

**Math-model Based Machinery and AI-based Diagnostic Technologies
for Detecting and Locating the Inner-faults of Three-phase
Squirrel-cage Induction Motors**

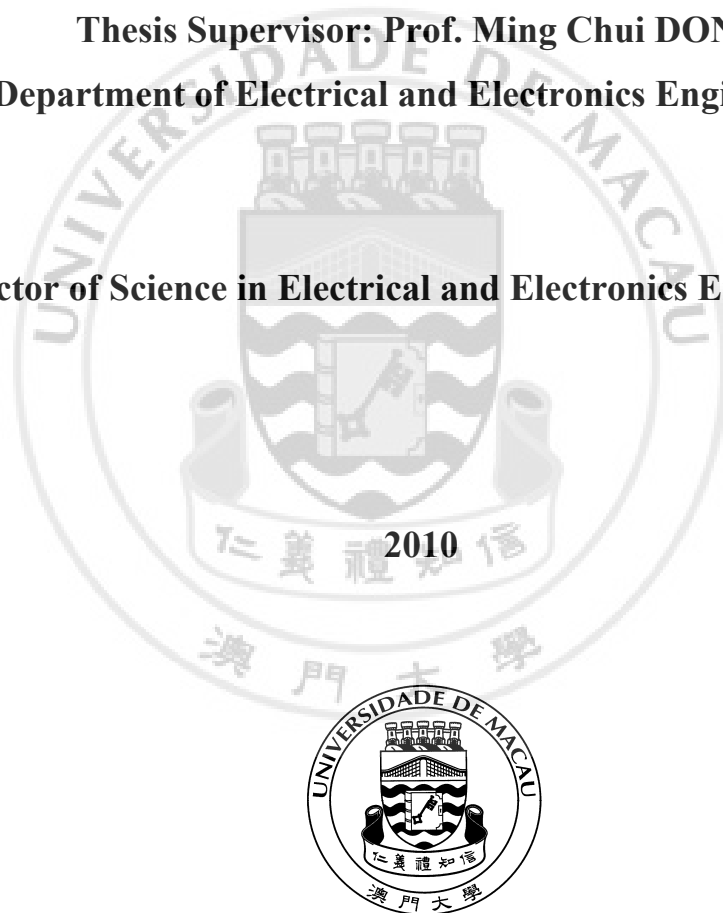
By

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Thesis Supervisor: Prof. Ming Chui DONG

Department of Electrical and Electronics Engineering

Doctor of Science in Electrical and Electronics Engineering



Faculty of Science and Technology

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A thesis submitted in partial fulfillment of the requirements for the degree

of

Doctor of Science in Electrical and Electronics Engineering

Faculty of Science and Technology
University of Macau

2010

澳門大學

Approved by

Supervisor: Prof. Ming Chui DONG

Date

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ABSTRACT

Math-model Based Machinery and AI-based Diagnostic Technologies for Detecting and Locating the Inner-faults of Three-phase Squirrel-cage Induction Motors

by Tak Son CHEANG, Thomas

Thesis Supervisor: Prof. Ming Chui DONG

Induction motors are core elements in many industrial and agricultural applications due to their ruggedness and versatility. The on-site motor monitoring and inner-faults diagnosis might offer early warning of motor fault so that to save motor's life in time, avoid malfunction or disaster of industrial operation. Take Coloane Power Stations A and B of Macau Electricity Company (CEM) as example, there are totally 33 sets induction motors and ever caused 840 hours generation unavailability due to motors' malfunctions in past 5 years, although some commercial motor fault protection systems had been purchased and installed on site. Due to this reason, CEM demands a better fault diagnostic system to detect and correct the motors' malfunction before their operation quality is degraded and the overall system is jeopardized for production, this consequently becomes one of the important reasons to motivate and initiate the dissertation research.

Researches on fault diagnosis of induction motor have been a keen area of interest for more than 33 years in the past. Many researchers have proven that the stator winding inter-turn short circuit and rotor bar broken are the major causes of motor failures. This has prompted researchers to consistently investigate different techniques to diagnose inner-faults of motors.

