FAULT DETECTION AND DIAGNOSIS OF INDUCTION MOTORS USING THE FUZZY MIN-MAX NEURAL NETWORK AND THE CLASSIFICATION AND REGRESSION TREE

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by

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AI	Artificial Intelligence
AC	Alternating Current
ADC	Analog-to-Digital Converter
AE	Acoustic Emission
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
ARTMAP	Adaptive Resonance Theory MAPping
BOM	Bill of Materials
CART	Classification and Regression Trees
CI	Computational Intelligence
CIMS	Center for Intelligent Maintenance Systems
CWRU	Case Western Reserve University
DAB	Data Acquisition Board
DAT	Digital Audio Tape
DAQ	Data Acquisition
DC	Direct Current
DFT	Discrete Fourier Transform
EA	Evolutionary Algorithms
ESD	Electro Static Discharge
FAM	Fuzzy ARTMAP
FDD	Fault Detection and Diagnosis
FEM	Finite Element Method
FFT	Fast Fourier Transform

FMCN	FMM classifier with Compensatory Neurons
FMM	Fuzzy Min-Max
FS	Fuzzy System
GA	Genetic Algorithm
GFMN	General Fuzzy Min-Max
GUI	Graphical User Interface
IC	Integrated Circuit
ID3	Iterative Dichotomizer 3
IAS	Instantaneous Angular Speed
IFAM	Improved Fuzzy ARTMAP
IM	Induction Motor
Ksps	Kilo samples per second
KM	Kaplan–Meier
LED	Light Emitting Diodes
LM	Levenberg-Marquardt
Max	Maximum
MCA	Motor Circuit Analysis
MCSA	Motor Current Signature Analysis
MDS	Motor Diagnostic Software
Min	Minimum
MLP	Multi-Layered Perceptron
MMF	Magneto-Motive Force
NEMA	National Electrical Manufacturers Association
OFDDS	Online Fault Detection and Diagnosis System
PCA	Principal Component Analysis

PCB	Printed Circuit Board
PDF	Probability Density Function
PLS	Partial Least Squares
PSD	Power Spectral Density
PSH	Principal Slot Harmonics
QTA	Qualitative Trend Analysis
RBF	Radial Basis Function
RM	Rotating Machine
ROM	Read Only Memory
RSH	Rotor Slot Harmonics
SPI	Serial Peripheral Interface
SRAM	Static Random-Access Memory
StdDev	Standard Deviation
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
UCI	University of California, Irvine
USB	Universal Serial Bus
WPD	Wavelet Packet Decomposition

PENGESANAN KEROSAKAN DAN DIAGNOSIS MOTOR ARUHAN DENGAN MENGGUNAKAN RANGKAIAN KABUR MIN-MAX DAN POKOK KLASIFIKASI DAN REGRESI

ABSTRAK

Dalam tesis ini, satu pendekatan baru untuk mengesan kerosakan dan mendiagnosis Motor Aruhan (IMs) yang komprehensif menggunakan rangkaian Kabur Min-Max (FMM) dan Pokok Klasifikasi dan Regresi (CART) dicadangkan. Model pintar gabungan, yang dikenali sebagai FMM-CART, mengeksploitasi kelebihan kedua-dua FMM dan CART untuk masalah pengelasan data dan pengekstrakan peraturan. Pengubahsuaian terhadap FMM dan CART diperkenalkan untuk memastikan model pintar gabungan yang terhasil bekerja dengan cekap. Untuk membandingkan prestasi FMM-CART, data penanda aras dari kerosakan alas motor dan repositori pembelajaran mesin UCI digunakan untuk analisis, dan keputusan dibincangkan dan dibandingkan dengan keputusan daripada kaedah lain. Hasil kajian menunjukkan bahawa FMM-CART mampu mendapatkan kadar ketepatan yang setanding, sekiranya tidak lebih baik, berbanding dengan yang dilaporkan dalam literatur. Kemudian, model IM disimulasikan dengan pelbagai kerosakan, dan diikuti dengan satu siri eksperimen ke atas IM sebenar. Teknik pemantauan keadaan tidak invasif, iaitu teknik Analisis Tandatangan Motor Semasa (MCSA), digunakan untuk mewujudkan satu pangkalan data yang terdiri daripada tandatangan semasa pemegun di bawah keadaan kerosakan yang berbeza. Beberapa nilai harmonik diekstrak daripada Ketumpatan Kuasa Spektral (PSD) bagi tandatangan arus motor, dan digunakan sebagai ciri masukan diskriminasi untuk mengesan kerosakan dan diagnosis dengan FMM-CART. Satu senarai komprehensif keadaan kerosakan IM, iaitu bar pemutar patah, bekalan kuasa yang tidak seimbang, kerosakan pemegun, dan masalah kesipian, telah berjaya dikelaskan menggunakan

FMM-CART dengan kadar ketepatan yang baik, iaitu lebih daripada 98.53% dengan gabungan semua keadaan kerosakan dan bebas kerosakan. Keputusan adalah setanding dengan, jika tidak lebih baik daripada, yang dilaporkan dalam literatur. Peraturan penjelasan yang berguna dalam bentuk pokok keputusan daripada FMM-CART dapat digunakan untuk analisa dan pemahaman keadaan kerosakan IM yang berbeza. Tambahan pula, satu Sistem Pengesanan Kerosakan dan Diagnosis Dalam Talian (OFDDS) yang terdiri daripada papan perolehan data (DAB) and Perisian Motor Diagnostik (MDS) yang direkabentuk sendiri untuk perolehan data dan pengesanan kerosakan dan diagnosis secara dalam talian bagi IM dilaksanakan. OFDDS tersebut mampu mendapatkan tandatangan arus dari dua IM serentak sementara memproses sampel data yang diperoleh dan mengemaskini ramalan keadaan dua IM dalam suatu mod operasi dalam talian. OFDDS tersebut juga mempunyai keupayaan untuk memantau dan mengesan keadaan IM dari jauh dan memberhentikan motor dengan segera jika kerosakan awal dikesan.

