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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

**MODEL-BASED DIAGNOSIS AND PROGNOSIS
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WINDING FAULT**

NGUYEN VIET HUNG

**SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING
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SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING

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Abstract

Induction machines are widely used in industries and essential parts of industrial systems. They are found in various applications of marine propulsion, aerospace actuators, and traction in electric/hybrid vehicles. Despite their rugged construction, they are subject to fault due to aging, severe operating conditions, and harsh environments. Industrial surveys have shown that stator winding accounts for a significant portion of faults in electrical machines. Stator winding inter-turn short is one of the most common root cause of stator winding fault which can spread over and lead to catastrophic damages. Therefore, diagnosis and prognosis of this kind of fault can help increase the availability and reliability of electrical machines and the associated systems, and thereby, reduce maintenance cost, and support maintenance decision making.

Diagnosis is the process of detecting fault occurrence, isolating the true fault from ambiguous factors, and estimating the severity information. Prognosis is subsequent to diagnosis process. It predicts the fault progression and estimates the remaining useful life, the time left before the machine must be stopped. Therefore, early fault detection is critical for an effective prognosis. However, the current research has the limitation on incipient fault detection due to the effects of ambiguous factors including the inherent asymmetry and voltage imbalance. Fault severity estimation/measurement is another essential part of diagnosis process. The fault is represented by two electrical fault parameters, viz. fault loop resistance and percentage of shorted turns, and the estimation of both these direct electrical fault parameters has achieved limited success. Therefore, the early fault detection and fault parameters estimation are required to be further investigated and improved. Regarding prognosis, it has been identified that prognosis using fault parameters for inter-turn fault is a new research to be explored. This has potential to provide an effective prognosis method based on direct physical parameters. This thesis

aims to develop a model-based diagnosis and prognosis framework using the electrical fault parameters and propose techniques to address the aforementioned challenges.

Model-based technique is the key approach to address the challenge of early fault detection under the influence of the ambiguous factors. Its strength lies in the ability to incorporate the electrical fault parameters in the model and hence the analysis of fault effects. Two generic methods are proposed. The first is a multiple-indicators approach, based on the multi-physics nature of electrical machines, in which certain supplementary indicators are concurrently used. The second is a decomposition method in which the effect of fault is decomposed from that of the ambiguous factors, so that a fault-dependent quantity, sensitive to only fault severity level, is extracted.

The electrical fault parameters are direct severity quantities, but they are unknown and unmeasurable. In this thesis, an estimation process is proposed to identify these parameters, linking the diagnosis and prognosis process. The filter-based approach, using particle filter, is applied to estimate the fault parameters. Particle filter is chosen since it can be applied to nonlinear systems under non-Gaussian noises. Also, a significant advantage of particle filter-based approach is that the statistical quantities of the particles can be employed to quantify the performance of remaining useful life estimation results based on the estimates of fault parameters.

Other methods for estimation of electrical fault parameters are also proposed. They are based on unique characteristics of electrical machines. The first method is based on the characteristic of electrical machines under sinusoidal excitation voltages, in which differential equations can be transformed to trigonometry equations, and thereby, a closed-form solution for the estimates of fault parameters can be obtained. The second method is based on the multiple forms of model of electrical machines in which sequence component model is exploited to derive an equality constraint, and the constraint is employed to simplify state-space model, which is used to estimate the fault parameters.

The theoretical development is supported by experimental results, where various fault severity levels and different loads and voltage imbalance conditions are taken into account to validate the incipient fault detection, electrical fault parameter estimation, degradation model identification and remaining useful life prediction. The proposed framework and associated techniques are generic in nature and can be diversified to include other faults/machines.

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List of Abbreviations

1AD	One-Phase Angular Deviation
1OV	One-Phase Overvoltage
1UV	One-Phase Undervoltage
2OV	Two-Phase Overvoltage
2UV	Two-Phase Undervoltage
3OV	Three-Phase Overvoltage
3UV	Three-Phase Undervoltage
AI	Artificial Intelligence
AC	Alternative Current
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average
BL	Balanced Voltage
CBM	Condition-Based Maintenance
DC	Direct Current
DST	Dempster-Shafer Theory
EKF	Extended Kalman Filter
EMF	Electromotive Force
FEM	Finite Element Method
FFT	Fast Fourier Transform
FFNN	Feed-Forward Neural Network
FL	Full-Load
GA	Generic Algorithm
HL	Half-Load
HMM	Hidden Markov Model
ICA	Independent Component Analysis
IM	Induction Machine
IMM	Interacting Multiple Model
KF	Kalman Filter
LMI	Linear Matrix Inequality
MCSA	Motor Current Signature Analysis
MMF	Magnetomotive Force
NN	Neural Network

NL	No-Load
NKF	Nonlinear Kalman Filter
PCA	Principal Component Analysis
PDF	Probability Density Function
PF	Particle Filter
PLS	Partial Least Squares
PMSM	Permanent Magnet Synchronous Motors
RUL	Remaining Useful Life
SOC	State-of-Charge
SOH	State-of-Health
SOL	State-of-Life
SWITS	Stator Winding Inter-Turn Short
SWITSF	Stator Winding Inter-Turn Short Fault
SVM	Support Vector Machine
T-S	Takagi-Sugeno
UKF	Unscented Kalman Filter

List of Notations

as_f	The shorted winding portion of stator phase a
as_h	The healthy winding portion of stator phase a
B	The friction coefficient
γ	The complex number representing the faulty phase
$\boldsymbol{\gamma}$	The vector representing the faulty phase
i_{0r}	The 0-component of rotor currents in stator-fixed reference frame
i_{0s}	The 0-component of stator currents in stator-fixed reference frame
i_{ar}	The current of the equivalent rotor winding phase ar
i_{br}	The current of the equivalent rotor winding br
i_{cr}	The current of the equivalent rotor winding cr
i_{as_f}	The current of the stator winding portion as_f
i_{as_h}	The current of the stator winding portion as_h
i_{bs}	The current of the stator winding bs
i_{cs}	The current of the stator winding cs
i_{dr}	The d -component of rotor currents in stator-fixed reference frame
i_{ds}	The d -component of stator currents in stator-fixed reference frame
i_f	The fault loop current
i_{qr}	The q -component of rotor currents in stator-fixed reference frame
i_{qs}	The q -component of stator currents in stator-fixed reference frame
$\tilde{I}_{rn}$	The negative sequence rotor current
$\tilde{I}_{rp}$	The positive sequence rotor current
$\tilde{I}_{sn}$	The negative sequence stator current
$\tilde{I}_{sp}$	The positive sequence stator current

J	The rotor inertia
λ_{0r}	The 0-component of rotor flux linkage in stator-fixed reference frame
λ_{0s}	The 0-component of stator flux linkage in stator-fixed reference frame
λ_{ar}	The flux linkage of the equivalent rotor winding ar
λ_{br}	The flux linkage of the equivalent rotor winding br
λ_{cr}	The flux linkage of the equivalent rotor winding cr
λ_{as_f}	The flux linkage of the inter-turn winding portion as_f
λ_{as_h}	The flux linkage of the healthy winding portion as_h
λ_{bs}	The flux linkage of the stator winding bs
λ_{cs}	The flux linkage of the stator winding cs
λ_{ds}	The d -component of stator flux linkage in stator-fixed reference frame
λ_{qs}	The q -component of stator flux linkage in stator-fixed reference frame
λ_{dr}	The d -component of rotor flux linkage in stator-fixed reference frame
λ_{qr}	The q -component of rotor flux linkage in stator-fixed reference frame
μ	The fraction of shorted turns in faulty phase
L_{lr}	The rotor winding leakage inductance
L_{ls}	The stator winding leakage inductance
L_{ms}	The stator and rotor magnetizing inductance
N_{as_f}	The number of turns in the faulty winding portion as_f
N_{as_h}	The number of turns in the healthy winding portion as_h
ω_r	The electrical rotor speed
ω_s	The electrical excitation frequency
P	The number of poles
r_f	The fault loop resistance
R_r	The rotor winding resistance
R_s	The stator winding resistance
θ_r	The rotor angle
T_e	The electromagnetic torque
T_L	The load torque
v_{0s}	The 0-component of terminal stator voltages in stator-fixed reference frame
v_{as_f}	The terminal voltage of the stator winding portion as_f
v_{as_h}	The terminal voltage of the stator winding portion as_h
v_{bs}	The terminal voltage of the stator winding bs
v_{cs}	The terminal voltage of the stator winding cs

v_{ds}	The d -component of terminal stator voltages in stator-fixed reference frame
v_{qs}	The q -component of terminal stator voltages in stator-fixed reference frame
$\tilde{V}_{sn}$	The negative sequences stator voltage
$\tilde{V}_{sp}$	The positive sequences stator voltage
$y(1 : k)$	The values of y at instants from 1 to k
$z(k)$	The value of z at instant k
Z_{nn}	The negative sequence impedance
Z_{pp}	The positive sequence impedance
Z_{pn}	The cross-sequence impedance from negative to positive model
Z_{np}	The cross-sequence impedance from positive to negative model

Chapter 1

Introduction

1.1 Background

1.1.1 CBM

Reliability and availability of industrial systems can be significantly improved by maintenance process. It has a long history consisting of three main techniques. The earliest technique is run-to-failure, in which the maintenance activities are implemented at breakdowns. It is very lagging strategy since the systems have suffered severe damage at the time of maintenance. Time-based technique periodically performs maintenance activities. Since it implements maintenance without exactly knowing the actual condition of real systems, it may be ineffective and costly if the maintenance is not needed yet or overdue. CBM technique can overcome the limitations of the former techniques by implementing maintenance strategy based on the actual condition of the systems, which is monitored through diagnosis and prognosis processes. Fig. 1.1 is the overview of maintenance methods in term of complexity and benefits. CBM, with its advantage of cost saving, efficiency, and timely maintenance scheduling, is the current trend of modern monitoring systems.

Fig. 1.2 is the block diagram of a CBM system. In the diagram, diagnosis process performs fault detection, isolation, and identification, while prognosis is the process subsequent to diagnosis. It predicts how a fault will develop and estimates the RUL, i.e., the time left before a complete failure. They provide inputs for decision making process, which proposes and plans suitable actions accordingly.

Figure 1.1: Overview of benefits and complexity of different maintenance methods [1].

Figure 1.2: Block diagram of a CBM system.

1.1.2 Diagnosis process and prognosis process

In this section, diagnosis and prognosis processes are described. First, the concept of fault is explained. A condition is defined as a fault if it is an abnormal condition or defect, which progresses towards a failure in a relatively short time. A failure, on the other hand, is assumed as that enough deterioration has occurred for the component, equipment, or system to be not suitable for further operation. Taking electrical motors as an example, SWITS, the condition that the insulation between two different winding

portions is deteriorated, is a fault, which can lead to phase-to-phase short, or phase-to-ground short failure. Other faults in electrical machines are broken rotor bar, spalling in bearing, etc., which can develop to catastrophic failures.

Diagnosis process consists of three parts, fault detection, isolation, and identification [2]. These concepts are explained in Fig. 1.3. The fault detection identifies if there is any fault in the system using fault indicator(s). However, the change in the fault indicators can be due to the effects of ambiguous factors or other faults. Some examples of ambiguous factors are inherent asymmetry due to the non-idealities in manufacturing process, voltage imbalance, and load variation in electrical machines. In the figure, $F_1, F_2, \dots$, and F_n are different types of fault. After a fault is detected in the system, the fault isolation step is performed to identify the true fault, for instance, F_k , and distinguish it from the effects of the ambiguous factors. The following fault identification step will then estimate fault severity information. This can be in qualitative form like high, medium, or low severity levels. It can also be in quantitative form, i.e., how much percentage of the failure level.

Figure 1.3: Three steps of a diagnosis process.

There are few definitions of failure prognosis among industrial and academic communities. According to [3], prognosis is “*the process by which the evolution of a system variable or vector indicating its health is tracked over time under current and proposed future usage, until its value no longer falls within the limits set forth by the system specifications*”. It means that in prognosis, a scalar or vector representing system/component health is tracked over time. In addition, the current and future usage is necessary in

order to project the system health into the future. The usage can be interpreted as input information which assumes to be given. The failure space is also required to define the failure condition.

In this thesis, failure prognosis is the subsequent process after diagnosis, and estimates the RUL, as defined in [4], “*What is the RUL of a machine or a component once an impending failure condition is detected, isolated, and identified?*”. Prognosis process exploits the fault severity information getting from the diagnosis process, and identifies the degradation model. After the degradation model is identified, it is projected into the future to estimate the RUL. RUL is the time from the prediction moment to the instant the system degrades to a certain failure threshold, at which the system must be stopped working. Fig. 1.4 depicts the different steps in prognosis process. One necessary condition for the fault severity information is that it must be monotonic over time to represent the fault progression to higher severe condition. Also, one important demand for diagnosis process is that the fault needs be detected at the early stage of its development process, so that the estimated RUL is long enough for any timely and useful maintenance activities.

Figure 1.4: Prognosis as a subsequent step to diagnosis process.

Diagnosis and prognosis are two essential processes of CBM. The essential difference between them is that diagnosis process detects if there is a fault in the system, and identifies the fault severity if a fault occurred, while prognosis process predicts the degradation

process and projects it in the future to estimate the RUL. In other words, diagnosis process identifies the current status of system, while prognosis process predicts the system status in the future.

There are three main approaches in diagnosis and prognosis. Fig. 1.5 describes the model-based and data-driven methods and the difference between them. Both approaches compare the actual signals to the reference signals to generate the diagnostic/prognostic parameters. The difference between the two approaches lies in how the reference signals are created. For the model-based approach, a model is used to generate the reference signals. The model is derived from the physic laws. It can be dq axis model, sequence component model, state-space model, circuit model, thermal model, etc. On the other hand, in the data-driven approach, the reference signals are generated from a nonlinear mapping h , which is found from a learning process. Fig. 1.6 explains the signal-based approach. It is based on measured signals in place of explicit models of input and output signals. The tools of time-domain, frequency-domain, or time-frequency signal analysis are explored to generate the diagnosis and prognostic parameters.

Figure 1.5: Model-based and data-driven methods.

Figure 1.6: Signal-based methods.

1.1.3 Stator winding fault of electrical machines

Electrical machines are essential parts of industrial systems. Hence, the reliability and availability of industrial systems can be significantly improved by the installation of diagnosis and prognosis for these components. Induction machines are widely used in industries. They are found in applications of marine propulsion, aerospace actuators, and traction in electric vehicles/hybrid electric vehicles [5–7]. Despite their rugged construction, they are subject to fault due to aging, severe operating conditions, and harsh environments. These faults can be categorized into different groups, including stator-related fault, rotor electrical fault, rotor mechanical fault, and power electronic component fault in the drive system [8]. Industrial surveys have shown that stator winding accounts for a significant portion of failures in electrical machines. According to a survey conducted by Motor Reliability Working Group, IEEE Industry Applications Society for motors greater than 200 hp in size and no older than 15 years, the percentage of fault on winding is accounted for about 25.5% regarding various kinds of machines and about 24.7% regarding induction motors [9]. Table 1.1 summarizes the failure statistics.

The winding fault is usually originated from winding insulation deterioration due to the effects of thermal, electrical, mechanical, and environmental stresses [10]. Fig. 1.7 lists the common factors of each mentioned stress.