Researchers initially adapted the traditional methods (math-model based machinery diagnostic methods), such as parameter estimation method, finite element method, multi-loops method and adaptive observer scheme etc., all of them had inevitable drawbacks of relying upon the accurate mathematical model and detailed understanding of motors under consideration. The later appeared signal analysis based diagnostic approaches such as Motor Current Signature Analysis (MCSA), Wavelet Analysis etc. require complicated signal preprocessing procedures such as Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT). On the other hand, some fault symptoms, such as negative phase sequence currents (I_2) and side-band frequencies $(1-2s)f_1$ and $(1+2s)f_1$ for indicating the stator and rotor faults respectively, may sometimes occur due to the imbalance in power supply and imperfection of motor structure. These may lead to motor fault misdiagnosis in above mentioned methods.

In recent years, due to complexity and deficiency of math-model based machinery fault diagnostic technologies, researchers gradually shifted to artificial intelligence (AI) based approaches, such as expert system (ES), fuzzy logic (FL), artificial neural networks (ANN), fuzzy-neural networks (Fuzzy-NN) and other hybrid soft-computing technologies. Each of these approaches has its own advantages and disadvantages in solving fault diagnostic problems. For instance, ANN has advantages of non-linear function approximation and adaptive learning capabilities. Whereas it faces some major drawbacks of requiring digitized input data, high computational burden in networks training, lack of perceptible casual explanation to hypothesis/conclusion etc.; instead ES is advantageous in efficiently handling certainty/uncertainty issues with good explanations to hypothesis/conclusion but faces knowledge acquisition and knowledge base dynamic generalization difficulties, i.e. difficult in acquiring expert's deep and shadow knowledge for constructing dynamic rule base, and also hardly to handle some new strange cases. Some researchers, interested in advantages of both NN and FL, had used the hybrid "Fuzzy – NN" technology to solve fault diagnostic problems recently.

Talking about on-site motor fault detection and diagnosis, the main concerns and difficulties can be listed out as following:

- No obvious symptoms appear while incipient fault occurs;

- Symptoms have large scale differences between each other;
- Symptoms might be caused by true fault or non-fault factors;
- Many variables can affect motor fault diagnostic process and can result in hundreds of possible scenarios under different combinations of these variables;
- Symptoms vary time by time due to variation of circumstance factors;
- No mapping or projective relationship between symptoms and motor faults;
- There exists the serious affection of intrinsic uncertainty, imprecise, dynamic variation in signal measurement;
- Any inaccuracy diagnosis would conduce non-reversal motor damage or production disaster;
- The diagnostic ahead time is as short as few seconds and much too urgent for saving motor's life;
- No existing mature knowledge or experience so far can be used for reference.

The above concerns and difficulties challenge both of hardware/software design and motor fault diagnostic technologies.

Based on the above facts and concerns, my thesis research work, however, has made some significant contributions and achievements on thoroughly studying math-model based machinery and AI-based motor inner-fault diagnostic technologies, as:

- **Novel math-model based machinery motor inner-fault diagnostic technologies**

The “Bi-directional Revolving-Magnetic-Field Theory” was developed to analyze stator winding inter-turn short circuit and inversely connected fault of the stator windings, including investigation of different number of turns and winding factors. That is a novel method to analyze this type of fault with the advantages of using simpler and more accurate math-models than conventional methods. For the rotor bar breakage, two novel methods were proposed to find out the additional stator currents at frequency f_1 and $(1-2s)f_1$ caused by breaking one rotor-bar. No special harmonic measurement tools were needed, which improved the existing signal processing methods. The basic ideas of the first method are based on the “Bi-directional Revolving-Magnetic-Fields Theory” and

the superposition theorem. According to its procedures, the additional stator currents are calculated at frequency f_1 and $(1-2s)f_1$ respectively. Then those stator currents are added to the original stator currents in healthy case so as to form the total fault stator currents while the inner-fault of squirrel-cage rotor occurs. For the second method, based on the hybrid system of 1, 2, 0 axes and d, q, 0 axes, the ratio between the amplitude of the stator current at frequency $(1-2s)f_1$ and that at frequency f_1 is found. Various machine factors, such as saturation effects and fractional pitch, are considered. A new method was proposed to separate the stator and rotor impedances, considering the changes on stator parameters and the effect of harmonics while the inter-turn fault occurs. Some modified math-models and experiments, for example, rotor-drawn-out tests, were proposed for obtaining the actual parameters of faulty motors on-site.