FAULT DETECTION AND DIAGNOSIS OF INDUCTION MOTORS USING THE FUZZY MIN-MAX NEURAL NETWORK AND THE CLASSIFICATION AND REGRESSION TREE

ABSTRACT

In this thesis, a novel approach to detecting and diagnosing comprehensive fault conditions of Induction Motors (IMs) using an Fuzzy Min-Max (FMM) neural network and the Classification and Regression Tree (CART) is proposed. The model, known as FMM-CART, exploits the advantages of both FMM and the CART for undertaking data classification and rule extraction problems. Modifications to FMM and the CART are introduced in order for the resulting model to work efficiently. In order to compare the FMM-CART performance, benchmark data sets from motor bearing faults and from the UCI machine learning repository are used for analysis, with the results discussed and compared with those from other methods. The results show that FMM-CART is able to obtain comparable, if not better, accuracy rates with respect to those reported in the literature. Then, an IM model is first simulated with various faults, which is then followed by a series of experiments on real IMs. A non-invasive condition monitoring technique, i.e., the Motor Current Signature Analysis (MCSA), is applied to establish a database comprising stator current signatures under different fault conditions. A number of harmonics values are extracted from the Power Spectral Density (PSD) of the motor current signatures, and used as discriminative input features for fault detection and diagnosis with FMM-CART. A comprehensive list of IM fault conditions, *viz*. broken rotor bars, supply unbalanced, stator winding faults, and eccentricity problems, has been successfully classified using FMM-CART with good accuracy rates, i.e., more than 98.53% with all potential faulty and fault-free conditions combined. The results are comparable, if not better, than those reported in the literature. Useful explanatory

rules in the form of a decision tree are elicited from FMM-CART for analysis and understanding of different IM fault conditions. In addition, an Online Fault Detection and Diagnosis System (OFDDS), which comprises a self-designed Data Acquisition Board (DAB) and a Motor Diagnostic Software (MDS), for online data acquisition and fault detection and diagnosis of IMs is implemented. The OFDDS is capable of acquiring current signatures from two IMs simultaneously while processing the acquired data samples and updating the predicted conditions of the two IMs in an online operation mode. The OFDDS also features the ability to remotely monitor and detect various motor conditions and to turn off the IMs if incipient faults are detected.

CHAPTER 1

INTRODUCTION

1.1 Background

In recent years, the demand of early and accurate fault detection and diagnosis (FDD) methods has increased for complex industrial systems to be safer and more reliable, while minimizing the process downtime and unscheduled machine downtime (Aydin et al., 2011). Indeed, every second of downtime contributes to financial losses of a company (Nandi et al., 2005). In general, FDD covers two main parts, i.e., fault detection for determining the system conditions (either normal or abnormal), and fault diagnosis for classifying the system conditions (the type of faults) (Wang, 2008). Fault detection tasks can be in the form of a simple decision, whether the system is working well or something has gone wrong (Martins et al., 2011). Classifying the fault is as important as detecting it, as the fault could be of varying degrees of severity. In this regard, fault diagnosis specifically classifies the existence of fault in a system, which may include isolation of the fault (Reppa & Tzes, 2011).

Faults may occur in a process or an instrument, either independently or simultaneously. Simple faults can be detected by a single measurement. However, in complex systems, it is difficult to directly measure process states. As such, more elaborate and automated measures are necessary. Automating FDD for condition-based maintenance can assist in reducing wastage caused by poorly maintained, degraded, and/or improperly controlled equipment (Han et al., 2011). As an example, FDD in the operation of chillers (Cui & Wang, 2005; Han et al., 2011) has resulted in less expensive repairs, timely maintenance, and shorter downtimes. Other examples of FDD applications include a class of nonlinear systems with modelling uncertainties (Huang & Tan, 2009). To detect faults in robotic systems, a combination of FDD with artificial neural networks (ANNs) has been used (Huang et al., 2007a). Besides, FDD systems have been employed for improving safety, reliability, and availability of nuclear power plants (Ma & Jiang, 2011) and steam turbine power plant (Salahshoor et al., 2010). All these demonstrate the importance of FDD in complex systems.

One of the key demands of FDD in complex system is on motors. Motors are used in many applications to transform electrical energy into mechanical energy (Saidur, 2010). In general, electric motors can be classified by the source of electrical power, i.e., either Alternating Current (AC) or Direct Current (DC). Among different types of AC motors, induction motors (IMs) contribute more than 60% of the electrical energy consumed (Cusidó et al., 2008). IMs are widely used in different areas, which include manufacturing machines, belt conveyors, cranes, lifts, compressors, trolleys, electric vehicles, pumps, and fans (Montanari et al., 2007). Indeed, IMs are the workhorses of a lot of complex systems, owing to their rugged configuration, versatility, and simple operation capability.