Thermal aging process and thermal overloading are the two most common stresses relating to thermal effect. The aging process is inevitable process, but accelerated because of the operating condition at high temperature, and as a result, reduces the lifetime of the insulation. As a rule of thumb, a 10°C increase in temperature decreases the insulation

Table 1.1: Statistics of failure by components [9]

Failed Component	Number of failures				
	Induction motors	Synchronous motors	Wound rotor motors	DC motors	Total all types
Bearing	152	2	10	2	166
Windings	75	16	6	-	97
Rotor	8	1	4	-	13
Shaft or coupling	19	-	-	-	19
Brushes or slip ring	-	6	8	2	16
External device	10	7	1	-	18
Not specified	40	9	-	2	51

Figure 1.7: Causes of stator winding fault.

life by 50%. The other stress is thermal overloading, which occurs due to voltage variations, supply voltage imbalances, cycling, overloading, obstructed ventilation, or ambient temperature. As a rule of thumb, the temperature in the phase with the highest current will increase by 25% for a voltage imbalance of 3.5% per phase [10].

The most common factors of electrical stress are the dielectric material, the phenomena of tracking and corona, and the transient voltages. The type of dielectric material subject to the impact of the voltage stresses can have an effect on lifetime of the insulation significantly. Tracking and corona are phenomena that only occur at operating voltages above 600 V and 5 kV, respectively, but also cause noticeable effects. The voltage transients can cause either deterioration of the insulation or even inter-turn or turn-to-ground failures.

The two frequent mechanical stresses are coil movement and strikes from the rotor. Under certain circumstances, MMF causes the movement and vibration of winding coils. This eventually deteriorates the coil insulators or conductors. The strikes from the rotor are stemmed from bearing failures, shaft deflection, and rotor-to-stator misalignment.

The contact between rotor and stator can be formed due to the strike effect, leading to grounded coil condition.

Contamination, high humidity, aggressive chemicals, and radiation in nuclear plants are other forms of stresses. They are also the factors causing significant consequences such as the reduction in the heat dissipation due to the presence of foreign contamination material. Other stresses such as aggressive chemicals can directly deteriorate the insulation or combine with other stress like mechanical one to further decrease the insulation resistance. Radiation is found in nuclear power plants or nuclear powered ships and its aging process is comparable to thermal aging process.

The stator winding, therefore, is highly subject to fault due to the aforementioned stresses. Stator winding fault, once occurred, usually begins with SWITS, spreading over and eventually leading to further severe faults such as phase-to-phase and phase-to-ground [11, 12]. Even with emergent SWITSF taking place in only a few turns, the current in the fault loop winding can be of the order of twice locked-rotor current [13]. It ensues the local heating effect, and hence accelerates the degradation process. As a result, the fault propagates to the adjacent windings, extends to other winding area, and finally causes the catastrophic damage. Therefore, the SWITSF is of important interest and significance, motivating the research on diagnosis and prognosis of this fault in this thesis.

1.2 Problem Statement

The research on diagnosis of SWITSF has a long history of several decades of research with success. Compared to the history of diagnosis, prognosis is a relatively new research area. There still exists some research gaps of both diagnosis and prognosis processes.

First, there is little research on incipient fault detection, and the existing work pertaining to this problem has its limitation. As mentioned in the previous section, early fault detection is critical for CBM. If a fault is detected at the late stage of its degradation process, the machines and the associated systems may have been damaged severely. Moreover, in that case, the estimated RUL will be not long enough for an appropriate decision making or planning a timely maintenance action. The challenge of early fault

detection is twofold. When an incipient fault occurs, the fault indicator is discreet. Also, there is always certain level of inherent asymmetry in electrical machines, which is due to non-idealities in manufacturing process, can also cause the change in the indicator, leading to the difficulty in distinguishing the fault from effect of the inherent asymmetry. In addition, the imbalanced supply voltages also affect the fault indicator. While the tools for sensitivity analysis are available for both model-based [14–22] and data driven approaches [23, 24], and also hybrid approach of signal-based and data-driven methods [25], so that the fault sensitivity can be maximized or improved, the model-based approach is preferred in this thesis due to physical nature of electrical machines. In order to guarantee the robustness against non-idealities and to improve the sensitivity to the fault, the multiobjective H_-/H_∞ fault detection observer design has been proposed in [14–17, 22] for both linear and nonlinear systems. Eigenstructure assignment has been proposed [18–21] to address the similar problem. On the other hand, the research in this thesis attempts to identify different components in the fault indicator, and decompose the fault-dependent component from that under the effects of inherent asymmetry and voltage imbalance for detecting incipient fault and concurrently extracting only the fault-dependent quantity for fault severity estimation, specifically to SWITSF of induction machines.

Second, the research on prognosis of SWITSF is very limited. Prognosis has been studied mostly for mechanical faults such as bearing, gear, shaft and rotor bar. For these mechanical faults, vibration signals are used to generate the prognostic features and the data-driven approach is applied. The approach is computationally expensive, and it usually requires a large amount of historic data, including both healthy and failure data that, in some cases, has destructive effect to the components/systems. In addition, for electrical fault like SWITSF, the physical connection between the vibration signal and the winding status may not exist, and hence, the use of vibration signal is not a suitable choice. This motivates the research on using the electrical signals for the prognosis of SWITSF. Prognosis for SWITSF has been proposed in [26], using the feature generated from the voltage and current signals. However, its limitation is that the prognostic parameter is not directly related to electrical fault parameters.

Third, the estimation of severity condition is needed. It relates to both diagnosis and prognosis processes. For diagnosis process, once a fault is detected, the severity

information helps identify accurately the current fault condition. For prognosis process, it relies on the existence of prognostic parameters. The severity information can be used as prognostic parameter if it represents the fault condition in monotonic manner, indicating that the fault progresses to severer condition, and eventually to complete failure. The features from vibration signal can be used as the prognostic parameters assuming a relationship between the features and the fault can be generated from the data-driven approach. However, since the SWITSF is an electrical fault, it will be not reliable to use such mechanical parameter. A few works have been proposed to estimate the fault severity information based on the electrical signals. However, the monotonicity in the estimated quantity is not fully achieved [27] or the treatment of the effect of both voltage imbalance and inherent asymmetry concurrently has not been fully considered [28, 29]. In other research [30–32], the problem of estimating the direct electrical fault parameters have been considered, but they are limited to only the pure inter-turn fault condition.

1.3 Contribution

In this thesis, a framework for diagnosis and prognosis of electrical machines under SWITSF, and the associated techniques for sub-problems including early fault detection, fault severity estimation, and degradation modeling and RUL estimation, are proposed. The considered machines are line-connected induction motors. The research is significant since it can be applied to CBM in order to ensure and improve the reliability and availability of electrical machines and the associated systems. Also, it can support decision making and maintenance strategy.

The contributions of this thesis are as follows.

- Propose a model-based diagnosis and prognosis framework based on the direct diagnostic and prognostic parameters. They are the electrical fault parameters, which are unknown and unmeasurable. Therefore, an estimation process is required to estimate these parameters. Once the fault occurrence or the change in fault severity condition is detected, the estimation process is triggered to estimate the

direct fault parameters. The degradation model is identified and RUL is predicted based on these parameters. PF-based approach, due to its advantage of statistically quantifying the estimation performance, is employed for both the estimation process and the degradation model identification and RUL prediction. The framework is generic in nature and can be diversified to other faults in other machines/systems.

- Propose methods to detect the incipient fault. The challenge of incipient fault detection lies in the effect of ambiguous factors including inherent asymmetry and voltage imbalance. Two approaches are proposed. The first one is based on the sequence component approach, separating the effect of fault from that of ambiguous factors and extracting the fault-dependent quantity. The other approach is based on multiple-indicator approach, in which indicators supplementing with each other are used simultaneously, for increasing the robustness and early fault detection capability.
- Propose methods to estimate the unknown and unmeasurable diagnostic and prognostic parameters. The method uses only the measurements of stator voltages and currents. Hence, it is suitable to implement in real-time and non-intrusive manner. Besides the aforementioned PF approach, other approaches, based on the unique characteristics of electrical machines and the multiple forms of models of a faulty machine, are proposed.
- Experimentally validate the diagnosis and prognosis framework using electrical fault parameters, and the incipient fault detection and fault parameter estimation methods. Developing the experimental test bed is also a part of validation process. The tests are conducted under various fault severity levels, different load conditions, and different voltage imbalances in order to investigate the diagnosis and prognosis performance under various operational conditions.

1.4 Outline

This thesis is organized into eight chapters. Chapter 1 introduces about the background, problem statement, and contributions of this thesis. Chapter 2 provides the

literature survey on diagnosis and prognosis of SWITSF. Chapter 3 presents the theory and experimental validation of the model of an induction machine under SWITSF, which will be used in subsequent chapters due to the nature of model-based approach of this thesis. Chapter 4 presents the model-based framework for diagnosis and prognosis. In this chapter, the successive steps and components of a complete diagnosis and prognosis process is defined. A generic approach, in which multiple indicator approach is applied for diagnosis process, and PF approach is applied for parameter estimation and RUL prediction, is proposed. The subsequent chapters propose different methods to the diagnosis and fault parameter estimation, which actually is a part of the proposed framework in Chapter 4. Chapter 5 discusses about the early fault detection method based on the sequence component approach. Chapter 6 and Chapter 7 provide other approaches for parameter estimations. Chapter 6 presents the method using the phasor quantities, while Chapter 7 discusses the method exploiting the multiple forms of model of electrical machines. All are based on model-based approach. Chapter 8 provides the conclusion and future work.

Chapter 2

Literature Survey

2.1 Introduction

2.2 Literature Survey on Diagnosis

Over the last few decades, enormous diagnosis methods have been proposed and applied in various engineering systems. There are also numerous survey papers on this topic.

The survey papers in [33–37] provide good summary of diagnosis. They can be generally categorized as model-based, signal-based, and knowledge-based approaches. Model-based approach is outlined in [33, 35, 38, 39]. It can be grouped into deterministic fault diagnosis, stochastic fault diagnosis, fault diagnosis for discrete-events and hybrid systems, and fault diagnosis for networked and distributed systems, based on types of the models used. It can also be classified as observer-based, parity equation, and parameter estimation approaches. While observer-based approach aims to design an observers, which are also dynamic systems, but other than process itself, the parity equation directly explores the process model, to form the residual. On the other hand, the parameter estimation approach attempts to estimate the model parameters and examine the deviation of parameters for residual generation. Fig. 2.1 sums up the different methods of model-based approach.

An intuitive classification of signal-based approach are time-domain, frequency-domain, and time-frequency methods [33]. Fig. 2.2 lists down the different methods of signal-based approach. The names of the methods are self-explained. The time quantities

Figure 2.1: The list of model-based approaches. (a) Based on applied techniques. (b) Based on type of models used.

such as mean, standard deviation, magnitude, phase, skewness, or kurtosis are utilized in time-domain approach. Spectrum analysis such as Fourier transform is exploited in frequency-domain methods. The time-frequency method emerges when either pure time-domain or frequency-domain are not qualified to identify fault from non-stationary signals. Under that circumstance, the time-frequency approach helps extract the time-variant features, proclaiming the fault occurrence. The common tools in this group are short-time Fourier transform (STFT), wavelet transforms (WT), HilbertHuang transform (HHT), and WignerVille distribution (WVD).

Fig. 2.3 summarizes the different methods of knowledge-based i.e., data-driven approach. The approach exploits the historical data and underlying knowledge about the systems for diagnosis purpose [34, 37]. Both expert system and qualitative trend analysis belong to qualitative branch, while the two other is under the quantitative approach. The expert system incorporates human expertise in a set of rules, and the qualitative trend analysis extracts the process trend from retrospective data and connects it to fault trend. Both statistical and non statistical-analysis-based methods belong to quantitative

Figure 2.2: The list of signal-based approaches.

approach, in which quantitative feature are generated using pattern recognition. PCA, ICA, PLS, and SVM are the major techniques in the former, while NN and fuzzy logic are dominant in the later methods. In addition, the joint approach merging techniques of the both is also available. The knowledge-based methods are well outlined in [23, 40], .

Figure 2.3: The list of knowledge-based approaches.

There are also prolific number of survey papers providing good overview of diagnosis on aerospace systems [41], wind turbines [42–44], analog circuits [45], planetary gearboxes [46], nuclear power plants [47], wireless sensor networks [48], and wind energy conversion systems [49].

Considering that electrical machines have been widely used in industries, and substantial research has been dedicated to them, this chapter contributes to the literature survey with focus on electrical machines. However, in some sections, the survey of other engineering systems are covered as well if necessary, i.e., to embrace methods or approaches which can be applied to electrical machines. On the other hands, due to the

younger history of prognosis, its literature survey presents the methods and applications in also other components and systems.

The methods for fault diagnosis of electrical machines can be categorized based on different criteria. They can be categorized into offline testing and online monitoring methods. The former methods need to stop machines before any testing, and the later ones examine the machine while it is still in operation. In relation to sensor installation, diagnosis methods are grouped into non-intrusive and intrusive methods. The difference between two approaches is that while the non-intrusive methods require only measured stator voltages and currents, the intrusive methods require additional sensors for measuring other physical quantities such as vibration, flux, etc. For the applied techniques, they can be classified as model-based, signal-based, and data-driven methods, or more specifically sequence component-based, signature-based, model-based, and AI-based methods, as shown in Fig. 2.4. The name AI-based is due to the fact that most of knowledge-based approaches are based on AI techniques.

Figure 2.4: Diagnosis methods of electrical machines.

2.2.1 Testing methods

The term “testing” implies that they require specific devices/signals to test the machine and it is stopped from service. Usually, the testing methods can provide direct and accurate diagnosis results. Insulation resistance, polarization index [50], voltage surge [51], and partial discharges [52] tests are among the most common methods in industry. The two former methods are suitable for machines rated 400 V and above while

the others are fitting for those rated at least 4 kV [13, 53]. In the insulation resistance test, a DC voltage is applied between the winding copper and ground and the insulation resistance is calculated as the ratio between this voltage and the resultant current. The specific values of the applied voltage and the resistance threshold for evaluating the insulation condition follow industrial standards such as IEEE 43-2000 and NEMA MG-1-1993. This insulation resistance method has simple test procedure. Nonetheless, it depends strongly on the operational temperature. The polarization index can be used to overcome this drawback. It measures the time required for molecules of insulation to polarize in order to resist the flow of current. Therefore, it can be used for assessing the capability of groundwall insulation to polarize. It is calculated as the ratio of the insulation resistance at one-minute and ten-minutes instances. The specific value of polarization index for testing is available at several standards such as IEEE 43-2000. Due to its easy implementation, this testing method is widely used. However, it is mainly used for testing phase-to-ground insulation. The voltage surge test applies a high voltage between the tested turns, and hence, can probe inter-turn fault. The premise of this test is to create a voltage surge between the winding to charge and discharge the winding capacitor subsequently. Since the capacitor and the motor forms a RLC-series circuit, if the inter-turn insulation is deteriorated at certain level, there will be a change in the frequency and the magnitude of the impulse response. Although this method can test inter-turn fault, it has appearance drawback that the life time of the tested machine can reduce significantly due to effect of voltage stress. The other method is the partial discharges test, in which an AC external voltage is applied between the winding and ground. This method requires an additional device to measure the partial discharges. In addition, it is only applicable to medium- and high-voltage machines since the voltage magnitudes in low-voltage machines may not be high enough to generate a proper partial discharges indicator.

Insulation resistance, polarization index, voltage surge, and partial discharges tests are standardized for medium- and high-voltage machines. However, they are not standardized for low-voltage machines. In addition, they are more suitable for testing purpose, i.e., to check if a machine is at healthy or failure conditions other than to continuously monitor the condition of a machine. High frequency impedance/inter-turn capacitance

method [54] has the similar nature with the voltage surge test by exploiting the inter-turn capacitance effect for fault diagnosis. It is based on the principle that if a high frequency signal is injected in the stator winding and the frequency is close to the series resonance frequency of the system, the induced flux caused by the structured high frequency signal will vary the phase lag between the flux and the injected signal. Actually, this change represents the change in the resonance frequency caused by the corresponding change in the inter-turn capacitance. This has the advantage of considering the capacitance effect, which is neglected by most of other research. Nonetheless, the significant disadvantage of this method is its invasive nature requiring the injection of high frequency signal.

