrudeepreechacharn, S., Utthiyoung, T., Kruepengkul, K., & Puongkaew, P. (2002). *Induction motor fault detection and diagnosis using supervised and unsupervised neural networks*. Paper presented at the Industrial Technology, 2002. IEEE ICIT'02. 2002 IEEE International Conference on.

Radhika, S., Sabareesh, G., Jagadanand, G., & Sugumaran, V. (2010). Precise wavelet for current signature in 3ϕ IM. *Expert Systems with Applications*, *37*(1), 450-455.

Riley, C. M., Lin, B. K., Habetler, T. G., & Kliman, G. B. (1997). *Stator current-based sensorless vibration monitoring of induction motors.* Paper presented at the Applied Power Electronics Conference and Exposition, 1997. APEC'97 Conference Proceedings 1997., Twelfth Annual.

Riley, C. M., Lin, B. K., Habetler, T. G., & Kliman, G. B. (1999). Stator current harmonics and their causal vibrations: a preliminary investigation of sensorless vibration monitoring applications. *Industry Applications, IEEE Transactions on*, *35*(1), 94-99.

Sadri, H. (2004). Induction Motor Broken Rotor Bar Fault Detection Using Wavelet Analysis. *Master's Thesis, Iran University of Science & Technology*.

Shi, L., Sun, Z., Li, H., & Liu, W. (2007). *Research on diagnosing coronary heart disease using fuzzy adaptive resonance theory mapping neural networks.* Paper presented at the Control and Automation, 2007. ICCA 2007. IEEE International Conference on.

Shyu, M.-L., Chen, S.-C., Sarinnapakorn, K., & Chang, L. (2003). A novel anomaly detection scheme based on principal component classifier: DTIC Document.

Siddique, A., Yadava, G., & Singh, B. (2003). *Applications of artificial intelligence techniques for induction machine stator fault diagnostics: review.* Paper presented at the Diagnostics for Electric Machines, Power Electronics and Drives, 2003. SDEMPED 2003. 4th IEEE International Symposium on.

Siddiqui, K. M., & Giri, V. (2012). *Broken rotor bar fault detection in induction motors using wavelet transform.* Paper presented at the Computing, Electronics and Electrical Technologies (ICCEET), 2012 International Conference on.

Siddiqui, K. M., Sahay, K., & Giri, V. (2014). Health Monitoring and Fault Diagnosis in Induction Motor-A Review. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 3*(1), 6549-6565.

Stikeleather, L. F. (1976). Review of ride vibration standards and tolerance criteria: SAE Technical Paper.

Styvaktakis, E., Bollen, M. H., & Gu, I. Y. (2002). Expert system for classification and analysis of power system events. *Power Delivery, IEEE Transactions on, 17*(2), 423-428.

Sun, J., Xie, Y., Zhang, H., & Faloutsos, C. (2007). *Less is more: Compact matrix representation of large sparse graphs.* Paper presented at the Proceedings of 7th SIAM International Conference on Data Mining.

Tandon, N., Yadava, G., & Ramakrishna, K. (2007). A comparison of some condition monitoring techniques for the detection of defect in induction motor ball bearings. *Mechanical systems and signal processing*, 21(1), 244-256.

Thomson, W. T., & Fenger, M. (2001). Current signature analysis to detect induction motor faults. *Industry Applications Magazine, IEEE, 7*(4), 26-34.

Thottan, M., & Ji, C. (2003). Anomaly detection in IP networks. *Signal Processing, IEEE Transactions on, 51*(8), 2191-2204.

Toliyat, H. A., Nandi, S., Choi, S., & Meshgin-Kelk, H. (2012). *Electric Machines: Modeling, Condition Monitoring, and Fault Diagnosis*: CRC Press.

Torkaman, H., Afje, E., & Yadegari, P. (2012). Static, dynamic, and mixed eccentricity faults diagnosis in switched reluctance motors using transient finite element method and experiments. *Magnetics, IEEE Transactions on, 48*(8), 2254-2264.

Trutt, F. C., Sottile, J., & Kohler, J. L. (2002). Online condition monitoring of induction motors. *Industry Applications, IEEE Transactions on, 38*(6), 1627-1632.