While IMs are reliable, it is common to have situations where these motors malfunction, owing to wear and tear as well as other inter-related causes in complex systems. Indeed, failure of a single motor could potentially shut the entire production line (Penman et al., 1994). In daily usage, IMs are subject to unavoidable stresses, such as electrical, environmental, mechanical, and thermal stresses, which could lead to faults in different parts of the motor (Bonnett & Soukup, 1988). It is imperative to avoid sudden breakdowns of these motors, as a direct influence on production, which may result in substantial productivity losses, could occur. As explained earlier, an effective FDD method can reduce maintenance expenses by preventing unscheduled downtimes. In recent years, a lot of investigations on monitoring IM faults have been reported, with the aim to reduce maintenance costs and to prevent unscheduled downtimes (Martins et al., 2011). A detailed review is presented in Chapter 2.

Ideally, an FDD method should require minimum information from the process/instrument under monitoring while quickly determining its condition (Bellini et al., 2008). In general, FDD methods can be broadly classified into two: model-based and model-free methods. In order for model-based FDD methods to be highly effective, the system model must be known and must be accurate. However, a good model of an IM system not only is difficult to obtain, but also may be inaccurate owing to component values, parasitic components, and unavoidable limitations (Diallo et al., 2005). In this aspect, quantitative FDD approaches which do not require process models (i.e., model-free methods) have attracted much interest lately.

Pattern recognition methods provide an approach to solving FDD problems, whereby an exact process model is not known or is very complicated (Sorsa & Koivo, 1993). The task of pattern recognition is carried out daily by humans, without much conscious effort. Humans receive patterns using sensing organs, in which the patterns acquired are processed by the brain to form useful information, and subsequently, a decision for action to be taken for the patterns is made (Duda et al., 2002). Research in pattern recognition has inspired researchers from many disciplines owing to its cross-fertilization nature, which include physics, cognitive science, engineering, mathematics, and computer science (Wang, 2003). In general, the task of pattern recognition can be divided into two stages (Young & Calvert, 1974; Duda et al., 2002):

- *Feature Extraction*: Procedure of finding and mapping features from an input pattern, and then transforming the input features using some selected functions so as to provide informative measurements for the input pattern.
- *Pattern Classification*: Procedure for categorizing measurements that are taken from the extracted features, and then subsequently assigning the input pattern to one of the target classes by applying some forms of decision rule.

As part of the pattern recognition approaches, FDD methods based on intelligent learning systems have been investigated owing to their fast and robust implementation, their performance in learning arbitrary nonlinear mappings, and their ability for pattern recognition and association (Maki & Loparo, 1997). The focus of this research is to extract and classify faults in IMs using intelligent learning systems. In order to analyse and interpret the acquired signals from IMs, feature extraction is an important step in a pattern recognition task (Pittner & Kamarthi, 1999). One of the earliest approaches was statistical methods (Fisher, 1936; Rao, 1948). However, one of the weaknesses of statistical approaches is inefficiency in handling contextual or structural information in patterns (Pal & Pal, 2002). Hopcroft and Ullman (1979) turned to the theory of formal languages due to this weakness, and explained the usage of syntactic approaches for pattern classification. Classified patterns in the syntactic approaches are not represented as arrays of numbers; rather they are described in simple sub-elements, called primitives. For an idealized pattern, this approach works well, but is inefficient in handling noisy and distorted patterns (Pal & Pal, 2002).

Another useful approach to pattern recognition is intelligent systems based on Computational Intelligence (CI). CI is an interdisciplinary emerging field that is useful for designing and developing intelligent systems (Jain et al., 2008). In the following sections, an introduction to CI is first given. This is followed by the motivations for developing CI systems, as undertaken in this research. The research objectives and scope are then explained, which is followed by the research methodology. Finally, an overview of the organization of this thesis is presented.

1.2 Computational Intelligence

CI is a term used to describe an attempt to achieve smart solutions, with the aid of computers, in complex situations, imperfect domains, or practical problems that are hard or impossible to solve effectively (Dounias & Linkens, 2004). Unlike computers, humans learn naturally on what needs to be done, and how to get it done. The information-processing ability of the human brain emerges primarily from the interactions of networks of neurons (Kolman & Margaliot, 2009). The field of CI has evolved with the objective for developing machines that can think like humans, such as microwave ovens and washing machines that decide on their own what settings to use in order to perform their tasks optimally (Chen, 2010).

One of the earliest definitions of CI is given by Bezdek (1994), as:

> *"A system is computationally intelligent when it: deals with only numerical (low-level) data, has pattern recognition components, does not use knowledge in the AI sense; and additionally when it (begins to) exhibits i) computational adaptivity, ii) computational fault tolerance, iii) speed approaching human-like turnaround and iv) error rates that approximate human performance."*

Besides, Fogel (1995) explained CI as:

> *"... these technologies of neural, fuzzy, and evolutionary systems were brought together under the rubric of computational intelligence, a relatively new trend offered to generally describe methods of computation that can be used to adapt solutions to new problems and do not rely on explicit human knowledge".*

Based on Fogel (1995), one can see that various CI models, i.e., ANNs and Fuzzy Systems (FSs), can be combined to form integrated systems. An introduction to individual CI models (i.e., ANNs and FSs), is first provided. This is followed by an explanation on CI models.