For the past few decades, various monitoring methods have been proposed for detecting faults in electrical machines in general and SWTSF in particular based on different characteristics and behaviors of faulty machines. Moreover, due to the multi-physics nature of electrical machines, different physical quantities have been applied for generating diagnosis indicators. MCSA [55–60], sequence impedances [12, 27, 28, 61–70], voltages [71, 72], electrical fault parameters [29, 73–75], electrical parameters [75], EMF [76], fluxes [77–83], vibrations [84–87], torques [88], and the others [89–93] calculated from stator current and voltage measurements have been proposed as different fault indicators.

2.2.2 Sequence component-based method

Symmetry analysis is one of the most common methods for fault diagnosis of rotating electrical machines and power systems. Under the healthy condition, the stator windings are symmetrical, and hence, the stator currents are also balanced. However, under the faulty condition, the stator windings are no longer symmetrical. As a result, the stator currents become imbalanced. Therefore, asymmetrical property of stator currents can be exploited for fault diagnosis. The sequence component analysis is the tool of symmetry analysis. The concept of sequence components is proposed in [94]. Considering an induction machine of three phases, the sequence component analysis decomposes the multi-phase quantities such as stator currents, stator voltages in term of positive-sequence, negative-sequence, and zero-sequence components. Fig. 2.5 explains the concepts of these components. Assuming three-phase quantities, such as the currents of stator phase a , phase b , and phase c , are represented by rotating vectors A , B , C ,

respectively. The positive sequence components are $A+$, $B+$, $C+$ of same magnitudes and 120° in phase difference, and rotating in clock-wise direction. On the other hand, the negative sequence components are $A-$, $B-$, $C-$ of same magnitudes and 120° in phase difference, but rotating in the counter clock-wise direction. The zero sequence components $A0$, $B0$, $C0$ are static and identical vectors. The original vectors A , B , C can be derived back from the vector sum of their sequence components.

Figure 2.5: The concepts of sequence components.

Different quantities can be used in symmetry-based method, as shown in Fig. 2.6. The most common quantity is the stator currents. One of the pioneering research exploring the sequence components of stator current for fault diagnosis is presented in [69]. In this work, it shows that the negative sequence current is less sensitive to speed variation. In [28, 61], both the magnitude and phase of negative- and zero-sequence currents are proposed as fault indicators. The magnitude is used for evaluating the fault severity, while the phase is used to identify the faulty phase. However, the method is more suitable to balanced voltage supplies. In [12, 62, 64, 67], the negative sequence stator current is found as sensitive to inherent motor asymmetry, supply voltage imbalance, and measurement errors. In [64], it is shown that the effects of both the supply voltage imbalance and fault are actually nonlinear. The negative sequence stator current becomes even more

balanced under fault. The experiment in [62] points out that a small percentage of voltage imbalance around 0.3% is enough to resemble a 7% inter-turn fault. It means the voltage imbalance has significant effect on the negative sequence component. In [12], a method to compensate the impact of supply voltage imbalance, non-linear motor effects, and static eccentricity on negative sequence current is proposed. However, it requires a semi-empirical approach fusing both theoretical analysis and processing of experimental data. Sequence components of higher order harmonic of stator current is also studied. In [27], a technique using the positive- and negative-sequence third-harmonic components of line currents to identify the effect of inherent asymmetry. However, the estimated severity is not fully monotonic.

Figure 2.6: The list of sequence component-based methods.

The symmetry-based method is not only using negative sequence current, but also other quantities. The sequence component model of an induction machine is described by the following equations

$$\tilde{V}_{sp} = Z_{pp}\tilde{I}_{sp} + Z_{pn}\tilde{I}_{sn}, \quad (2.1)$$

$$\tilde{V}_{sn} = Z_{np}\tilde{I}_{sp} + Z_{nn}\tilde{I}_{sn}, \quad (2.2)$$

where $\tilde{V}_{sp}$ and $\tilde{V}_{sn}$ are positive sequence and negative sequence stator voltages, respectively. $\tilde{I}_{sp}$ and $\tilde{I}_{sn}$ are positive sequence and negative sequence stator currents, respectively. Z_{pp} and Z_{nn} are positive sequence and negative sequence impedances, respectively. Z_{pn} and Z_{np} are sequence impedance components indicating the coupling effects of positive and negative sequence models. They are also called the off-diagonal sequence impedances or cross-sequence impedances. Instead of using negative sequence current, in [63], a method using the off-diagonal element in the sequence component impedance

matrix is proposed. The proposed method can handle supply voltage imbalance, the slip-dependence, the influence of inherent motor asymmetry, and measurement errors. However, its major drawback lies in the fact that it requires an off-line stage for calculating the off-diagonal term in the healthy condition under various slip values. In [70], the Z_{np}/Z_{pp} is exploited as diagnostic parameter for SWITSF. It proves the advantage of impedance-based approach that it is robust to the variation in measurement error. Unfortunately, the relationship between the parameter and fault parameters is absent in the research. The challenge of fault diagnosis of SWITSF at the early stage of its degradation process is posed in [65, 66]. The effective negative sequence impedance detector, defined as the ratio of the negative sequence voltage over the negative sequence current is explored in [65]. It is shown that the detector is subject to unpredictable change at the incipient fault due to the effect of voltage imbalance. In order to overcome that, the voltage mismatch detector approach is proposed in [66]. The experiment shows that the indicator is insensitive to supply voltage imbalance up to 5.2%. Nonetheless, it requires an expensive process to calculate and store the values of off-diagonal sequence impedances.

The symmetry-based method has been also found in other electrical machines, such as PMSM. Due to its high efficiency and high torque density, PMSM is widely used in modern wind energy conversion system and transportation system. The zero sequence voltage component and zero sequence current are applied in [95]. The negative sequence component is investigated in [96]. The sequence components are also used in [97–99], in hybrid approach, i.e., combining with NN, Fuzzy logic, or model-based methods.

In overall, the symmetry-based method are non-intrusive, as only the measurements of terminal quantities are required. In addition, it provides a simple medium to model and analyze the asymmetrical characteristic of machines. However, the challenge with this technique is to discriminate the effect of fault from that of inherent asymmetry and voltage imbalance in a simple implementation.

2.2.3 Signature-based method

The signature analysis approach also attracts much attention in diagnosis of industrial systems in general and electrical machines in particular due to the abundance of signals

and signal processing techniques. In electrical machines, the signals consist of stator current, voltages, axial and radial flux, EMF, vibration signal, and torque. The techniques are both frequency and time-frequency tools including FFT, bispectrum, high-resolution spectrum analysis, and wavelet analysis. They are summarized in Fig. 2.7.

Figure 2.7: The list of signature-based methods. (a) Based on signals. (b) Based on applied techniques.

MCSA is one of the most commonly used method due to its non-intrusive and non-invasive nature and requiring only stator current measurement. The rotor slots harmonics [55, 57], third harmonic [60], the lower sideband of field rotational frequency with respect to the fundamental frequency, the components relating to slots [59], and the other frequency proposed in [58] suggest certain types of frequencies for fault detection. The study in [60] provides a detailed analytical analysis, using winding function approach, to arrive at the conclusion that under SWTSF, there is no new frequency components emerging in the stator current spectrum, but only the rise in some frequency components instead. In the research, it is also verified by experiments. It is shown that these fault indicative frequency components are sensitive to voltage supply imbalance. In addition, the third harmonic is proved as a not reliable indicator because it also appears under magnetic saturation. Moreover, it is sensitive to machine non-idealities. A method using the positive- and negative-sequence third harmonic components of line currents to address the effect

of inherent asymmetry is proposed in [27]. However, the estimated severity is not fully monotonic. Therefore, while MCSA is widely applied and easy to implement, it tends towards being fairly sensitive to voltage imbalance and machine non-idealities.

The harmonics of stator voltages are also studied in [71, 72]. The rotor-slot-related harmonics, the third and other triple-related harmonic of terminal voltages switched off, are proven to be effective indicators for detecting SWITSF. Because the fault signatures are calculated from the measured terminal voltages after they are switched off, there is no effect of voltage imbalance to the fault signatures. Due to this advantage, the method has potential to detect early fault, to extend of a few number of shorted turns. However, since the method is based on the transient voltages, it is only applicable to certain operational circumstances.

Axial leakage flux has been also used for fault detection. In [79, 83], the flux is proposed, as the occurrence of inter-turn fault is associated to the flux. The premise of the approach is that the machine asymmetry, caused by SWITSF, brings about a change in the air gap space harmonic distribution, which is reflected in the axial leakage flux. In details, when SWITSF occurs, it establishes a closed-loop, and the circular current in the loop generates EMF. This results in a corresponding MMF pulse, superimposing on the main field distribution. This in turn modifies the harmonic of axial leakage flux. In [83], the spectrum component of voltage induced by leakage flux in the axial direction is used for fault diagnosis. In order to measure the leakage flux, a simple device called search coil is installed. It is wound by copper wires, similar to stator winding coil. The search coil can quantify the time-varying magnetic flux in terms of terminal voltage. Subsequently, applying the frequency analysis, such as FFT, the spectrum components of the induced voltage are monitored to detect fault [81, 83]. Besides axial leakage flux, the leakage flux in the radial direction is also applied. For measuring this flux, the search coil is placed perpendicular to the machine radial direction near the vicinity of machine body [77, 80]. The radial direction leakage flux based fault detection has been reported to be more reliable than MCSA [82]. To further improve the fault detectability, multiple search coils can be used to measure both axial and radial leakage fluxes, as presented in [100]. The flux-based method, however, is invasive and fairly dependent on load conditions.

Vibration signal is a mechanical quantity but it is well-known that there is interrelationship between it and electrical quantities. Owing to that fact, vibration signal has

been also proposed for fault diagnosis. The second harmonic of bearing vibration is investigated in [87]. The research shows that the signal can provide information involving to the air-gap flux created by winding deterioration, that may be unable to be captured by voltage and current quantities. In [86], the slot and supply frequency of vibration signal is explored. However, it requires also the flux signal to decide the specific diagnostic frequencies. In [85], complex wavelets is applied to discriminate SWITSF from bearing fault. With that capability, the fault can be detected without concern of false fault detection due to other potential mechanical faults such as bearing and broken rotor bar faults. However, wavelet transform is relatively computationally expensive in general. In [84], the vibration signal is exploited to even detect the incipient stator winding fault although the effect of imbalanced supply voltages is not studied in the research. Electromagnetic torque also has close link to current and flux linkage quantities, and hence, it has been proposed for fault detection, as proposed in [88]. Nonetheless, the experimental results show that their performance does not outperform the other methods using other physical quantities. Both vibration and torque-based methods require the installation of additional sensors, which makes their application are fairly limited compared to other non-intrusive methods.

Besides standard techniques like FFT, advanced techniques have been also applied for fault diagnosis. Bispectrum, also called third-order spectrum, is a high order statistics which can be suitable for detecting electrical-based faults, such as stator voltage imbalance [101, 102]. Therefore, its application can be to evaluate the stator voltage imbalance condition or diversify to fault diagnosis of electrical faults like stator winding fault. Wavelet analysis is computationally expensive, but it can overcome the drawback of Fourier analysis, which is more suitable to stationary signals. In order to increase the resolution and also capture the sudden changes, wavelet is preferred, as proved in [85]. It is shown in [103, 104] that wavelet analysis can differentiate the fault from supply voltage imbalance under various load conditions. The zero crossing time signal of stator currents can be used to reduce volume of data acquisition and analysis for signature analysis approach [56]. The techniques based on the stator current space vector and its variances [105–107], Park’s vector modulus [89] are some other methods. In other works [90–93], different indicators using the measured voltages and currents in various

ways are also proposed. Due to the advance of computation software and hardware, the advanced signal-based approach has been receiving more interest. They are applied to other machines as well such as PMSM. Wavelet transform is applied in [97, 108]. FFT combined with PCA and Bayesian network is used in [109]. FFT combined with Linear Discriminant Analysis is proposed in [110].

Even though abundant research has been proposed, the signature-based approach is found to be difficult to analytically discriminate the effect of fault from that of voltage imbalance and inherent asymmetry.

2.2.4 Model-based approach

While sequence-component-based method is mostly suitable for power systems and electrical machines, and signal-based method is suitable to specific systems and signals, the model-based approach can be both generically and specifically applicable. In addition, thanks to advance in control theory and control system applications, model-based approach provides abundant tools for both robustness and sensitivity fault diagnosis. Therefore, in this section, model-based approach will be discussed in wider range of systems in general and electrical machines in particular. For general system, the literature survey will focus more on research on robustness against non-idealities and disturbances, and improving of fault sensitivity. It is critical for diagnosis closely related to prognosis as in this thesis. For electrical machines, relevant research will be presented.

Fig. 2.8 describes the general scheme of model-based approach, adapted from [38]. The process model is critical element, which helps generate the features based on input and output signals. The features can be residual, parameter estimates, or state estimates. In general, they are corresponding to parity equations, parameter estimation, and observe-based approaches, respectively.

Observer-based approach plays a significant role in model-based methods, and substantial research has been studied for fault detection, isolation, and identification. In order to achieve incipient fault detection, under disturbances due to model uncertainty, process noise, and measurement errors, the fault detection is formulated as an optimization problem. The structure and parameters of the observers is optimized to guarantee

Figure 2.8: The list of model-based methods [38].

that the residual signal is sensitive to fault, but robust against disturbances. Eigenstructure assignment has been proposed [18–21] to address this problem. The other approach is LMI-based method applicable to both nonlinear and linear systems [14–17, 22]. For fault isolation, a bank of observers are required. The idea is to make a residual only sensitive to its corresponding fault [111], or other faults [112–114], but robust against other faults and disturbances. The other idea is to decompose the different components in the residual signals, as discussed in [115–117]. In fault identification, the observer-based approach is applied to estimate the fault parameters. They are modelled as augmented state variables, and the observer estimate both the states and fault parameters simultaneously. The approach is presented in [118–120] to name a few. Parameter estimation approach tries to estimate the process parameters and compare them with the normal values for fault diagnosis. In the approach, the measured inputs and outputs, and model structure are employed for parameter estimation. The fault diagnosis is also formulated

as optimization problem in which either equation or output error is minimized. Depending on the complexity of the problem, either direct estimation of the parameters or numerical optimization methods are required [38]. Parameter estimation has been found in applications where process parameters are closely linked to physical conditions or structure of the system, such as aerospace systems, as presented in [121–125]. The essence of parity equation approach is to check the consistency between the model and measured, i.e., process outputs [126–132]. The similarity of parity equation to observer-based approaches has been discussed in [133, 134]. In the parity equation approach, the residuals are under effect of model uncertainty, process noise, besides faults. However, the approach allows the flexibility to reorganize the model structure to improve the fault detection and isolation. Related to this, the parity equation is also relatively similar to unknown input observer approach in [115], in which the decomposition of components of fault and disturbances is discussed.

The stochastic methods are also widely used in diagnosis. The basis of the approach is to monitors the mean and variance of the innovation of a KF, as proposed first in [135]. The fault is detected and diagnosed based on the statistical tests thereby. Similar to observer-based approach, banks of filters are applied for fault isolation and identification. Multiple model adaptive estimation (MMAE) is based on the idea of multiple models in order to estimate the probability for each model, providing confidence level to achieve fault isolation, as proposed in [136, 137]. IMM, presented in [138, 139] also uses multiple models approach to estimate the probability of model switching and its parameters. KF is also widespreadly used for the same aforementioned problem of state and parameter estimation in augmented system for fault identification [140–142]. Some applications of KF and its variants on fault diagnosis can be found in [143–145] and aerospace systems [146–148] to name a few.