As the results, the solutions of proposed methods are rather promising with the diagnostic error less than 10% and the wide diagnostic range from the slight stator fault (turn to turn) to severe stator fault (inversely connected fault); from one bar broken rotor fault to multi-bar broken rotor fault.

- **Creative APVD method for preprocessing sampled signals**

Even after conditioning and analogue to digital conversion (ADC), the on-site sampled or measured data sets still cannot be directly used by AI-based methods due to their big scale differences. To tackle this problem, a creative data preprocessing method, APVD, was created to convert such input signals to the ones with same scale rank. As discovered from the data sets, phases A, B and C are balanced in the healthy motor, but such a balance is lost when the motor is faulty. The absolute phase value difference (APVD) of input signals between each pair of phases shows a greater variation in the input data sets, which reflects the different fault status. Consequently, the preprocessed results APVDs have been adapted as the input diagnostic symptoms.

- **Innovated method of using on-site pre-measured data sets and experts' rich fault diagnostic knowledge/experiences as basis to construct the fuzzy sets and membership functions so that to diminish the affection of static factors**

A novel technique of constructing the fuzzy sets and membership functions to diminish affection of stator factors was proposed. The data sets, which were obtained through testing the healthy and artificially created faulty motors under mimic quasi-real working circumstance, and experts' rich motor fault diagnostic knowledge/experiences, were further used to construct the fuzzy sets, membership functions, mapping relationship matrix of symptoms vs. faults as well as used for training and testing the AI-based methods. The on-site pre-measured data have absorbed affections of those static factors, i.e. the asymmetry of the motor, slight asymmetrical input voltage, operation saturation and motor misalignment etc. Consequently, when the true fault occurs, the symptoms APVDs could reflect its features caused by true fault only. Based on these, the AI-based approaches proposed in this dissertation could deduce the type and location of true fault and relieve the affection of aforementioned static factors.

- **Explore mapping relationship of symptoms vs. motor faults**

To explore the non-linear mapping relationship between symptoms and various motor faults, the fuzzy sets were defined, and the fuzzy membership functions based on huge on-site pre-measured data sets and their 2-dimension plots and experts' rich motor fault diagnostic knowledge/experiences were constructed. The linguistic hedge was adapted to adjust the slope of membership functions for improving the diagnostic sensitivity. Such non-linear mapping relationship cannot be found in other research papers or text books. Consequently it is the first time in this dissertation to find out such relationship.

- **Create general Bayesian inference model (GBINM) and propose novel method of defining and assigning Bayesian statistical parameters for constructing easily Bayesian inference nets**

To overcome the difficulties of constructing the multistage hierarchical Bayesian inference nets, and fill up the gape of defining and assigning the Bayesian statistical parameters such as prior probability, LS and LN, a creative GBINM and a method for defining/assigning Bayesian statistical parameters for each node in inference nets were proposed. None of research papers or books even gave clear description or clue about such knowledge. This model could illustrate

compactly the combination of all possible factors needed to construct a functional node as well as its connections in forming multistage hierarchical Bayesian inference nets. It was more or less like a branch of tree or branch of networks. The user would just use this branch, define inner formulas according to node's specific functions, link or connect its input and output terminals properly, and construct the tree (or inference nets) easily. The brief name format/Backus-Naur form (BNF) was adapted to express the functions inside of GBINM briefly and more clearly.

- **Multistage hierarchical BFIN-MFD**

Using GBINM as well as the method of defining and assigning the Bayesian statistic parameters, the multistage hierarchical Bayesian inference nets for motor fault diagnosis, BFIN-MFD, were constructed. The dynamic values of Bayesian statistical parameters were defined and assigned through mapping symptoms to membership grades on individual well defined membership function and calculating the propagation of probabilities. The proposed approach not only simplified the process of constructing Bayesian fuzzy inference nets but also made it possible to deduce the inference results faster with high reliability. The testing results have indicated the robustness of BFIN-MFD in presence of all evidences and in absence of some evidences respectively.