McCulloch and Pitts (1943) sought to understand the organizing principles of the mind. They initiated mathematical modelling of neurons, which aimed to imitate this structure using ANNs. ANNs can be viewed as a mathematical representation, loosely inspired by the massively connected set of neurons that form the biological ANNs in the brain (Chen, 2010). The ability of ANNs to learn and generalize from examples can be developed using suitable training algorithms (Kolman & Margaliot, 2009). Some of the popular ANN models include the Multi-Layered Perceptron (MLP) network (Rumelhart & Zipser, 1986; Bishop, 1995), Hopfield network (Hopfield, 1982; 1984), and Radial Basis Function (RBF) network (Broomhead & Lowe, 1988; Moody & Darken, 1989).

FSs, on the other hand, process information in a different form. FSs are based on a set of If-Then rules stated using natural language (Kolman & Margaliot, 2009). Zadeh (1965) introduced fuzzy sets with an attempt to reconcile mathematical modelling and human knowledge in the engineering sciences. Fuzzy logic provides a framework to model the perception process, uncertainty, human way of thinking, and reasoning (Abraham, 2005). The main attribute of fuzzy logic is the robustness of its interpolative reasoning mechanism. A fuzzy expert system, commonly used to reason about data, uses a collection of fuzzy membership functions and rules instead of Boolean logic.

Further advancement has resulted in the development of integrated CI models, and this area has evolved in recent years. While each CI paradigm has its own advantages and disadvantages, integrating CI models exploit the advantages of different CI paradigms and, at the same time, avoid their shortcomings (Jain et al., 2008). The integration of different models aims to overcome the limitations of individual techniques, which can be resolved by fusion of various techniques. Based on the background of CI in this section, the next section focuses on problems and motivations of this research.

1.3 Problems and Motivations

IMs are widely used worldwide and often in critical applications where the motors reliability must be at high standards (Ghate & Dudul, 2010). As an example, three-phase IMs make up 87% of the total AC motors used in Europe (Frost & Sullivan, 2003; Almeida, 2006; Commission EC, 2009). These IMs are exposed to a wide variety of environments, and coupled with the natural aging process of any machine; make these motors subject to various faults. These faults, which can occur in different parts of the motor, contribute to the degradation and eventual failure of the motors, if left undetected (Ghate & Dudul, 2010). As shown in Figure 1.1, a comprehensive list of IM faults includes bearing, stator, rotor and other related faults, as reported by Electric Power Research Institute (IAS Motor, 1985; Rodríguez et al., 2008).

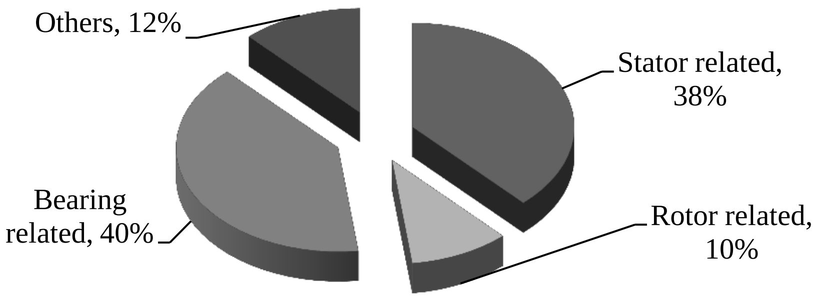

Figure 1.1. Failure Surveys by Electric Power Research Institute
(Source: Rodríguez et al., 2008)

Researchers have used different monitoring techniques with various types of ANNs to detect and diagnose these faults. In faults relating to bearing and eccentricity, Adaptive Neuro-Fuzzy Inference Systems (ANFIS) has been used by Lei et al. (2008) and Zhang et al. (2010), ANN with Back Propagation (BP) by Hwang et al. (2009) and Taplak et al. (2006). Other ANNs used are the RBF (Önel et al., 2009), fuzzy ARTMAP (Xu et al., 2009), Support Vector Machine (SVM) (Widodo & Yang, 2008; Samanta & Nataraj, 2009) and Adaptive Resonance Theory (ART)-Kohonen (Han et al., 2007). Multil-Layered Perceptron with BP (Bouzid et al., 2008) has been used for stator-related faults. For rotor-related faults, MLP (Sadeghian et al., 2009; Arabacı & Bilgin, 2010), multiple discriminant analysis (Ayhan et al., 2005), fuzzy wavelet ANN (Guo et al., 2008), and Kalman algorithm (Ondel et al., 2008) have been used. ANFIS (Ballal et al., 2007) and RBF (Ghate & Dudul, 2010) were used for detection of both bearing and stator faults. For combination of both bearing and rotor faults, MLP was used by Su and Chong (2007) and Lee et al. (2010), SVM by Nguyen et al. (2008), a CART-ANFIS model by Tran et al. (2009) and fuzzy system by Liu et al. (2009).

Majority of these investigations only focus on a single fault or two faults, out of the four main faults (further details on the various condition monitoring techniques with ANN types is described in Chapter 2, Section 2.4). In this research, the major faults: bearing-related, stator-related, rotor-related and others, as shown in Figure 1.1 are taken into account. In addition, the FDD system should be able to function as a single-source condition monitoring technique in a non-invasive manner, with the ability of online learning and capability of rule extraction. This forms the motivations of this research.

In this research, ANNs are explored as an alternative to model-based techniques that use mathematical models of an IM, in order to avoid the requirement of a detailed knowledge pertaining to motor components (Aydin et al., 2007). ANN techniques require no detailed analysis of the fault mechanism, nor is any modeling of the system required (Filippetti et al., 2000). ANNs are commonly used to solve pattern recognition and classification problems, as they are capable of handling non-linear as well as noise-corrupted data from real environments. However, some ANN models such as RBF and MLP suffer from catastrophic forgetting (Polikar et al., 2000; 2001). This occurs when the ANN models fail to remember previously learned information while attempting to learn new information incrementally (Polikar et al., 2000; 2001). This catastrophic forgetting phenomenon is also known as the stability-plasticity dilemma, i.e., how a learning system is able to retain the stored memory while learning new information (Carpenter & Grossberg, 1987; 1988). Indeed, in real world environments, data samples increase with time, and it is crucial for an ANN to be able to learn these samples in an incremental and autonomous manner.