Model-based methods of parameter estimation, observer design, and parity equation are applied for fault diagnosis of electrical machines in general and SWTSF in particular. Related the models, dq-axis, sequence component, and state-space models have been used.

dq-model has been applied to analyze the behavior of an induction machine under fault, and also for fault indicator generation. In [75], a dq-model, which models a fault

simultaneously occurring on multiple phases, is proposed. The parameter estimation, based on output error technique, is employed. Both the motor and fault parameters are estimated, and the fault phases are identified. The experimental results show interesting point that the change of motor parameters is negligible, while the fault parameters are more noticeable. However, the research is limited to the pure inter-turn fault, i.e., small value of fault loop resistance, representing relatively high severity level. In [32], both local and global search method has been applied to estimate the fault parameters and identify the faulty phase and compared. The local method applies the techniques of gradient descent and nonlinear least squares, while the global search method is based on pattern search method. It is shown that the global search method is insensitive to initial search and can converge to the global minima. However, its drawback is more computation time. Noise is added to the data to analyze the robustness of the methods. However, similar to many other works, the fault resistance is omitted in the work, implying that the research do not cover incipient fault represented by fault loop resistance component. In [149], an estimation method based on particle swarm optimization is proposed. The third harmonic component in the supply line current is used as the input for the estimator to estimate the percentage of shorted turn. In [150], the particle swam and bacterial foraging optimization have been explored for fault detection and severity estimation, and also faulty phase identification. The both methods have the advantage of not requiring prior knowledge of fault signatures. Nonetheless, they own inherent drawback of computational expensiveness.

In [142], an adaptive KF method is proposed for dual estimation of the state variables and electrical parameters in induction machines. The two types of fault are studied in the research. They are increased phase resistance and SWITSF. Although the simulation result shows the imbalance of parameters under the faults, it also shows that parameter estimates change differently to what intuitively might be expected. In detail, the parameters that are not under effects of stator faults, have been changed. In [141], EKF is applied for parameter and state estimations of brushless wound-field synchronous generator. The rotor field current, damper bar currents, and fault parameters are estimated in the work. Based on the estimates, the fault signatures of SWITSF under load imbalance is proposed. The paper also helps demonstrates the advantage of KF-based approach on

estimating unmeasurable quantities. In [145], the sensor fault detection and isolation of interior PMSM is proposed, based on EKF. Three types of fault, which are faulty position sensor, DC-Link voltage sensor, and phase current sensor, are shown to be detected and isolated. The element of this approach is to use different quantities which are differently sensitive to different types of faults, and achieve the isolation thereby. However, it is assumed that only one sensor is faulty during operation, the probability of faults in more than one sensor is low though.

In [29], model-based approach is developed for investigating the fault in any single phases. The observer-based approach and parity equation are applied to calculate deviation between the simulated stator currents and measure stator currents. However, the effects of both non-idealities and fault are mixed in the generated signal. The inherent asymmetry is also not considered in this research. In addition, the experiment is only conducted on a small value of fault loop resistor, which implies the fault severity is relatively high. A model independent of rotor speed is developed in [78]. In this paper, observer-based technique and frequency analysis are applied to generate a fault indicator which is insensitive to load. Observer design is also used for estimating the fault parameter in [73, 74]. The system under fault is a bilinear system, in which an adaptive observer can be applied to estimate the fault parameters. In [151], a summary of disturbance/uncertainty estimation and attenuation (DUEA) techniques in PMSM drives is presented. It shows the existence of various DUEA techniques and the key differences between them. Even though the paper focuses on PMSM, it provides good summary for electrical machines in general. However, it lacks the overview of the techniques for diagnosis purpose.

Since only the fraction of shorted turns is estimated in mostly of the works, the applications of the above research to early fault detection, where the fault loop portion has relatively high resistance at the beginning of degradation process, need further investigation. However, the model-based approach is potential to estimate the direct fault parameters. This is critical considering that parameters can be employed in prognosis process. In addition, the approach has the advantage of using only the measurements of terminal quantities.

It should be noted that H_-/H_∞ observer has been proposed in [14–17] to achieve a multiobjective fault detection, i.e., guarantee the robustness against non-idealities and

to improve the fault sensitivity, simultaneously. Eigenstructure assignment has been proposed [18–21] to address the similar problem. In general, these method can be considered to detect the fault at the early stage of its development. However, the research in this thesis is not explored towards that direction. Instead, it attempts to decompose the fault-dependent quantity from that under the effect of the ambiguous factors, i.e., inherent asymmetry and voltage imbalance, and extract the fault-dependent component from the fault indicator to get the fault signal directly pertaining to fault parameters. In addition, the thesis also attempts to estimate directly the fault parameters, which is used to estimate the degradation process, and subsequently, project it into the future for estimating RUL. In other words, the thesis focuses on parity equation and parameter estimation methods of model-based approach. The thesis also exploits the sequence component approach, which is well suited to electrical machines. In addition, it also provides analytical but simple tool for diagnosis purpose.

2.2.5 AI-based approach

AI-based approach has been also applied to diagnosis of electrical machines. Essentially, the AI-base approach consists of three mains steps, including signature extraction, fault identification, and fault severity evaluation, as discussed in [152]. With the advance of computation software and hardware, AI-based approach has been also received substantial attention. In addition, AI-based methods can be combined with other methods, usually signal-based, to improve learning model and feature extraction, and hence, diagnosis performance. For electrical machines, AI-based methods are also found more commonly applied to mechanical faults such as bearing, broken-rotor bars rather than stator winding fault.

In [153], a hybrid feature-reduction methodology based on ANN is proposed to classify bearing, broken-bar rotor, and stator faults. The method combines Fishers discriminant ratio to maximize the separability between classes and error probability model to select an optimal number of extracted features. In [154], a study is conducted to find out if the time-frequency, or the time-domain features, or the combination of the both provide greater performance of ANN-based diagnosis. The result shows that the joined features produce higher performance, and hence implicitly, suggests hybrid signals for ANN-based

approach. NN is also widely applied to fault diagnosis of bearing fault. It is used for statistical-time features in [155], and for entropy of wavelet components in [156]. Another AI-based method using SVM technique are proposed to classify rotor and bearing faults in [157, 158], respectively. In [159], the envelope analysis of vibration signals is explored for bearing fault diagnosis using FFT and PCA techniques. The PCA method is also used for fault diagnosis of open-circuit faults in power inverters in [160]. A FFNN method is proposed in [161]. In the training stage, the negative sequence current of a healthy machine under several different load conditions and supply voltage imbalance is used for offline training. In other words, the inputs to FFNN are of terminal quantities. In the monitoring stage, the measured negative sequence current is compared with the estimated value by FFNN, and the deviation between them is the indicator of fault severity. Experimental results show the technique can detect the incipient fault, and also is insensitive to supply voltage imbalance. However, to obtain the data for offline global training is a challenge in practice. In order to overcome this drawback, the continual-online-training algorithm is proposed in [162] so that the modified FFNN method is less computational complexity, and no lookup table is required. In [163], an ANN approach is applied to a wound-rotor induction generator. The ANN is trained directly by digital signals coming from sensors. Therefore, the diagnosis system can be implemented in a simplified architecture on a low-cost hardware. In [164], an ANN approach is applied to a squirrel-cage IM fed through an inverter. The variation of the phase shift between the phase voltages and the line currents is used for fault diagnosis.

Fuzzy logic-based approach is proposed fault detection and classification. It is also combined with other methods in fusion approach for fault identification. In [165], fuzzy logic-based approach based on the stator current Concordia patterns is validated as an effective method to detect stator fault in [165]. In [166], T-S fuzzy model and GA is proposed. Two T-S fuzzy models are developed of which one is used for detecting turn fault and the other is used for estimating fault turns, while the GA is adapted for optimizing model parameters. It is shown that the method is robust under various load conditions and supply voltage imbalance up to 4% of rated voltage. The fuzzy decision tree is proposed in [167] for fault classification of broken rotor bars and broken connector faults. The boundary of phase space represented in image form is extracted for

feature generation. The fuzzy decision tree approach is compared with Gaussian Mixture Models, ANN, and few other methods, and verified to provide better performance. The another application of fuzzy logic-based approach for fault classification is found in [168] for bearing fault. Taking advantage of both fuzzy and NN methods, the fuzzy-neural data fusion is proposed in [169]. The improved state-awareness of system monitoring is achieved via fusing input data from multiple sources and combining self-organizing fuzzy logic system for anomalous behavior detection, and ANN for system modelling and behavior prediction.

The AI-based methods have the advantage of learning capability under the lacking of quantitative domain knowledge, i.e., mathematical model. A few works have been proposed to reduce the computational load and complexity, such as the application of PCA for the unsupervised NN method, proposed in [170]. The AI-based techniques are, however, computationally expensive, and not really suitable for online implementation.

2.3 Literature Survey on Prognosis

Prognosis is relatively new topic compared to diagnosis. Therefore, the number of research on prognosis is not as substantial as that on diagnosis. However, it has been also investigated across various applications including disease prognosis, weather forecasting, stock market prediction, and different industries such as manufacturing, electric vehicle, and power systems. Different components of industrial systems have been also considered for prognosis. In [171], it presents a good summary of prognostic methods and suggests best practices for manufacturing industry. In [172], another review of prognosis methods and the cloud-enabled prognosis for manufacturing industry is presented. In [173], an excellent review of modelling options for prognosis and RUL estimation is proposed.

2.3.1 Prognosis methods

Given the explanation about different approaches in Section 2.1, this section will discuss about different prognosis models and methods applied for different systems in general and electrical machines in particular. The methods in prognosis can be categorized into experience-/probability-based, knowledge-based, data-driven approach, and model-based

approaches [2, 26, 174] with slightly difference in terminologies. The knowledge-based approach denotes qualitative methods, while data-driven approach implies the quantitative methods. They are listed in Fig. 2.9.

Figure 2.9: The list of prognostic methods.

The experience-based approach is applied in case the repair and failure histories are available [174]. These are also called event data. The data are fitted to a statistical failure distribution, which are commonly Weibull, Poisson, Exponential, or log-Normal distributions [175]. Weibull is the most common distribution due to its advantage of modelling various types of failure behaviors. In the experience-based approach, the mean-time-to-failure of the population is estimated. However, the nature of the approach is that the result represents only the entire population assuming that all the units are identical. As a result, the approach finds it more useful in manufacturing sectors for quantifying the product reliability instead of health conditions of individual units. Therefore, the method is generally feasible for interval-fixed maintenance and non-critical components/systems.

The model-based approach exploits the domain knowledge to establish the mathematical models of systems under the effect of faults [2, 26]. The models are usually constructed from first principles. The degradation process is incorporated into the model through the parameters which represents the fault severity information. Based on the developed models, the fault residuals are generated. In addition, since the model is available, the analytical relationship between the residuals and fault severity can be derived. However, in the presence of model error, measurement noises, and other non-idealities, the residual is nonlinear and may not respond proportionally to fault severity. This

requires the high fidelity models which may be computationally expensive, or even unavailable. Therefore, the balance between the complexity of the model and the treatment of non-idealities plays an important role in this approach. Compared to other methods, the model-based approach has the advantage of taking into account the physical knowledge of the system into the monitoring process, which helps analyze the fault effects and extract the fault-dependent quantities. In modern model-based approach, it implicitly means probability distribution-based techniques. Based on the process and measurement models, the system states and parameters can be estimated in form of posterior PDF. The various methods for estimating of this PDF is shown in Fig. 2.10. KF is applied for Gaussian Markov linear process assuming that both process and measurement noises are Gaussian, while EKF and UKF are its variants to nonlinear systems but with the same assumptions. There is numerous work based on KF, EKF, and UKF have been presented for different models and applications. and also in fusion approach. EKF and expectation-maximization are applied for an hidden and age-dependent nonlinear degradation process in [176]. In [177], recurrence quantification analysis technique is applied to extract features from vibration signals, and both KF and auto regression are used to optimize prediction results, for failure prognosis of rolling bearings. PF-based is the solution without assumptions of linear and Gaussian noises. The key difference between PF and KF is that in PF, all particles, representing the PDF, are updated, not only mean in the KF approach. It is found in various applications and forms as presented in [3, 178–184], and has been in strong momentum in prognosis.

Similar to the model-based approach in the aspect to exploit the domain knowledge, however, the knowledge-based approach do not require model development. In order to employ the expert knowledge, it usually uses expert systems and fuzzy logic techniques. In the expert system-approach, the human expertise is modeled and utilized in the forms, simulating the way experts do thinking and interference. CASSANDRA [185] and PROMISE [186] are two typical knowledge-based prognostic systems in this group. However, the approach has its limitations. First, to obtain the domain knowledge and convert it to rules is generally complicated. Second, if the number of rules is large, it brings out the computation issues, reducing the efficacy. Fuzzy logic technique is also applied to exploit expert knowledge in term of linguistic variables and fuzzy sets. However, it lacks the learning capability. This drawback can be overcome by combining fuzzy

Figure 2.10: Different methods estimating posterior PDF in prognostic model-based approach [172, 173].

logic with other learning methods such as NN, as the Alarm Filtering and Diagnostic System in [187] and Fuzzy Back Propagation Network in [188]. Despite of that, the knowledge-based method is not scalable and diversified to the new situations, if they are not captured in the knowledge bases.

Data-driven approach generates the prognostic parameters without requiring system physics and human expertise [189]. The approach is based on the statistical and learning techniques to find out the relationship between the degradation process and the features, calculated from measured signals. The techniques of data-driven approach is various, including multivariate statistical methods such as PCA, linear and quadratic discriminant, SVM, or black-box methods based on ANN, or other methods such as HMM, regressive models, autoregressive-moving average models, etc. Due to that nature, data-driven approach is especially suitable for practical problems where it is easier to have data than expert knowledge on physics-of-failure. However, the physical link between features and fault parameters is generally lost on data-driven approach. Moreover, in many cases, it takes substantial time and high cost to collect abundant data. Many algorithms and data training models require a great amount of historic data, including both healthy and failure data, which are collected from accelerated tests where the fault is introduced to

simulate the fault behaviors of systems. ANN is one of the most common method in data-driven approach. The essential components of a neural network are nodes and associated weights, which link input, output, and middle layers. In that meaning, it actually is a nonlinear approximation of systems. However, due to its advantage on learning capability, it is well suited for data-driven approach. It is applied in wide range of applications, as in [190–192]. While ANN-based approach is widely used, it has limitation to handle process linguistic and inaccurate input data. Therefore, it is also combined with other methods such as expert system, fuzzy logic, and Bayesian inference. Fuzzy logic is also applied in data-driven approach, but usually fused with other methods [193, 194]. In [195], ANFIS is integrated with high-order PF to estimate p-step-ahead predictions. It is also shown that the fusion approach outperforms conventional ANFIS and PF-based predictors.

2.3.2 Prognosis for mechanical faults

Prognosis for mechanical systems using vibration measurements is relatively mature compared to prognosis for other systems.