- **6-layer FNN-MFD with elaborately designed hardware and software for fast on-site multi motors' inner-faults diagnosis**

The fuzzy neural networks motor fault diagnosis scheme, FNN-MFD, was proposed. With elaborated hardware and software designs as well as high computational capability, this on-site fast motor inner-fault diagnostics clearly and promptly indicates the fault type, location, and severity of running motors to the operators on site. Practically, the output of FNN-MFD was displayed on screen of computer and/or large scale LCD at console side with color/sound/light fault-alarms and auto cut-off controllers to notify the operators and auto/manually cut-off damaged motors in early time. Again, it utilized on-site pre-measured data sets as the basis for constructing the fuzzy sets, membership functions and mapping relationship matrix as well as for network training to reduce the effects of various static factors and increased the diagnostic accuracy.

The proposed technology has been proved to be successful in detecting & locating the multi motors' inner-faults and distinguishing the true fault with static factors.

- **The proposed technologies are adaptable to other engineering applications**

The above AI-based motor inner-fault diagnostic technologies are adaptable to other engineering applications, such as fault detection/diagnosis in circuit boards, IC chips, power systems, machines and equipment etc., and even more complicated human disease prognosis, on which our team is currently researching now.

Key words: Inner-Fault Diagnosis of Induction Motor, Bi-Directional Revolving-Magnetic-Field Theory, Hybrid System of 1, 2, 0 Axes and d, q, 0 Axes, Membership Function, Fuzzy Inference, Absolute Phase Value Difference (APVD), Generalized Bayesian Inference Nets Model (GBINM), Bayesian Fuzzy Inference Nets (BFIN), Fuzzy Neural Networks (FNN).

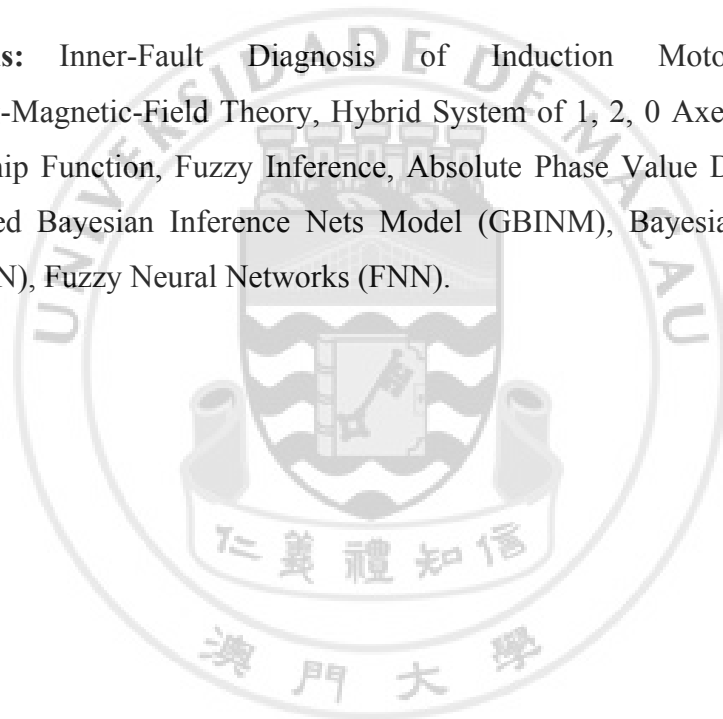


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ACKNOWLEDGMENTS

Being the part-time student, first of all, I would like to express my sincere appreciation to my supervisor, Prof. Ming Chui DONG, for his valuable and inspiring guidance, and strong encouragement during the course of completing this research and preparing this dissertation. I have appreciated the wisdom of his methodology, which encouraged me to think over all the details of this dissertation. I would like to thank for his valuable comments and suggestions, which have improved this dissertation.