Simpson proposed two different ANNs; one for pattern classification (Simpson, 1992) and another for pattern clustering (Simpson, 1993). The pattern classification Fuzzy Min-Max (FMM) network is a supervised learning model, while the pattern clustering FMM network is an unsupervised learning model. Simpson (1992) explained that the supervised FMM network possesses some useful and important properties in handling pattern recognition and classification problems, which include online learning, nonlinear separability, no overlapping between classes, and quick training time. (The properties of FMM are further detailed in Section 3.2.1)

Owing to the advantages of the supervised FMM network (hereafter simplified as FMM), it has been chosen in this research. However, FMM is not free from limitations. One criticism of FMM (as well as other ANN models), which is especially crucial for FDD tasks, is the inability to explain its predictions. Most ANNs, which include FMM, are known as black-boxes (Benitez et al., 1997; Kolman & Margaliot, 2005). In order to explain the predictions, various ANN rule extraction techniques have been introduced. Two important properties that a rule extraction method should possess is prediction accuracy and rule comprehensibility (Taylor & Darrah, 2005). Based on various rule extraction approaches, one commonly used approach is to build a decision tree from the training samples, and extract rules from it (Pal & Chakraborty, 2001). An important feature of decision trees is their capability to break down a complex decision-making process into a collection of simpler decisions, therefore providing an easily interpretable solution (Mitra et al., 2002).

The concept of decision trees has become popular by the introduction of Iterative Dichotomizer 3 (ID3) (Quinlan, 1986). However, ID3 is not suitable in problems with numerical values. As many real world problems deal with numeric and continuous data samples, these samples have to be discretized prior to attribute selection when ID3 is used (Mitra et al., 2002). On the other hand, Classification and Regression Trees (CART) (Breiman et al., 1984) does not require a *priori* partitioning or discretization of data samples. CART is a classification method that uses historical data to construct decision trees. A tree is formed of nodes and branches, after the feature space is partitioned. Each node has either no child nodes (called a leaf node) or has one and more child nodes. Some of the useful properties of CART include the ability to effectively handle large data sets and noisy data (Breiman et al., 1984; Steinberg & Colla, 1995). (The properties of CART are further detailed in Section 3.3.1)

Owing to the advantages of CART, it has been selected in this research for rule extraction purposes. In order for both FMM and CART to work efficiently, modifications to both models are introduced in this research. The resulting FMM-CART model is able to overcome the limitations of individual FMM and CART models, and, at the same time, to produce an intelligent learning system with online learning and rule explanation capability. In the next section, the research objectives and scope are explained.

1.4 Research Objectives and Scope

The main aim of this research is to design and develop a CI model that capitalises the advantages of both FMM and CART for FDD of IMs. FMM has the advantage of one-pass training with online learning capabilities while CART provides rule extraction capability in an easy to understand manner. They form ideal candidates for designing an effective FDD system. The research objectives are as follows:

1) to design a computational model combining FMM and the CART with the capabilities of online learning and rule extraction, and to evaluate its performance using benchmark data;
2) to develop an FDD system based on FMM-CART with the capabilities of handling comprehensive IM faults from a single source of input in a non-invasive manner;
3) to evaluate the effectiveness of the FDD system based on simulated data and laboratory experiments, and to implement an online FDD system for IMs.

In this research, IMs represent one of the research scopes. IMs are of focus, being workhorses of many complex systems. The next scope takes into account the usage of model-free methods with CI models. Usage of model-free methods speeds up the development work, when compared to model-based methods, as complicated mathematical models are not needed.

1.5 Research Overview and Research Methodology

An overview of the research is shown in Figure 1.2, and is explained as follows. First, the motivation of this research lies on popularity of IMs in various complex systems, and it is important to perform FDD for IMs, in order to reduce unnecessary financial losses due to process/instrument downtimes. Next, the research problem addresses the need to have a cost-effective FDD system. Based on the literature review, many researchers have used various methods to detect individual or a few IM faults. In this research, a single source, non-invasive monitoring technique for FDD of comprehensive IM faults is proposed. Then, a framework is put in place to develop a CI model capable of both online learning and rule extraction. The CI model capitalises the advantages of both FMM and the CART. In order not to confine to a specific type of IM, various IM sizes (i.e., 0.5 Hp, 1 Hp, and 2 Hp) are evaluated in this research. The main objective is to design and develop the FMM-CART model for FDD of IMs. Simulated and laboratory experiments on IMs with various faults are conducted, with the results analysed. Finally, the research goal is to have an online FDD system for IMs with cost-effective and non-invasive operation. In this aspect, an online system for data acquisition and FDD (hereafter simplified as OFDDS) of IMs is designed and implemented. The Online Fault Detection and Diagnosis System (OFDDS) comprises two parts, i.e., a self-designed

Data Acquisition Board (DAB) for data acquisition of IMs, and the Motor Diagnostic Software (MDS) to process the acquired data samples, and to monitor incipient faults of two IMs simultaneously.