In traditional model-based model approach, the physical behavior of the degradation process is mathematically modelled. Due to its nature, it usually provides reliable RUL estimation. However, the complete representation of the system behavior maybe not available. In addition, the coefficients and parameters in the physical models are mainly determined experimentally. It is mostly found in manufacturing application where the evaluation of tool condition and machine degradation is required. Taylor model and its variants are used to model tool life considering the cutting speed, cutting depth, and also cutting temperature, as discussed in [196–198]. The difference in wear mechanisms lead to different tool wear rate models. The tool wear rate model can be considered as a particular type of crack growth model or fatigue spall progression model [172]. These models are commonly found in prognosis of mechanical components such as bearing, gearbox, rotor bar, and crack faults in vehicle suspension system, aerospace system, and electrical machines. While in traditional approach, the extensive experiments and empirical methods are required, in modern approach, the physical models and law are combined with modern techniques such as IMM, PF to name a few. In [199], the crack

fault due to fatigue based on Paris law has been studied for vehicle suspension system. In [200], the prognosis for planetary carrier plate in helicopter gearbox is proposed based on physic model and PF-approach. In [201], a recursive least squares based prognosis method is proposed for rolling element bearing using Paris-Erdogan law. The parameters extracted from vibration signal in the model are tuned by an adaptation method. In [202], a model-based framework is proposed for prognostics and health management for flight control actuators. A mathematical dynamic model of the considered system pertaining to the physical process and parameters is used. The parameter estimation algorithm is applied to estimate the physical parameters. These estimates are compared with the reference parameters, so called baseline, under healthy conditions to diagnosis the systems/components. In a system which is complex enough, the degradation process can be subject to multiple mechanisms. It is the case when multiple components are interconnected, and multiple operational stress are acting in one system. Multiple fault growth models are considered in this case. In [199], the crack fault due to fatigue has been studied for vehicle suspension system. IMM technique is utilized for prognosis of suspension system under unknown load conditions. IMM is employed to perform mixing mode-based life predictions via time-averaged mode probabilities. An approach to multi-fault modeling of prognosis of a rolling element bearing of a helicopter's oil cooler is developed in [203], assuming corrosion, spalling, and cracking occurs to the bearing. In [204], a PF-based method is proposed and Akaike Information Criterion is applied for determining the number of degradation mechanisms, and identifying the dominant one.

In [190], a NN method is applied to bearing fault. The method uses the database of degradation signal, which is vibration defective frequencies, to build the degradation models. The models are used to predict the RUL of a bearing component at any time during its service life. In [191], a data-driven prognostic framework is proposed. It uses dynamic wavelet neural networks for data modeling. Since the direct measurement of the crack dimension is not possible, the virtual sensor is introduced to take the measured signals and correlate them to direct fault quantities. The framework is demonstrated via the prognosis of bearing component. In [192], another data-driven prognostic framework is proposed. Neural network is used for feature extraction, fuzzy logic is applied for reasoning the damage from features, and KF is exploited to predict the damage progression

and estimate the RUL. The framework is validated on actual aircraft actuator components, FIA-I8 stabilator electro-hydraulic servo valves using test stand data provided by Boeing Phantom Works. In [205], a method to employ HMM for both diagnosis and prognosis is proposed. HMM is applied for modeling sensor signals. It is validated using data from drill bits in a drilling process. In [206], an integrated fault diagnostic and prognostic approach is proposed for bearing fault. The method applies PCA to extract the features, and HMM is utilized to generate the degradation index. The fault growth model is updated when new data are available using adaptive algorithm. In [207], diagnostic and prognostic method based on SVM and HMM is proposed.

2.3.3 Prognosis for batteries and electrochemical cells

Batteries have the increasing importance in the power and storage systems in aerospace systems, and electric and hybrid electric vehicles. Accurate estimates of SOC, SOH, and SOL for batteries would provide a significant value for battery management system. Various methods have been proposed for prognosis of battery covering both model-based and data-driven approaches. A review of prognosis methods for batteries can be found in [208].

In [209], the model-based and data-driven methods are combined in a fusion approach. It proposes and verifies a primary model-based fusion approach in which the internal electrical impedance of the battery is found as the parameter closely representing aging process, and robust identification routine is applied to identify the parameter. The combination of ARMA, Fuzzy Logic, and NN helps estimate SOC, SOH, and SOL. The method is also validated across different chemistries and sizes, like lithium batteries, nickel-cadmium batteries under different size and loading conditions. In [210], the KF and EKF have been applied for prediction of SOC and SOH of batteries for hybrid-electric vehicles for better energy management within vehicles. It is shown that KF has predictor-correct mechanism, so that the complex model of the cell to closely match the real system, is not required. In [211], a method for SOH and RUL estimations for lithium-ion batteries using DST and PF is proposed. The training data is supplied to DST to generate initial model parameters. PF is then used to update the model parameters and predict the RUL based on available data through battery capacity monitoring. As

more data become available, the accuracy of the model in predicting RUL improves. The result in [211] also shows the advantage of PF approach over the EKF-based approach in term of accuracy and prediction confidence. In [178], an improved PF, called unscented PF, is proposed. A comparison study is conducted in [212] to compare PF and other methods, which are autoregressive integrated moving average and EKF, for prognosis of batteries. PF is shown to have more advantages over the other methods. Instead of simply estimating the mean of RUL, it generates a probability distribution of the RUL, and hence, can represent the inherent uncertainties of degradation models and prediction results. In [213], it proposes a method to tackle the challenge of uncertain future operating profile. In order to achieve that, the PF-based method characterizes the uncertainty through the maximum likelihood estimates of transition probabilities for a two-state Markov chain. In [214], a Lebesgue sampling-based fault diagnosis and prognosis is proposed to reduce PF computation time. the experiment result shows that it is much faster than Riemann sampling framework. In addition, the Lebesgue sampling-based method provides a reasonable a need-based diagnosis and prognosis mechanism. It can be seen that PF have been widely applied to prognosis of batteries and electrochemical cells and the approach has achieved certain success. It seems one of the reasons behind is that PF is well suited to applications of batteries and electrochemical cells where the mathematical models are available. It can be said that PF has been a standard approach for prognosis of batteries.

2.3.4 Prognosis for stator winding and other components in electrical machines

Electrical machines are widely used in industries. They are subject to faults due to aging, severe operating conditions, and harsh environments. These faults can be categorized into different groups, including stator-related fault, rotor fault, bearing fault and power electronic component fault in the drive system [8]. Sections 2.3.2 covers numerous prognosis methods for mechanical faults, and these methods are definitely directly applicable to mechanical components of electrical machines, especially rotor and bearing. In this section, the prognosis methods are devoted to mostly electrical faults.

In [215], the HMM is proposed for prognosis of an intermittent increased contact resistance, a transient electrical fault in the winding of PMSM. The torque producing

component of the field oriented stator current is measured signal. The time-frequency features are extracted from this signal, and they are classified using linear discriminant classifier. The features and classifier are used for estimating parameters of HMM model. This model is employed to estimate the probability of failure states, which is used for prognosis. The same HMM-based method is applied for prognosis gear fault occurring to automotive starter DC machines [216]. In order to train the HMM parameters in the presence of limited data, an algorithm using a mix of experiments and heuristic methods is proposed to estimate the probabilities of next fault severity state. In [217], a fatigue test is designed to produce the rotor bar breakage in an induction machine. Both stationary and transient features are generated from the current signals. FEM is used for determining physical parameters relating the features to the damage state. Once again, the PF is used for state estimation of rotor bar breakage and predict the time at the final breakage. In [26], a prognosis method is proposed for a brush-less DC motor, used in aircraft electro-mechanical actuator, under winding insulation fault. In the approach, the measured signals of stator voltages and currents are used for generating the prognostic features. This is different from vibration signal-based approach applied for mechanical fault and bearing degradation. The reason may be due to fact that the winding insulation is a kind of electrical faults. The Arrhenius law is used for establishing a relationship between the rate of degradation against temperature, which depends upon the features based on an assumed linear approximate model. In order to identify the model and predict the winding degradation process, PF-based approach is applied. In [218], a prognosis method is proposed for induction machine used in vapor compressor applications. A nonlinear observer with neural network online approximator is employed for identification and projection of degradation process. Both stator winding insulation degradation and broken rotor bars are considered in the work. However, the fault are simply modeled as the increase of q-axis current component or the increase of rotor resistance for the stator fault and rotor fault, respectively. In [219], a health-index (HI) is proposed to predict the RUL of electrical machines. The characteristics of HI including monotonicity, gradualness, and consistency, are incorporated to dynamically smooth the HI values, and hence, improve RUL estimation. In addition, the multimodel ensemble method to integrate RUL estimates from different models is also presented in the paper.

2.4 Revisit of the Research Approach in This Thesis

Different diagnosis and prognosis methods have been developed for different components and systems. The selection of suitable methods for stator winding fault studied in this thesis is discussed here.

For diagnosis, while there is a substantial amount of research proposed, there is small amount of work coping with early fault detection and only the limited success has been achieved. This thesis attempts to address this challenge by proposing the idea of either using some supplementary indicators simultaneously or employing sequence component approach to distinguish the fault effect from that of inherent asymmetry and voltage imbalance. This takes the advantages of various indicators proposed for diagnosis of electrical machines, and the sequence component approach.

For prognosis, stator winding insulation fault is different from mechanical fault. It can be considered as a kind of electrical fault, and hence, the vibration signal may not be a suitable signal to generate the fault features. The research on [26] uses stator voltages and currents to generate the feature for stator winding fault. However, as shown in this thesis, it is possible to bypass the feature extraction. Instead, the estimation process can be applied to directly estimate the fault parameters. Different approaches are proposed for estimation of fault parameters in this thesis. They are based on filter-based approach, such as using PF, or the unique characteristic of electrical machines under sinusoidal excitation voltage by which differential equations can be represented in trigonometry form, or the multiple forms of models of electrical machines under fault. They will be discussed in subsequent chapters.

Moreover, the unique characteristic of stator winding insulation fault is that to be different from mechanical fault in which the mathematical expressions to relate the crack size to vibration signal is unavailable or complicated, for the stator winding insulation fault, the electrical fault parameters and the voltage and current quantities are mathematically well defined. Due to this characteristic, the diagnostic model can be utilized for both diagnosis and prognosis.

In addition, electrical machines have the dynamics that electrical quantities like currents, voltages are sinusoidal signals of several tens of Hertz in frequency, but faults can

occur and progress in units of hours, days, weeks, months, or even years. Under this circumstance, fault parameters, directly representing for the fault existence and its severity, can be considered as constant for each severity level, and degradation process can be approximated by the step changes of these parameters. This thesis proposes the RUL method based on this assumption. One advantage of this is the estimation process is not required to run all the time. Only when the fault occurs and it degrades to a higher severity condition, the estimation process is triggered.

PF has been applied to the prognosis of motor bars under fatigue, spalling in bearing, turn-to-turn winding fault in a brush-less DC motor of an aircraft electro-mechanical actuator, various faults in pneumatic valves, planetary carrier crack in helicopter gearbox, battery state-of-charge, battery RUL prediction, crack in blades of a turbine engine. PF is a sequential Monte Carlo technique that has been proven as an effective technique for various prognosis problems [179, 180]. It can be applied to any given nonlinear systems of both Gaussian and non-Gaussian noise since it does not require analytical forms of PDF. Instead, it approximates PDF by using a set of particles and the associated weights [220]. Moreover, compared to other estimation methods for non-linear systems, such as EKF, it does not require linearization using Jacobian matrix. The significant convenience of PF based approach for RUL estimation is that the statistical quantities of the particle sets can be employed to quantify the performance of RUL estimation results. Therefore, it is employed in this thesis for estimation of fault parameters and RUL.

Chapter 3

Model of Induction Machines under SWITSF

3.1 Introduction

As discussed in Section 1.1.2, the model is essential component of model -based approach, and the selection of a suitable model is of significant importance. Different models have been proposed for induction machines under SWITSF. The circuit-based model establishes a set of differential equations for stator and rotor currents and flux linkages. This model requires the least computation and hence is preferred for online applications. On the other hand, the FEM is accurate but requires substantial computation time. For a reasonably accurate model and reduced computation, a coupled magnetic circuit approach is considered. This chapter will give the overview about these models, the selection of a suitable model for study in this thesis, and the theory and validation of the selected model.

The theoretical model is necessary since it will be explored to estimate fault parameters using measured terminal quantities, as presented in Chapter 4. In addition, the theoretical model will be used to analyze the effect of fault and ambiguous factors, so that an method to decompose the fault-dependent quantity from that under the effect of ambiguous factors can be proposed, as in Chapter 5. The model is also explored for proposing other estimation methods of fault parameters in Chapters 6 and 7. The MATLAB Simulink model is used to validate the model. It produces the simulates signals, which are compared to the actual signals for validation. As shown in Section 3.4, the simulated signals are comparable to the measured quantities.

3.1.1 Circuit-based model

A circuit-based model for an induction machine under SWITSF occurring to a single phase using stator fixed reference frame $qd0$ is proposed in [64]. A set of differential equations convenient for simulation and analytical analysis is proposed. The model can be transformed to the equivalent sequence component model. This model is basis for many other works on diagnosis using the circuit-based model approach.

In [221], the asymmetry of the winding is considered to represent the fault effect. The healthy machine with asymmetrical winding is proposed first and then it is extended for modeling a machine under SWITSF. The healthy machine is modeled assuming that there are different number of turns in three stator windings. This model is employed to model the fault machine assuming that the stator winding is decomposed into two portions of which one is the healthy portion and the other is the shorted portion. The transformation from abc to dq reference frame shows that the shorted portion is included in the q axis only. The simulation under various conditions is studied to validate the sequence component analysis of stator currents, the developed torque, and the effect of unbalanced stator voltages, based on the developed model.

In [222], a new model of an asynchronous machine under unbalanced stator winding structure due to SWITSF is proposed using abc axis. A new transformation function is introduced bringing the rotor current and magnetic flux in the same frequency as the counterparts in the stator. It means the motor variables are transformed to the stator coordinate system after this transformation. In addition, without transforming to $qd0$ reference frame, the inductances and mutual inductances are still in abc frame but are independent of the relative position between the stator and the rotor. The stator variables are unchanged by this transformation. Therefore, the transformed model is applicable to model the imbalance of stator winding structure.

In [75], a study on modeling of the machine under SWITSF show that it is insufficient to model the faulty machine as simply as an unbalanced two-axis Park's model. The authors developed a model based on standard Park's model to represent a faulty induction machine. The model is characterized by two equivalent modes. The common mode model, i.e., Park's model, applies to the healthy dynamics of the machine, and the differential

model does to the fault. In addition, the global stator fault model is proposed to consider the case of faults occurring simultaneously to different phases.

The circuit-based model has the advantage of simple mathematical equations. In addition, the effect of faults can be represented by three direct fault quantities, three quantities, viz. the insulation fault loop resistance, the percentage of shorted turns, and the shorted turn current. However, it has limitations on modeling saturation flux and other nonlinear effects.

3.1.2 Coupled magnetic circuits and permeance network method

Model accuracy and computation time are two significant properties when analyzing, simulating, and diagnosing of induction machines under faults. In general, to have an accurate model improves the accuracy of the results for observer-base approach, parameter estimation, and fault indicators generated based on the model. However, there is always a compromise between model accuracy and computation time when choosing a model. The model based on coupled magnetic circuits and permeance network method provides a fairly good balance between accuracy and computation time.

In [223], a coupled magnetic circuits approach is proposed for modeling a squirrel cage induction machine under SWITSF with only a few assumptions. However the actual geometry and winding layout of the machines are required to calculate inductances using the winding function approach. The accuracy of inductance calculation under SWITSF is actually one advantage of this approach. In this approach, stator winding is modeled as a set of independent stator coils connected in any configuration when integrated to form the stator phases. In the similar manner, the rotor cage consists of identical and equally spaced rotor coils plus end-ring coils and is connected to form the correct rotor bars/end-rings configuration. Another model based on the coupled magnetic circuits theory is proposed in [224]. It enables the accurate simulation of an induction under the fault. The machine inductances are calculated by applying the winding function approach. The magnetic circuit saturation is also taken into account by considering the fundamental saturation harmonic in the inductance calculation.