Tsang, A. H. (1995). Condition-based maintenance: tools and decision making. *Journal of Quality in Maintenance Engineering, 1*(3), 3-17.

V Spyropoulos, D., & D Mitronikas, E. (2013). A Review on the Faults of Electric Machines Used in Electric Ships. *Advances in Power Electronics, 2013*.

Valyon, J., & Horváth, G. (2003). A weighted generalized ls-svm. *Periodica Polytechnica Electrical Engineering*, 47(3-4), 229-252.

Vas, P. (1993). *Parameter estimation, condition monitoring, and diagnosis of electrical machines*: Oxford University Press, USA.

Vas, P. (1999). *Artificial-intelligence-based electrical machines and drives: application of fuzzy, neural, fuzzy-neural, and genetic-algorithm-based techniques* (Vol. 45): Oxford University Press.

Vico, J., Stankovic, D., Voloh, I., Zhang, Z., & Swigost, D. (2010). Enhanced algorithm for motor rotor broken bar detection.

Vitek, O., Janda, M., Hajek, V., & Bauer, P. (2011). *Detection of eccentricity and bearings fault using stray flux monitoring*. Paper presented at the Diagnostics for Electric Machines, Power Electronics & Drives (SDEMPED), 2011 IEEE International Symposium on.

Wang, X., & Elbuluk, M. (1996). *Neural network control of induction machines using genetic algorithm training.* Paper presented at the Industry Applications Conference, 1996. Thirty-First IAS Annual Meeting, IAS'96., Conference Record of the 1996 IEEE.

Widodo, A., & Yang, B.-S. (2007). Application of nonlinear feature extraction and support vector machines for fault diagnosis of induction motors. *Expert Systems with Applications, 33*(1), 241-250.

Widodo, A., Yang, B.-S., & Han, T. (2007). Combination of independent component analysis and support vector machines for intelligent faults diagnosis of induction motors. *Expert Systems with Applications*, *32*(2), 299-312.

Yam, R., Tse, P., Li, L., & Tu, P. (2001). Intelligent predictive decision support system for condition-based maintenance. *The International Journal of Advanced Manufacturing Technology*, 17(5), 383-391.

Yamamura, S. (1979). Theory of linear induction motors. *New York, Halsted Press, 1979. 246 p., 1*.

Yang, H., Mathew, J., & Ma, L. (2003). Vibration feature extraction techniques for fault diagnosis of rotating machinery: a literature survey.

Ye, Z., Wu, B., & Sadeghian, A. (2003). Current signature analysis of induction motor mechanical faults by wavelet packet decomposition. *Industrial Electronics, IEEE Transactions on, 50*(6), 1217-1228.

Zarei, J. (2012). Induction motors bearing fault detection using pattern recognition techniques. *Expert Systems with Applications, 39*(1), 68-73.

Zhang, J.-W., Zhu, N.-H., Li, Y., Qi, Y., & Qing, L. (2007). A fault diagnosis approach for broken rotor bars based on EMD and envelope analysis. *Journal of China University of Mining and Technology, 17*(2), 205-209.

Zhang, J. S. Y. X. H., & Faloutsos, C. (2007). *Less is more: Compact matrix decomposition for large sparse graphs.* Paper presented at the Proceedings of the Seventh SIAM International Conference on Data Mining.

Zhang, P., Du, Y., Habetler, T. G., & Lu, B. (2011). A survey of condition monitoring and protection methods for medium-voltage induction motors. *Industry Applications, IEEE Transactions on, 47*(1), 34-46.

Zhang, Z., Ren, Z., & Huang, W. (2003). A novel detection method of motor broken rotor bars based on wavelet ridge. *Energy Conversion, IEEE Transactions on, 18*(3), 417-423.

Zolfaghari, S., Noor, M., Bahari, S., Mariun, N., Marhaban, M. H., Mehrjou, M. R., & Karami, M. (2014). *Broken rotor bar detection of induction machine using wavelet packet coefficient-related features.* Paper presented at the Research and Development (SCOReD), 2014 IEEE Student Conference on.