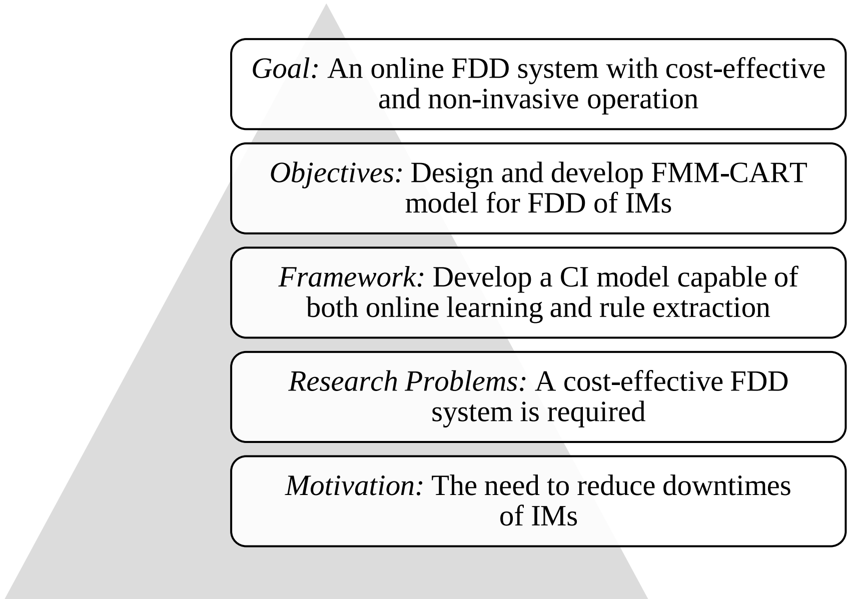

Figure 1.2. Research relationships

A summary of the research methodology is shown in Figure 1.3. In the process of developing FMM-CART model for FDD of IMs, the following steps are performed.

- *Step 1:* Developing a FMM and CART model. Modified FMM is used to enable confidence measure and centroid computation of each hyperbox. In CART, each class of the decision tree is given the confidence factor, based on FMM hyperbox centroids.
- *Step 2:* Benchmarking the FMM-CART model with available data sets. The results are analysed and compared with those from other methods in the literature. This is necessary to benchmark the performance and effectiveness of the FMM-CART model.

- *Step 3:* Simulating IM faults based on a real motor. A total of four common faults (broken rotor bars, supply unbalanced, stator winding faults, and eccentricity problems) are created and simulated using Finite Element Method (FEM). The results are analysed using the bootstrap method to quantify the performances of FMM-CART statistically.
- *Step 4:* Conducting real experiments on IMs in a laboratory environment. The faults created in the motors are similar to those in IM simulations. Again, the results are analysed and quantified using the bootstrap method.
- *Step 5:* Applying the FMM-CART model for online FDD of IMs. An OFDDS, consisting of a DAB is designed and used for data acquisition of two IMs, and an MDS is used to provide simultaneous prediction on the health state of the IMs.

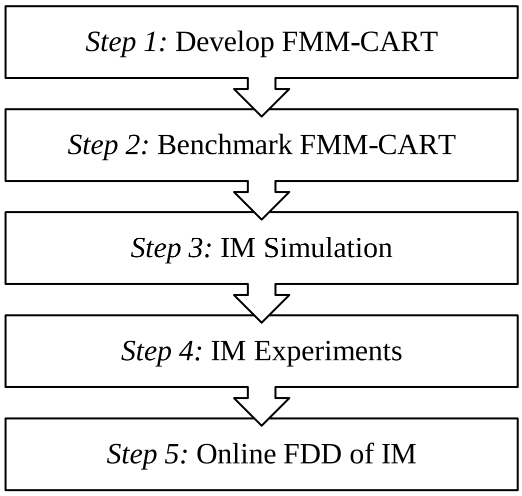

Figure 1.3. Research methodology

1.6 Thesis Outline

This thesis is organised in accordance with the objectives outlined in Section 1.4. A review on IMs and CI systems is presented in Chapter 2. The review first covers various condition monitoring techniques for FDD of IMs. Then, using the quantitative approach, condition monitoring techniques for single and multiple faults, with single and multiple sources are reviewed. Intelligent systems with rules are also reviewed.

The FMM-CART model is introduced in Chapter 3. First, the dynamics of FMM and CART are presented. This is then followed by a detailed description of the modifications of both models. Several experiments are conducted using benchmark data, which include data sets of motor bearings from Case Western Reserve University (CWRU) and Center for Intelligent Maintenance Systems (CIMS), and the results are compared with those from other methods. In addition, the results from the University of California, Irvine (UCI) machine learning data sets (i.e., Iris, Wine, Ionosphere, and Thyroid) are analysed and compared with those from General Fuzzy Min-Max (GFMN) and FMM classifier with Compensatory Neurons (FMCN) (i.e., variants of FMM).

Chapter 4 presents the results from simulations of IMs. An introduction to the motor, its specification, and the simulation process is first provided. Then, the feature extraction process is described. The results from experiments with individual faults (i.e., broken rotor bars, supply unbalanced, stator winding faults, and eccentricity problems) and from experiments with all faults combined are presented and discussed. Finally, a noise-induced simulation is conducted, with the results analysed and discussed.

Laboratory experiments of IMs are presented in Chapter 5. The IM specifications and test setup are detailed. Individual faults along with the methods of creating the faults, are described. Similar to Chapter 4, the experimental results on individual faults and with the faults combined are presented and discussed. A noise-induced experiment is also conducted, again, with the results analysed and discussed.