In [225, 226], a model is proposed, which is an integration of permeance network method (PNM) and the differential equation system governing the induction machine

behavior in presence of stator fault. Considering that the high loop current in the faulty winding portion is high, causing local magnetic saturation, the model is able to take into account this behavior. The flux in the machine is composed of a set of flux tubes, characterized by their magnetic permeances. These permeances depend on of the machine geometry and the instantaneous fluxes owing in each one of them. A simulation is conducted to validate the influence of magnetic saturation under SWITSF, and experiment is used to validate the PNM-based approach.

Although coupled magnetic circuits and permeance network method provide a compromise between accuracy and computation time, they are more suitable for analysis and simulation of electrical machines under faults, rather than generating direct and online fault indicators and diagnosis implementation.

3.1.3 FEM-based model

FEM is a technique used to solve complex problems. It is based on the idea that the geometry of an object can be discretized into a certain number of subdivisions and machine operation particularities can be obtained by applying the mathematical calculation on these subdivisions. These subdivisions are called the elements, which have simple geometry and do not overlap each other. FEM can be applied to any geometry of electromagnetic devices and deliver high degree of accuracy in predicting machine operation characteristics, and thus it works as a very popular tool in electric machine design and analysis [227–230].

FEM model has the advantage of taking into account the nonlinearity of the magnetic material and geometry of machines. For SWITSF, the fault loop current can cause the saturation in the flux, and under this situation, modeling saturation effect is useful. For the nonlinearity of the geometry, it has significant effect at the incipient stage of fault development. FEM model is also advantageous to model this nonlinearity.

3.1.4 The selection of a suitable model

In this thesis, the considered fault is at the early stage of its degradation process, and hence the consideration of the effect of saturation is not required, as experimentally validated in next sections. For the challenge of modeling the nonlinearity effects such

as inherent asymmetry, the sequence component model is an alternative and simple approach to model the nonlinearity, and hence can avoid using the expensive FEM model. This nonlinearity is modeled through the cross-sequence impedances. The challenge with this approach is that these impedances are unknown. However, as shown in Chapter 5, a method to compensate the effect of nonlinearity without requiring the values of these unknown quantities, is proposed. Also, it will be experimentally validated in this section that the circuit-based model is sufficient to model the fault when the fault severity is not severe, which actually is the case should be considered for incipient diagnosis and prognosis. The model presented in this chapter is similar with the models presented in [64], and [29]. The difference lies on the parameters to represent fault severity and location. In [29], a single vector $\boldsymbol{\mu}_{qd}$ is used to represent both fault severity and location, while in this chapter, parameter μ is used for fault severity and vector $\boldsymbol{\gamma}$ is used for fault location. Using two separate parameters helps describe clearly each of the effects of fault severity and location. The circuit-based model is simulated in MATLAB Simulink and compared with the actual measurement signals for its validation.

3.2 Model of Induction Machines under Fault in abc and $qd0$ Reference Frame

3.2.1 Model of induction machines under fault in phase a in abc reference frame

Fig. 3.1 shows the stator winding configuration of a three-phase induction machine under inter-turn fault in phase a . The fault is represented by two parameters, viz. the fraction of shorted turns and fault loop resistance. They are denoted as μ and r_f , respectively. In more detail,

$$\mu = \frac{N_{as_f}}{N_{as_f} + N_{as_h}}, \quad (3.1)$$

where N_{as_f} and N_{as_h} are the number of turns in the healthy (as_f) and faulty (as_h) portions of the faulty phase winding a , respectively, and r_f is the insulation resistance of the stator winding fault loop portion.

Figure 3.1: Stator winding under SWITSF in phase a .

The electrical and mechanical equations of a faulty induction machine are as follows [64].

$$\mathbf{v}_s = R_s \mathbf{i}_s + \frac{d\boldsymbol{\lambda}_s}{dt} - \mu i_f \mathbf{R}_s(:, 1), \quad (3.2)$$

$$\mathbf{0} = R_r \mathbf{i}_r + \frac{d\boldsymbol{\lambda}_r}{dt}, \quad (3.3)$$

where

$$\mathbf{v}_s = [v_{as} \quad v_{bs} \quad v_{cs}]^T, \quad (3.4)$$

$$\mathbf{i}_s = [i_{as} \quad i_{bs} \quad i_{cs}]^T, \quad (3.5)$$

$$\mathbf{i}_r = [i_{ar} \quad i_{br} \quad i_{cr}]^T, \quad (3.6)$$

$$\begin{aligned} \boldsymbol{\lambda}_s &= [(\lambda_{as_h} + \lambda_{as_f}) \quad \lambda_{bs} \quad \lambda_{cs}]^T \\ &= \mathbf{L}_{ss} \mathbf{i}_s + \mathbf{L}_{sr} \mathbf{i}_r - \mu i_f \mathbf{L}_{ss}(:, 1), \end{aligned} \quad (3.7)$$

$$\begin{aligned} \boldsymbol{\lambda}_r &= [\lambda_{ar} \quad \lambda_{br} \quad \lambda_{cr}]^T \\ &= \mathbf{L}_{sr}^T \mathbf{i}_s + \mathbf{L}_{rr} \mathbf{i}_r - \mu i_f \mathbf{L}_{sr}^T(:, 1), \end{aligned} \quad (3.8)$$

and the notation $\mathbf{A}(:, n)$ denotes the column numbered n of a matrix $\mathbf{A}$.

Stator and rotor resistance matrices $\mathbf{R}_s$ and $\mathbf{R}_r$ are given as

$$\mathbf{R}_s = R_s \mathbf{I}_{3 \times 3}, \quad (3.9)$$

$$\mathbf{R}_r = R_r \mathbf{I}_{3 \times 3}, \quad (3.10)$$

where $\mathbf{I}_{n \times n}$ denotes an identity matrix of order n .

Winding inductance matrices $\mathbf{L}_{ss}$, $\mathbf{L}_{sr}$, and $\mathbf{L}_{rr}$ are defined in equations (3.11), (3.12), and (3.13).

$$\mathbf{L}_{ss} = \begin{pmatrix} L_{ls} + L_{ms} & -L_{ms}/2 & -L_{ms}/2 \\ -L_{ms}/2 & L_{ls} + L_{ms} & -L_{ms}/2 \\ -L_{ms}/2 & -L_{ms}/2 & L_{ls} + L_{ms} \end{pmatrix}, \quad (3.11)$$

$$\mathbf{L}_{sr} = L_{ms} \cdot \begin{pmatrix} \cos \theta_r & \cos(\theta_r + 2\pi/3) & \cos(\theta_r - 2\pi/3) \\ \cos(\theta_r - 2\pi/3) & \cos \theta_r & \cos(\theta_r + 2\pi/3) \\ \cos(\theta_r + 2\pi/3) & \cos(\theta_r - 2\pi/3) & \cos \theta_r \end{pmatrix}, \quad (3.12)$$

$$\mathbf{L}_{rr} = \begin{pmatrix} L_{lr} + L_{ms} & -L_{ms}/2 & -L_{ms}/2 \\ -L_{ms}/2 & L_{lr} + L_{ms} & -L_{ms}/2 \\ -L_{ms}/2 & -L_{ms}/2 & L_{lr} + L_{ms} \end{pmatrix}. \quad (3.13)$$

Equations (3.2), (3.7), and (3.8) show that for faulty machines, there are additional terms depending on the fraction of shorted turns μ and fault loop current i_f , compared to their counterparts for a healthy machine. The model of a healthy machine is referred to [256]. In addition, the first element of the stator flux linkage vector $\boldsymbol{\lambda}_s$ is the sum of stator flux linkages in healthy portion as_h and inter-turn portion as_f .

For inter-turn portion as_f , the voltage and flux linkage equations are

$$v_{as_f} = r_f i_f = \mu R_s (i_{as} - i_f) + \frac{d\lambda_{as_f}}{dt}, \quad (3.14)$$

$$\lambda_{as_f} = \mu \mathbf{L}_{ss}(1, :) \mathbf{i}_s + \mu \mathbf{L}_{sr}(1, :) \mathbf{i}_r - \mu (L_{ls} + \mu L_{ms}) i_f, \quad (3.15)$$

where the notation $\mathbf{A}(n, :)$ denote the row numbered n of a matrix $\mathbf{A}$.

The differential equation for the fault loop current is

$$l_f \frac{di_f}{dt} = -r_{ff} i_f + \mu v_{as}, \quad (3.16)$$

where

$$l_f = \mu(1 - \mu)L_{ls}, \quad (3.17)$$

$$r_{ff} = \mu(1 - \mu)R_s + r_f. \quad (3.18)$$

The equation for electromagnetic torque also shows the dependency on μ and i_f .

$$T_e = \frac{P}{2} \mathbf{i}_s^T \frac{\partial \mathbf{L}_{sr}}{\partial \theta_r} \mathbf{i}_r + \mu \frac{P}{2} L_{ms} i_f \left(\frac{3}{2} i_{ar} \sin \theta_r + \frac{\sqrt{3}}{2} (i_{br} - i_{cr}) \cos \theta_r \right). \quad (3.19)$$

The rotor speed ω_r can be represented as

$$\frac{d\omega_r}{dt} = \frac{P}{2J} (T_e - T_L - B\omega_r). \quad (3.20)$$

3.2.2 Model of induction machines under fault in phase a in $qd0$ stator-fixed reference frame

An electrical machine is modeled in $qd0$ stator-fixed reference frame in order to remove the dependence of inductance in rotor speed, and hence results in a simpler model. The counterparts of the equations presented in the previous section in abc reference frame are derived here in $qd0$ stator-fixed reference frame. The q-axis and d-axis is described in Fig. 3.2.

Figure 3.2: q-axis and d-axis in stator-fixed reference frame.

$$\mathbf{v}_{qdos} = R_s \mathbf{i}_{qdos} + \frac{d\boldsymbol{\lambda}_{qdos}}{dt} - \mu R_s i_f \begin{bmatrix} \frac{2}{3} & 0 & \frac{1}{3} \end{bmatrix}^T, \quad (3.21)$$

$$\mathbf{0} = R_r \mathbf{i}_{qdr} + \frac{d\boldsymbol{\lambda}_{qdor}}{dt} + \omega_r \begin{pmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \boldsymbol{\lambda}_{qdor}, \quad (3.22)$$

$$\boldsymbol{\lambda}_{qds} = L_s \mathbf{i}_{qds} + L_m \mathbf{i}_{qdr} - \mu i_f \left[\frac{2}{3} L_s \quad 0 \right]^T, \quad (3.23)$$

$$\lambda_{os} = L_{ls} i_{os} - \frac{1}{3} \mu L_{ls} i_f, \quad (3.24)$$

$$\boldsymbol{\lambda}_{qdr} = L_m \mathbf{i}_{qds} + L_r \mathbf{i}_{qdr} - \mu i_f \left[\frac{2}{3} L_m \quad 0 \right]^T, \quad (3.25)$$

$$\lambda_{or} = L_{lr} i_{or}, \quad (3.26)$$

where

$$\mathbf{v}_{qd0s} = [v_{qs} \quad v_{ds} \quad v_{0s}]^T, \quad (3.27)$$

$$\mathbf{i}_{qd0s} = [i_{qs} \quad i_{ds} \quad i_{0s}]^T, \quad (3.28)$$

$$\boldsymbol{\lambda}_{qd0s} = [\lambda_{qs} \quad \lambda_{ds} \quad \lambda_{0s}]^T, \quad (3.29)$$

$$\mathbf{i}_{qd0r} = [i_{qr} \quad i_{dr} \quad i_{0r}]^T, \quad (3.30)$$

$$\boldsymbol{\lambda}_{qd0r} = [\lambda_{qr} \quad \lambda_{dr} \quad \lambda_{0r}]^T, \quad (3.31)$$

$$\boldsymbol{\lambda}_{qds} = [\lambda_{qs} \quad \lambda_{ds}]^T, \quad (3.32)$$

$$\boldsymbol{\lambda}_{qdr} = [\lambda_{qr} \quad \lambda_{dr}]^T, \quad (3.33)$$

$$\mathbf{i}_{qds} = [i_{qs} \quad i_{ds}]^T, \quad (3.34)$$

$$\mathbf{i}_{qdr} = [i_{qr} \quad i_{dr}]^T. \quad (3.35)$$

The voltage and flux linkage equations for inter-turn portion as_f are

$$v_{as_f} = r_f i_f = \mu R_s (i_{qs} + i_{os} - i_f) + \frac{d\lambda_{as_f}}{dt}, \quad (3.36)$$

$$\begin{aligned} \lambda_{as_f} &= \mu L_s i_{qs} + \mu L_m i_{qr} \\ &+ \mu L_{ls} i_{os} - \mu i_f (L_{ls} + \frac{2}{3} \mu L_m), \end{aligned} \quad (3.37)$$

where

$$L_m = \frac{3}{2} L_{ms}, \quad (3.38)$$

$$L_s = L_{ls} + L_m, \quad (3.39)$$

$$L_r = L_{lr} + L_m. \quad (3.40)$$

The electromagnetic torque becomes

$$T_e = \frac{3P}{4} L_m (i_{qs} i_{dr} - i_{ds} i_{qr}) - \frac{P}{2} \mu L_m i_f i_{dr}. \quad (3.41)$$

The differential equation of fault loop current in $qd0$ reference frame becomes

$$L_f \frac{di_f}{dt} = -R_f i_f + \mu v_{qs}, \quad (3.42)$$

where

$$L_f = \mu \left(1 - \frac{2}{3} \mu \right) L_{ls}, \quad (3.43)$$

$$R_f = \mu \left(1 - \frac{2}{3} \mu \right) R_s + r_f. \quad (3.44)$$

3.2.3 Model of induction machines under fault in phase b and c and the generalized model

In this section, only the equations for the cases of inter-turn faults in phase b and c which are different from the case of single faulty phase a are described. Also, the equations in $qd0$ stator-fixed reference frame are focused here. The equations for fault loop current in abc reference frame for the single faulty phase b and c are

$$l_f \frac{di_f}{dt} = -r_{ff} i_f + \mu v_{bs}, \quad (3.45)$$

$$l_f \frac{di_f}{dt} = -r_{ff} i_f + \mu v_{cs}, \quad (3.46)$$

respectively.

In order to generalize any single faulty phase, denote v_f and λ_f as the generalized terminal voltage and flux linkage in the inter-turn winding portion, respectively and define the localization vector γ so that for the fault in phase a , b , and c , respectively, it is given as

$$\gamma = [1 \quad 0]^T, \quad (3.47)$$

$$\gamma = [-1/2 \quad -\sqrt{3}/2]^T, \quad (3.48)$$

$$\gamma = [-1/2 \quad \sqrt{3}/2]^T. \quad (3.49)$$

The definition of this vector γ is based on the projection of vectors representing phase a , phase b , and phase c to qd coordinate, as described in Fig. 3.3.

 Figure 3.3: Vector γ under fault in different stator winding phases.