Also, I would like to express my thanks to my former supervisor, Prof. Lin Zheng ZHANG, for his valuable guidance during this research of the electrical machinery.

Special thanks to Prof. Rui MARTINS and academician Prof. Ying Duo HAN. They have provided me very helpful comments and supports to my study. They fully understand how hard for a part-time student, and always give me care in releasing my pressure.

Moreover, I would like to acknowledge and thank the M.Sc. colleagues, Mr. Si Leong CHAN and Ms. Booma Devi SEKAR, who worked as a team members on the topics of motor fault diagnosis. Mr. David UG, the laboratory technician, has supported me for the experiment works.

Finally, during the research, I would like to thank for my family members, especially my wife, for their full supports and intensive care. With their love, I can finally complete this dissertation.

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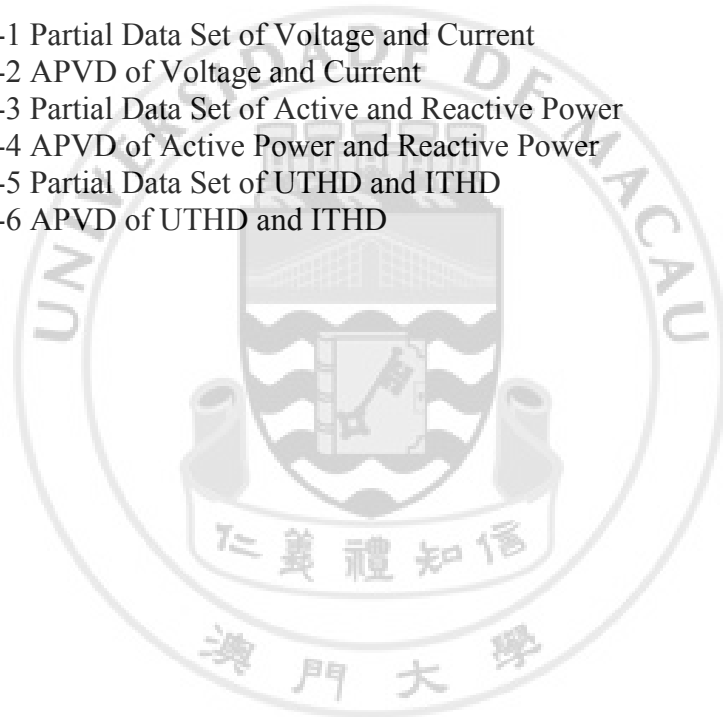
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GLOSSARY

ADC	Analogue to Digital Conversion
AI	Artificial Intelligent Technology
ANN	Artificial Neural Networks
APVD	Absolute Phase Value Difference
AP	Active Power
BFIN	Bayesian Fuzzy Inference Nets
BFIN-MFD	Bayesian Fuzzy Inference Nets for Motor Fault Diagnosis
BNF	Backus-Naur Form
BP	Back-propagation
CCA	Coloane A Power Station in Macau
CCB	Coloane B Power Station in Macau
CEM	Macau Electricity Company
CMOS	Complementary metal–oxide–semiconductor
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
ES	Expert System
emf	Electromotive Force
FFT	Fast Fourier Transform
FF	Feed-Forward
FL	Fuzzy Logic
FNN	Fuzzy Neural Networks
FNN-MFD	Fuzzy Neural Networks for Motor Fault Diagnosis
GA	Gravity-Average
GA	Generic Algorithm
GBINM	Generalized Bayesian Inference Nets Model
I	Current
IM	Induction Motor
ITHD	Total Harmonic Distortion of Current
LN	Likelihood of Necessity
LS	Likelihood of Sufficiency
LS	Least Squares

MB	Membership Belief
MCSA	Motor Current Signature Analysis
MD	Membership Disbelief
MF	Membership Function
MFD	Motor Fault Diagnosis
MLRA	Multiple Linear Regression Analysis
mmf	Magnetomotive Force
NN	Neural Network
PF	Power Factor
RMS	Root Mean Square
RP	Reactive Power
U	Voltage
UTHD	Total Harmonic Distortion of Voltage