An online system for data acquisition and FDD of IMs is detailed in Chapter 6. The OFDDS comprises two parts, i.e., a self-designed DAB for data acquisition, and an MDS to process the acquired data samples and to perform FDD of two IMs simultaneously. The OFDDS features the ability to remotely monitor the motor condition and to turn off the IMs if faults are detected.

Finally, conclusions are drawn in Chapter 7. Contributions of this research are presented and a number of areas to be pursued as further work are suggested.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

As explained in Chapter 1, this research focuses on the design and development of CI models for FDD of IMs. As such, a total of nine condition monitoring methods available for FDD of IMs are first reviewed. Next, quantitative methods for FDD of single and multiple IM faults from single and multiple sources are surveyed. Besides, intelligent systems with rule extraction capabilities are reviewed. A summary is given at the end of this chapter.

2.2 Condition Monitoring Methods for Induction Motors

Although IM are reliable, they are subjected to some undesirable stresses, which could lead to some faults and subsequently result in failures (Siddique et al., 2005). The faults can occur in different parts of the motor, with the various parts shown in Figure 2.1 and Figure 2.2. IM condition monitoring methods are performed either online or offline. Offline tests require interruption of motor operations or even shutdown of motors, while online methods offer advance warning of the imminent failures with minimum downtime. Online condition monitoring methods allow the users to acquire the replacement parts on time before the machine malfunctions, thereby reducing outage times (Mehrjou et al., 2011).

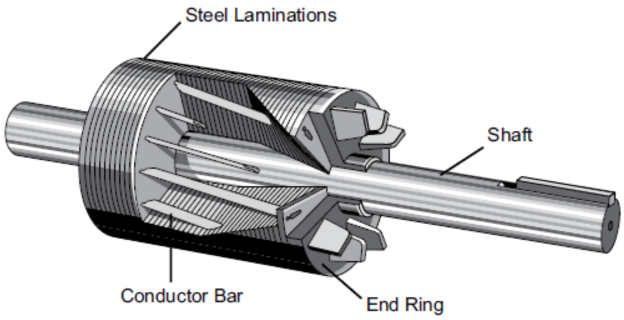

Figure 2.1. Cutaway view of IM rotor
(Source: Siemens, 2011)

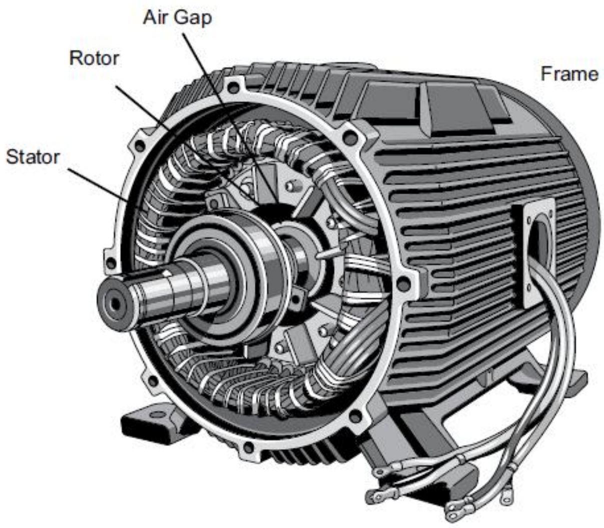

Figure 2.2. Front view of an opened IM
(Source: Siemens, 2011)

Prior to selecting a suitable IM condition monitoring method for this research, a literature review is first conducted. A number of researchers have used various condition monitoring methods for IMs using different machine variables. In the following section, a total of nine condition monitoring methods for FDD are reviewed. This is followed by a summary at end of the section.

(i) Electromagnetic Field

In the normal operation of an IM, the air gap flux varies sinusoidally, in time and space, and any asymmetries in the rotor or stator may cause differences of the sinusoidal variation (Thorsen & Dalva, 1999). Attaching a search coil around the motor shaft enables measurements of any distortion in the air gap flux density due to stator defects (Cameron et al., 1986). For detection of broken rotor bars, Elkasabgy et al. (1992) conducted an analysis using search coils placed internally and externally, in which the induced voltage in the external search coil is adequate for fault detection. The benefit of external stray flux sensors is the sensor can be easily connected to the motor. Sensing air-gap flux can be accomplished by sensing the voltage across two properly located motor coils. The signal can be acquired by subtracting the two voltages, independent of stator *IR*-drop and almost independent of motor leakage reactance drop (Perman et al., 1986; Dorrell et al., 1997). To locate the shorted turn location, four search coils can be placed on the axis, symmetrically to the drive shaft (Penman et al., 1994). The use of internal search coils is a highly invasive condition monitoring technique, and is deemed to be neither economical nor practical for FDD purposes.

(ii) Vibration

In an ideal IM, minimal vibration is generated during operation. Any malfunction in the internal parts may cause an intensive vibration. Kral et al. (2003) emphasized that monitoring vibration signals is a reliable and important technique to detect bearings failures. Vibration can be measured either radially and/or axially with transducers placed on bearings. It is commonly used for mechanical fault diagnosis, i.e., bearing problems, mass unbalance, rotor misalignment, and gear mesh defects (Wang & Gao, 2000; Kral et al., 2003). A main cause of noise production in electrical machines is the resonance between the exciting electromagnetic force and the stator (Singal et al., 1987). Li and Mechefske (2006) concluded that vibration monitoring is best for bearing faults.