Equations (3.22), (3.24), and (3.26) are unchanged over different cases of faulty phases, but equations (3.21), (3.23), (3.25), (3.36), (3.37), (3.41), and (3.42) needs to be updated. These equations are generalized as follows.

$$\mathbf{v}_{qdos} = R_s \mathbf{i}_{qdos} + \frac{d\boldsymbol{\lambda}_{qdos}}{dt} - \frac{2}{3} \mu R_s i_f \left[\boldsymbol{\gamma}^T \quad \frac{1}{3} \right]^T, \quad (3.50)$$

$$\boldsymbol{\lambda}_{qds} = L_s \mathbf{i}_{qds} + L_m \mathbf{i}_{qdr} - \frac{2}{3} \mu L_s i_f \boldsymbol{\gamma}, \quad (3.51)$$

$$\boldsymbol{\lambda}_{qdr} = L_m \mathbf{i}_{qds} + L_r \mathbf{i}_{qdr} - \frac{2}{3} \mu L_m i_f \boldsymbol{\gamma}, \quad (3.52)$$

$$v_f = r_f i_f = \mu R_s (\boldsymbol{\gamma}^T \mathbf{i}_{qds} + i_{os} - i_f) + \frac{d\lambda_f}{dt}, \quad (3.53)$$

$$\begin{aligned} \lambda_f &= \mu \boldsymbol{\gamma}^T (L_s \mathbf{i}_{qds} + L_m \mathbf{i}_{qdr}) \\ &\quad + \mu L_{ls} i_{os} - \mu i_f (L_{ls} + \frac{2}{3} \mu L_m), \end{aligned} \quad (3.54)$$

$$\begin{aligned} T_e &= \frac{3P}{4} L_m (i_{qs} i_{dr} - i_{ds} i_{qr}) \\ &\quad - \frac{P}{2} \mu L_m i_f [\boldsymbol{\gamma}(1) \quad -\boldsymbol{\gamma}(2)] [i_{dr} \quad i_{qr}]^T, \end{aligned} \quad (3.55)$$

$$L_f \frac{di_f}{dt} = -R_f i_f + \mu \boldsymbol{\gamma}^T \mathbf{v}_{qds}. \quad (3.56)$$

3.3 Model of Induction Machines under Fault in Sequence Component Quantities

The equations in qd reference frame can be transformed to that in positive and negative sequence component model due to the equivalence of vector and phasor represented by complex quantities. The equations in qd reference frame are transformed into the sequence component model. The transformation is based on the relationship that [231]

$$f_{qds} = F_p e^{j\omega_e t} + F_n^* e^{-j\omega_e t}. \quad (3.57)$$

In this equation, f_{qds} is a vector, F_p and F_n are positive and negative sequence components, respectively, F_n^* is the complex conjugate of F_n , and ω_e is the excited electrical frequency.

$$\tilde{V}_{sp} = (R_s + j\omega_e L_s)(\tilde{I}_{sp} - \frac{1}{3}\mu\gamma\tilde{I}_f) + j\omega_e L_m \tilde{I}_{rp}, \quad (3.58)$$

$$\tilde{V}_{sn} = (R_s + j\omega_e L_s)(\tilde{I}_{sn} - \frac{1}{3}\mu\gamma^*\tilde{I}_f) + j\omega_e L_m \tilde{I}_{rn}, \quad (3.59)$$

$$0 = (\frac{R_r}{s} + j\omega_e L_r)\tilde{I}_{rp} + j\omega_e L_m(\tilde{I}_{sp} - \frac{1}{3}\mu\gamma\tilde{I}_f), \quad (3.60)$$

$$0 = (\frac{R_r}{2-s} + j\omega_e L_r)\tilde{I}_{rn} + j\omega_e L_m(\tilde{I}_{sn} - \frac{1}{3}\mu\gamma^*\tilde{I}_f), \quad (3.61)$$

where γ is the complex number equivalent to vector $\boldsymbol{\gamma}$ in previous section, and γ^* is the complex conjugate of γ . ω_e is the excited electrical frequency, $\tilde{V}_{sp}$, $\tilde{V}_{sn}$ are positive and negative components of stator voltages, respectively. $\tilde{I}_{sp}$, $\tilde{I}_{sn}$ are positive and negative components of stator currents, respectively. $\tilde{I}_{rp}$, $\tilde{I}_{rn}$ are positive and negative components of rotor currents, respectively. $\tilde{I}_f$ is fault loop current phasor. s is motor slip.

The equation for fault loop current is

$$j\omega_e L_f \tilde{I}_f = -R_f \tilde{I}_f + \mu(\gamma\tilde{V}_{sp} + \gamma^*\tilde{V}_{sn}). \quad (3.62)$$

Based on these equations, the model of an induction machine under fault can be described for stator, rotor, and the loop winding portion, as shown in Fig. 3.4, Fig. 3.5, and Fig. 3.6, respectively.

Figure 3.4: Stator sequence component model of a faulty machine. (a) Positive sequence component model. (b) Negative sequence component model.

Figure 3.5: Rotor sequence component model of a faulty machine. (a) Positive sequence component model. (b) Negative sequence component model.

Figure 3.6: Sequence component model of the fault loop winding portion.

However, since the currents in rotor bars are not measurable, for applications in which only measured stator voltages and currents are available, the models of only measured quantities should be considered. Therefore, the new models are derived as follows and depicted in Fig. 3.7.

$$\tilde{V}_{sp} = ((R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{s} + j\omega_e L_r})\tilde{I}_{sp} - \frac{1}{3}\mu\gamma^*((R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{s} + j\omega_e L_r})\tilde{I}_f, \quad (3.63)$$

$$\tilde{V}_{sn} = ((R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{2-s} + j\omega_e L_r})\tilde{I}_{sn} - \frac{1}{3}\mu\gamma((R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{2-s} + j\omega_e L_r})\tilde{I}_f, \quad (3.64)$$

3.4 Model Validation

In order to validate the model, a test rig is built. The validation method is based on the comparison of real signals and simulated signals of an induction machine under SWITSF. Actual AC main voltages are applied o the model, for validation. The list of signals used for validation purpose is described in Fig. 3.8. They include fault loop current, three-phase stator currents, and rotor speed.

3.4.1 Description of experimental test rig

The machine used in the experiment is a squirrel cage induction motor of 1.5 kW, 415 V, and 10.2 Nm. The parameters of the motor are shown in Table 3.1.

The complete experiment test rig is shown in Fig. 3.9. Stator voltages are supplied from a programmable power supply so that the phase and magnitude of each phase can

Figure 3.7: Sequence component model of a faulty machine. (a) Positive sequence component model. (b) Negative sequence component model.

Figure 3.8: Signals used for model validation of induction machines under fault.

Table 3.1: Parameters of the induction motor used in test rig

Motor Parameter	Value	Motor Parameter	Value
R_s	7.2050 Ω	L_m	268.9 mH
R_r	6.8255 Ω	J	20.17 $\cdot 10^{-3}$ kg.m ²
L_{ls}	13.1 mH	P	4
L_r	282.0 mH	B	10 $\cdot 10^{-4}$ Nm.sec
Rated load T_L	10.2 Nm	Rated speed	1427 rpm

be selected. A dynamometer is used as the load on the motor under test. The sensors and associated hardware measure both the stator voltages and currents to transfer these measurement signals to a computer through NI data acquisition module and LabVIEW software. Also, a speed sensor is installed to measure rotor speed. A special arrangement has been made for emulating SWITSF. Different values of fault loop resistances can be set up by connecting a series of resistors in parallel using a relay system controlled by a dSPACE hardware module, as shown in Fig. 3.10. These values are designed as in Fig. 3.11. Their values are $25\ \Omega$ (K1 and K2 are closed), $11.7\ \Omega$ (K1, K2, and K3 are closed), $5.4\ \Omega$ (K1, K2, K3, and K4 are closed), and $2.5\ \Omega$ (K1, K2, K3, K4, and K5 are closed). Also, the percentage of shorted turns is configured as 10% (B1 is connected to N, and B2 is connected to A2). As shown in Fig. 3.11, the fault occurs at about 7 sec. moment, and the fault severity is changed from a condition ($r_f = 25\ \Omega$) to its higher severity conditions ($r_f = 11.7\ \Omega$, $r_f = 5.4\ \Omega$, then $r_f = 2.5\ \Omega$).

Figure 3.9: Test rig for validating the model.

The experiment is conducted under different load conditions, consisting of no-load, $T_L = 0\ \text{N.m}$, half-load, $T_L = 5\ \text{N.m}$, and full-load, $T_L = 10.2\ \text{N.m}$. Three different voltage conditions are tested, balance (BL), three-phase undervoltage (3UV), three-phase

overvoltage (3OV), as shown in Table 3.2. These conditions are selected in such a way that all have VUF=1% according to the IEC standard definition, but their magnitudes are different. This allows to test the robustness of the proposed technique against different load and voltage conditions.

Table 3.2: The list of different voltage conditions in experiment

Type	RMS-phase a (V)	RMS-phase b (V)	RMS-phase c (V)	phase a	phase b	phase c
BL	240.0	240.0	240.0	0°	-120°	120°
3UV	227.9	231.9	236.0	0°	-120°	120°
3OV	253.1	248.7	244.4	0°	-120°	120°

3.4.2 Validation results

Fig. 3.12, Fig. 3.13, and Fig. 3.14 shows the measured voltages of three phases. These values are fed to the model of induction machine, which is built using MATLAB Simulink, as shown in Fig. 3.15. This simulated model outputs the stator currents and fault loop current, will be compared with the counterparts of the measured signals. Fig.

Figure 3.10: Resistors and associated relay system for emulating SWITSF.

Figure 3.11: Emulation of fault occurrence and progression.

3.13, and Fig. 3.14 shows the imbalance of voltage in three phases under 3OV and 3UV conditions, respectively. The magnitudes of voltages in Fig. 3.13 is higher since it is under overvoltage condition, while the magnitude of voltages in 3.14, under undervoltage condition, is smaller.

Fig. 3.16(a), Fig. 3.16(b), and Fig. 3.16(c) depict the measured stator currents under balanced voltages and NL, HL, and FL load conditions, respectively. The fault has occurred in phase a , which is depicted in blue color in the figures. Fault occurs at about 7 sec. instant, and when fault severity is higher, i.e., r_f is smaller, the stator current i_{as} is also higher. However, the fault effect is only visually noticeable for high fault severity levels, which are corresponding to r_f smaller and equaling to 5.4Ω , after 25 sec. time instant. This implies the challenge of early fault detection. Also, it can be observed that the fault has effect to the currents in healthy phases, i.e., i_{bs} and i_{cs} . When the load is heavier in Fig. 3.16(b), and Fig. 3.16(c), the currents are increased in magnitudes, as expected.

Fig. 3.17 show the fault loop current, under balanced voltages and different load conditions. The currents are equal at each fault severity condition, i.e., each value of fault loop resistance r_f , implying that the fault loop current is independent of load conditions.

Figure 3.12: Measured stator voltages under BL voltage.

Figure 3.13: Measured stator voltages under imbalanced 30V voltage.

Figure 3.14: Measured stator voltages under imbalanced 3UV voltage.

Figure 3.15: Simulink model of induction machines under SWITSF.

In Fig. 3.18(a), Fig. 3.18(b), and Fig. 3.18(c), the measured fault loop currents and their simulated counterparts i_f under balanced voltages and NL, HL, and FL, respectively, are compared. The actual (blue color) and simulated currents (red color) in the three figures are closely matched under different load conditions. Fig. 3.19(a), Fig. 3.19(b),

Figure 3.16: Measured stator currents under BL voltage and different loads. (a) No-load. (b) Half-load. (c) Full-load.

 Figure 3.17: Measured fault loop current i_f under BL voltage.

and Fig. 3.19(c) depict the measured and simulated i_f for imbalanced voltages 3OV and NL, HL, and FL, respectively. Fig. 3.20(a), Fig. 3.20(b), and Fig. 3.20(c) show i_f for imbalanced voltages 3UV and NL, HL, and FL, respectively. In both cases, the measured

Figure 3.18: Measured and simulated fault loop current under BL voltage and different loads. (a) No-load. (b) Half-load. (c) Full-load.

and simulated quantities are comparable for different load conditions. This validates the accuracy of the theoretical model in the previous Section.

Figure 3.19: Measured and simulated fault loop current under imbalanced 30V voltage and different loads. (a) No-load. (b) Half-load. (c) Full-load.

In order to compare the stator currents, in Fig. 3.21(a), Fig. 3.21(b), and Fig. 3.21(c),

Figure 3.20: Comparison of measured and simulated fault loop current under imbalanced 3UV voltage and different loads. (a) No-load. (b) Half-load. (c) Full-load.

the measured (blue color) and simulated (red color) stator currents i_{as} , i_{bs} , and i_{cs} are depicted, respectively, for balanced voltages at NL condition. For each of the currents, i_{as} , i_{bs} , and i_{cs} , its actual and simulated values are closely matched in both phases and magnitudes. Fig. 3.22(a), Fig. 3.22(b), and Fig. 3.22(c) show the currents under HL condition. Fig. 3.23(a), Fig. 3.23(b), and Fig. 3.23(c) show the currents under FL condition. The simulated and measured currents are also comparable for these loaded cases. Moreover, the magnitudes of stator currents in these figures are higher compared to the that under NL conditions, in Fig. 3.21(a), Fig. 3.21(b), and Fig. 3.21(c).

Figure 3.21: Comparison of measured and simulated stator currents under BL voltage and NL.

Fig. 3.24 shows the three stator currents under the imbalanced 30V voltages and NL. The actual (solid curves) and simulated (dash curves) quantities of i_{as} , i_{bs} , and i_{cs} are not closely matched as in the case of balanced voltages above. This can be explained due to the effect of inherent asymmetry. However, for the imbalanced 30V voltages under HL and FL in Fig. 3.25 and Fig. 3.26, respectively, the actual and simulated currents of i_{as} , i_{bs} , and i_{cs} are more equal to each other. Their magnitudes are also higher for heavier loads in Fig. 3.25 and Fig. 3.26. The same observations are shown in Fig. 3.27, Fig.

Figure 3.22: Comparison of measured and simulated stator currents under BL voltage and HL.

3.28, and Fig. 3.29 for the stator currents under imbalanced 3UV voltages at NL, HL, and FL load conditions, respectively.

The rotor speed is also compared for the same operational conditions. In Fig. 3.30, the rotor speed of the real machine and that of model are compared for balanced voltages and different loads. They are very close to each other. Similarly, the actual and simulated rotor speeds under imbalanced 3OV voltages and 3UV voltages are also similar, as shown in Fig. 3.31 and Fig. 3.32, respectively.

In this section, it is shown that the circuit model is accurate to represent the real machine behavior under SWITSF even under the early stage of its progression. The actual quantities of fault loop current, stator currents, and rotor speed are closely matched with their counterparts in the simulated model. The model will be employed for both fault diagnosis and prognosis in the next chapter.

Figure 3.23: Comparison of measured and simulated stator currents under BL voltage and FL.

Figure 3.24: Comparison of measured and simulated stator currents under imbalanced 30V voltage and NL.

Figure 3.25: Comparison of measured and simulated stator currents under imbalanced 30V voltage and HL.

Figure 3.26: Comparison of measured and simulated stator currents under imbalanced 30V voltage and FL.

Figure 3.27: Comparison of measured and simulated stator currents under imbalanced 3UV voltage and NL.

Figure 3.28: Comparison of measured and simulated stator currents under imbalanced 3UV voltage and HL.

Figure 3.29: Comparison of measured and simulated stator currents under imbalanced 3UV voltage and FL.

Figure 3.30: Comparison of measured and simulated rotor speeds under BL voltage and different loads.

Figure 3.31: Comparison of measured and simulated rotor speeds under imbalanced 30V voltage and different loads.

Figure 3.32: Comparison of measured and simulated rotor speeds under imbalanced 3UV voltage and different loads.