(iii) Acoustic Emission

Acoustic Emission (AE) is the phenomenon of transient elastic-wave generation owing to rapid release of strain energy. It is caused by events such as structural alteration in a solid material (Tandon & Choudhury, 1999). In general, AE is used for bearing fault detection. It can be used for rotor fault detection too. In IMs, the noise spectrum is dominated by electromagnetic, ventilation, and acoustic noise. Doubling the motor speed gives up to 12 dB rise in electromagnetic noise (Singal et al., 1987). Interrogation on the ground wall insulation can be conducted by launching an ultrasonic wave into a stator bar, using the conductor as a waveguide (Lee et al., 1994). However, accuracy of broken rotor bars detection is reduced using acoustic measurement in a noisy background, when other machines are operating nearby (Li & Mechefske, 2006).

(iv) Instantaneous Angular Speed

Instantaneous Angular Speed (IAS), a less known condition monitoring technique, refers to variation of the angular speed that occurs within a single shaft revolution (Sasi et al., 2006). The pulsating torque owing to rotor faults modulates or alters the rotor speed, and can be used in rotor fault detection (Sasi et al., 2006). Asymmetry faults in IMs can be detected using IAS to monitor the stator core vibration. Vibration signals in an unbalanced supply and stator winding faults contain a significant component, with twice the supply frequency (Siddique et al., 2005). Gaydon (1979) and Feldman and Seibold (1999) used the IAS monitoring technique to detect the location and size of rotor defects. However, a major obstacle is the motors are assumed to be rotating at a constant speed, while they normally rotate with varying speed.

(v) Air Gap Torque

The air gap torque is produced by currents and flux linkage of a rotating IM. Unbalanced supply in IMs generates harmonics at special frequencies in the air gap torque (Mehrjou et al., 2011). Hsu et al. (1992) showed that the shape of the air gap torque is different between cracked rotor bars and unbalanced stator windings. However, one limitation of air gap torque measurement is that it cannot be performed accurately and directly (Mehrjou et al., 2011). The measured pulsating torque on IMs obtained with torque sensors can be different from the actual value of the air gap torque. This is because the rotor, shaft, and frame of the IM have their own natural frequency. Kral et al. (2005) used the Vienna monitoring method (a method for estimating electromagnetic torque) for inverter-fed IMs using both voltage and current sensors. However, this method is not cost-effective as it requires two different sensors.

(vi) Motor Current Signature Analysis

Motor Current Signature Analysis (MCSA) is a process of sensing stator currents. It uses the results from its spectral analysis to indicate an existing or incipient failure in an IM (Siddique et al., 2005). The stator current is commonly sensed during the normal operation of the IM, with the current drawn having a single component at the supply. Methods for detecting mechanical faults in the IM using MCSA generally ignore the load effects (Benbouzid et al., 1999; Thomson & Fenger, 2001), or assume that the load is known (Kim et al., 2003). As a rotor bar cracks, it restricts the current from flowing through, which results in no magnetic flux around the rotor bar. Any asymmetry in the rotor leads to a non-zero backward rotating field, which induces harmonics in the stator winding currents (Mehrjou et al., 2011). Siau et al. (2004) explored practicality of equations in determining the number of broken rotor bars using the stator current. It is found that the sideband component amplitude is dependent on both the load and the number of broken rotor bars.

(vii) Induced Voltage

Voltage induced along the motor shaft is an indication of the winding or stator core degradation. When an IM supply is disconnected, the stator currents rapidly drop to zero. The induced voltage in the stator is caused by currents in the rotor (Elkasabgy et al., 1992). In a healthy motor, the MMF produced by rotor bar currents when disconnected is predominantly sinusoidal. The voltages induced in the stator windings are directly influenced by broken rotor bars. One requirement is baseline data samples are required when the motor is operating with the normal condition, and the method is sensitive to changes in load, rotor temperature, system inertia, and supply voltage (Supangat et al., 2007). This method is also not practical for continuous condition monitoring as it is difficult to measure faults in a reliable way and it requires significant damage to the core or winding for detecting the fault (Mehrjou et al., 2011).

(viii) Surge Test

A surge comparison test is used for diagnosing winding faults (Kohler et al., 1999). During the test, two identical high voltages, high-frequency pulses are simultaneously imposed with the third phase of the motor winding grounded (Thorsen & Dalva, 1997). An oscilloscope is used to compare reflected pulses, which indicate the insulation faults between coils and windings (Thorsen & Dalva, 1997). Huang et al. (2007b) introduced a method using the surge test to detect rotor eccentricity, which causes an asymmetrical air gap. This leads to a surge waveform shape that changes per revolution, and can be used as an indication of the air gap problem.

(ix) Motor Circuit Analysis

Motor Circuit Analysis (MCA) seeks variations in the motor and identifies defects by measuring the motor electromagnetic properties. In MCA, low amounts of energy are applied, and the amplified responses are used to evaluate the winding and rotor conditions through comparative readings (Penrose & Jette, 2000; Penrose, 2001). Penrose and Jette (2000) used MCA, based on electromagnetic property measurements in the IM, to determine the presence of variation. The technique uses simple testing methods of inductance and resistance, which are taken on a de-energized IM. It is noted that the combination of resistance, impedance, phase angle, and inductance measurements provide a highly accurate view of the IM condition (Penrose & Jette, 2000).

(x) Summary of Induction Motor Condition Monitoring Methods

Based on nine different IM condition monitoring methods surveyed, a summary is given in Table 2.1.