Chapter 4

Model-Based Diagnosis and RUL Estimation

4.1 Introduction

In CBM, a vital task is to predict RUL of systems after a fault occurs. Electrical machines have the dynamics that electrical quantities like currents, voltages are sinusoidal signals of several tens of Hertz in frequency, but faults can occur and progress in units of hours, days, weeks, months, or even years. Under this circumstance, fault parameters, directly representing for the fault existence and its severity, can be considered as constant for each severity level, and degradation process can be approximated by the step changes of these parameters. The main objective of this chapter is to propose a framework and the associated techniques for the diagnosis and prognosis of electrical machines under this kind of degradation characteristic and SWITSF.

SWITS is one of the major types of fault in induction machines [232]. Also, an interesting, but challenging, characteristic of this fault is that the corresponding degradation process is characterized by the dynamics of two parameters instead of a single parameter. It is not the same with bearing fault, where the crack dimension is the only parameter representing the fault progression process [233]. Therefore, to study SWITSF, based on its development using the two parameters and validating them, forms the challenging aspect of this work. Since the two parameters are not measurable, an estimation process is required, linking the diagnosis and prognosis process. The estimates of fault parameters are used as the prognostic parameters for finding RUL. The framework and associate

techniques form a basis for detecting the incipient fault, tracking the degradation process, and estimating the RUL using the multiple indicators and PF based estimation of unknown and unmeasurable fault parameters.

The main contribution of this chapter is twofold. First, while there has been abundant research on diagnosis of SWITSF, the research on its prognosis is very limited. It is observed from prior art [175, 234, 235] that the prognosis of inter-turn fault for estimating the RUL has achieved limited success. Prognosis has been studied mostly for mechanical faults such as bearing, gear, shaft and rotor bar. For these mechanical faults, vibration signals are used to generate the prognostic features and the data-driven approach is used. However, for SWITSF, the physical connection between the vibration signal and the winding status may not exist, and hence, the use of vibration signal is not a suitable choice. In addition, even though prognosis for SWITSF has been proposed in [26], the features generated from the voltage and current signals are used as prognostic parameters. These features are not considered as direct fault parameters of SWITSF, which are percentage of shorted turns and fault loop resistance. To the best of authors' knowledge, there has been no work estimating the direct fault parameters for prognosis. This motivates for the research in this chapter. Second, it considers the diagnosis and prognosis from the viewpoint that degradation process can be approximated by the step changes of fault parameters. It requires two estimation steps in the framework. One is to estimate fault parameters, and the other is to estimate degradation process based on estimated parameters. However, the approach has advantage that instead of constantly running estimation process, it is only triggered when diagnosis process detects the change in fault severity. Since the dynamics of electrical machines are much faster than that of fault development, there is relatively substantial time and number of data at each fault severity level for diagnosis and prognosis. This is an important aspect of the approach, allowing implement multiple-indicator for reliable fault detectors and real-time estimation of fault parameters.

This chapter is divided into different sections as follows. Section 4.2 describes the real-time scheme for diagnosis, prognosis, and RUL estimation. Section 4.3 shows the details of modeling and analysis of induction machines under inter-turn fault. Section 4.4 discusses diagnosis using multiple indicators. Section 4.5 has the detailed analysis

for parameter estimation using PF approach. Section 4.6 discusses the experimental test bed and its details. Section 4.7 is the results obtained and 4.8 discusses and concludes the work.

4.2 Real-Time Scheme Diagnosis and RUL Estimation

The integrated scheme is shown in Fig. 4.1. Fig. 4.1(a) is the general framework which can be applied to any systems with unknown fault parameters. It consists of mainly two parts: 1) Fault indicators/diagnosis for beginning the prognosis, and 2) The prognosis scheme for RUL estimation. Even though these can be separately identified, they are interlinked closely for a reliable diagnosis and prognosis. Fig. 4.1(b) is the specific framework for inter-turn fault. In this approach, the changes in fault indicators have to be continuously monitored to obtain the changes due to the fault insulation degradation. Also, it is crucial to point out exactly when the change occurs in these indicators. It has two main roles. The first is to promptly commence the estimation process. The second is to identify the degradation model after the fault parameters are estimated. It is therefore imperative to estimate them accurately in order to predict the degradation process at a future time. The scheme is represented in Fig. 4.2.

The algorithm based on PF is the key part in order to link diagnosis and prognosis process, and statistically estimate RUL. A PF method is used to realize joint state and parameter estimation, where the motor model is augmented to include the unknown fault parameters. In the prediction stage based on PF technique, there is a set of different particles of which each will be propagated forward to its own end of life. As a result, there are totally N possible trajectories for the degradation process, assuming N is the number of particles. The significant convenience of PF based approach for RUL estimation is that the statistical quantities of this set of trajectories can be employed to quantify the performance of RUL estimation results. The steps from parameter estimation based on PF to RUL estimation are described in Fig. 4.3, in which $\mu_1^{(i)}, r_{f1}^{(i)}, \mu_2^{(i)}, r_{f2}^{(i)}, \dots, \mu_n^{(i)}, r_{fn}^{(i)}$, $i = 1 : N$, are estimated by PF.

The algorithm can be deployed in real time systems considering that the fault progresses slowly. First, the estimation process based on PF technique is not required to run

Figure 4.1: Framework for diagnosis and prognosis of electrical machines. (a) General framework. (b) Specific framework for inter-turn fault.

constantly. It is commenced only after a fault or a change in fault severity condition is detected, by diagnosis process. As shown later in Section 4.4, the sequence components of terminal quantities, stator voltages and currents are used for diagnosis. It means fault can be detected at the beginning stage of each fault severity level, and the majority of time during that level can be used for prognosis. Second, even though PF is more time consuming process compared to diagnosis, it also employs the terminal quantities for estimation. These signals have much faster dynamics than that of fault developments. In other words, during the time the fault severity level is constant and not yet change to the next severity level, there are sufficient time and substantial amount of data, relatively to dynamics of the machines, for estimation. The PF algorithm can run and converge to the correct value of fault parameter before the next fault severity level arrives. In addition, high performance processor can be used to run the algorithm if the larger number of particles are required. Moreover, the real-time PF algorithm is also available even if the rate of incoming measurement data is faster than that of the update of PF, as proposed in [236].

Figure 4.2: Triggering of fault parameter estimation when fault occurs or changes in its severity.

Figure 4.3: From parameter estimation to RUL estimation.

4.3 State-Space Model of Induction Machines under Stator Winding Inter-Turn Short Circuit Fault

In order to estimate fault parameters, the system is augmented so that fault parameters are incorporated as the new variables. Define $z_1 = i_{qs}$, $z_2 = i_{ds}$, $z_3 = -i_{qs} + \frac{a}{c}\lambda_{qr}$, $z_4 = -i_{ds} + \frac{a}{c}\lambda_{dr}$, $z_5 = \frac{2}{3}\mu i_f$, $z_6 = r_f$ and $z_7 = \mu$, and state vector $\mathbf{z} = [z_1 \ z_2 \ z_3 \ z_4 \ z_5 \ z_6 \ z_7 \ \omega_r]^T$, input vector $\mathbf{u} = [v_{qs} \ v_{ds} \ T_L]^T$, and output vector

$\mathbf{y} = [i_{qs} \ i_{ds}]^T$, the corresponding state equations are

$$\frac{d\mathbf{z}}{dt} = (\mathbf{A}_z + \omega_r \mathbf{A}_{\omega_r})\mathbf{z} + \mathbf{B}_z + \mathbf{B}_{1z}\mathbf{u} + \mathbf{B}_2\mathbf{u}, \quad (4.1)$$

$$\mathbf{y} = \mathbf{C}_z\mathbf{z}, \quad (4.2)$$

where

$$\mathbf{A}_z = \begin{bmatrix} A\mathbf{I}_{2 \times 2} & \frac{bc}{a}\mathbf{I}_{2 \times 2} & \begin{bmatrix} -a - \frac{R_s}{L_{ls}} - \frac{z_6}{z_7(1-\frac{2}{3}z_7)L_{ls}} \\ 0 \end{bmatrix} & \mathbf{0}_{2 \times 3} \\ B\mathbf{I}_{2 \times 2} & B\mathbf{I}_{2 \times 2} & \begin{bmatrix} \frac{r_s}{L_{ls}} + \frac{z_6}{z_7(1-\frac{2}{3}z_7)L_{ls}} \\ 0 \end{bmatrix} & \mathbf{0}_{2 \times 3} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & -\frac{r_s}{L_{ls}} - \frac{z_6}{z_7(1-\frac{2}{3}z_7)L_{ls}} & \mathbf{0}_{1 \times 3} \\ \mathbf{0}_{2 \times 2} & \mathbf{0}_{2 \times 2} & \mathbf{0}_{2 \times 1} & \mathbf{0}_{2 \times 3} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & 0 & [0 \ 0 \ -\frac{BP}{2J}] \end{bmatrix}, \quad (4.3)$$

$$\mathbf{A}_{\omega_r} = \begin{bmatrix} \frac{ce}{a}\mathbf{J} & \frac{ce}{a}\mathbf{J} & \mathbf{0}_{2 \times 4} \\ -(1 + \frac{ce}{a})\mathbf{J} & -(1 + \frac{ce}{a})\mathbf{J} & \mathbf{0}_{2 \times 4} \\ \mathbf{0}_{4 \times 2} & \mathbf{0}_{4 \times 2} & \mathbf{0}_{4 \times 4} \end{bmatrix}, \quad (4.4)$$

$$\mathbf{B}_z = \begin{bmatrix} \mathbf{0}_{7 \times 1} \\ \frac{3cL_m P^2}{8aL_r J}(z_1 z_4 - z_2 z_3 - z_2 z_5 - z_4 z_5) \end{bmatrix}, \quad (4.5)$$

$$\mathbf{B}_{1z} = \begin{bmatrix} \frac{2z_7}{3(1-\frac{2}{3}z_7)L_{ls}} & \mathbf{0}_{1 \times 2} \\ 0 & \mathbf{0}_{1 \times 2} \\ -\frac{2z_7}{3(1-\frac{2}{3}z_7)L_{ls}} & \mathbf{0}_{1 \times 2} \\ 0 & \mathbf{0}_{1 \times 2} \\ \frac{2z_7}{3(1-\frac{2}{3}z_7)L_{ls}} & \mathbf{0}_{1 \times 2} \\ \mathbf{0}_{3 \times 1} & \mathbf{0}_{3 \times 2} \end{bmatrix}, \quad (4.6)$$

$$\mathbf{B}_2 = \begin{bmatrix} g\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ -g\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{3 \times 2} & \mathbf{0}_{3 \times 1} \\ \mathbf{0}_{1 \times 2} & -\frac{P}{2J} \end{bmatrix}, \quad (4.7)$$

$$\mathbf{C}_z = [\mathbf{I}_{2 \times 2} \ \mathbf{0}_{2 \times 6}]. \quad (4.8)$$

$\mathbf{I}_{n \times n}$ is the n -by- n identify matrix, $\mathbf{0}_{n \times m}$ is the n -by- m zero matrix. $\mathbf{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$, $a = (-\frac{R_r L_m^2}{L_r \nabla} - \frac{R_s L_r}{\nabla})$, $b = \frac{R_r L_m}{L_r \nabla}$, $c = \frac{R_r L_m}{L_r}$, $d = -\frac{R_r}{L_r}$, $e = \frac{L_m}{\nabla}$, $g = \frac{L_r}{\nabla}$, $A = (a + bc/a)$, $B = (d - bc/a)$ and $\nabla = L_s L_r - L_m^2$.

4.4 Fault Detection for Commencing Prognosis

The change in the fault indicators can be submerged due to the influence of inherent asymmetry, voltage imbalance, and load variation. Therefore, several indicators are used to increase the robustness of fault detection. Among various indicators, sequence component-based indicators are selected. Firstly, they can be generated from the model-based approach, which can capture the fault characteristics, so that the fault effect can be discriminated from that of voltage imbalance and load variation. Secondly, they can be implemented requiring no sensors other than voltage and current measurements. Moreover, the sequence component quantities can be calculated easily in real-time implementation. Due to these characteristics, a robust and non-intrusive diagnosis can be obtained for incipient fault detection based on the sequence component model approach.

In order to derive two suitable indicators, the sequence component model is employed. The equations (3.58), (3.59), (3.60), and (3.61) are written here again for the fault occurring to phase a .

$$\tilde{V}_{sp} = (R_s + j\omega_e L_s)(\tilde{I}_{sp} - \frac{1}{3}\mu\tilde{I}_f) + j\omega_e L_m \tilde{I}_{rp}, \quad (4.9)$$

$$\tilde{V}_{sn} = (R_s + j\omega_e L_s)(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f) + j\omega_e L_m \tilde{I}_{rn}, \quad (4.10)$$

$$0 = (\frac{R_r}{s} + j\omega_e L_r)\tilde{I}_{rp} + j\omega_e L_m(\tilde{I}_{sp} - \frac{1}{3}\mu\tilde{I}_f), \quad (4.11)$$

$$0 = (\frac{R_r}{2-s} + j\omega_e L_r)\tilde{I}_{rn} + j\omega_e L_m(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f), \quad (4.12)$$

It can be observed that the fault has influence on both negative and positive sequence models. It manifests as $\frac{1}{3}\mu\tilde{I}_f$ in these models. From equation (4.12), we have

$$\tilde{I}_{rn} = -\frac{j\omega_e L_m}{\frac{R_r}{2-s} + j\omega_e L_r}(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f) \quad (4.13)$$

Substitute this into the equation (4.10), then the contribution of the fault can be identified as a current source as

$$\frac{1}{3}\mu\tilde{I}_f = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}}, \quad (4.14)$$

where

$$Z_{nn} = (R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{2-s} + j\omega_e L_r}. \quad (4.15)$$

Define the first indicator Δ_n as

$$\Delta_n = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}}. \quad (4.16)$$

This indicator can estimate the quantity $\frac{1}{3}\mu\tilde{I}_f$, and hence is a suitable indicator for both fault detection and fault progress tracking, which, as mentioned in Section 4.2, is a key task in the overall diagnosis and prognosis framework. Δ_n is almost independent of the slip (due to the term (2-s) appearing in Z_{nn}), and therefore the load on the induction motor. It is also less sensitive to voltage imbalance conditions due to second term in its equation, which increases its reliability.

Another indicator, effective negative sequence admittance, which is the reciprocal of the effective negative sequence impedance [65], is utilized primarily for improving the fault detection capability at the incipient stage of fault development, as illustrated later in this chapter. It is given by

$$Y_{sneff} = \frac{\tilde{I}_{sn}}{\tilde{V}_{sn}}. \quad (4.17)$$

The two indicators, therefore, can supplement each other to enhance fault diagnosis performance. As will be shown in the experimental result section, they are adequate since they can reliably provide the instants at which the fault is detected and progressed to the next severity stages.

4.5 Parameter Estimation Using Particle Filter

RUL can be predicted by estimating the time interval, from the moment the degradation model is identified to the one it reaches a certain threshold. The degradation model is estimated based on the estimates of fault parameters and the instants of fault occurrence and progression. Therefore, fault parameter estimation can be considered as the interlink between diagnosis and RUL estimation processes. When the fault parameters are incorporated in the augmented state-space model, the resultant model becomes nonlinear. In order to propose a generic technique which can generally apply to parameter estimation of electrical machines, PF is employed in this work. PF is a sequential Monte Carlo technique that has been proven as an effective technique for various prognosis problems [179, 180]. It can be applied to any given nonlinear systems of both Gaussian

and non-Gaussian noise since it does not require analytical forms of probability density function. Instead, it approximates PDF by using a set of particles and the associated weights [220]. Moreover, compared to other estimation methods for non-linear systems, such as extend Kalman filter, it does not require linearization using Jacobian matrix.

The basis for PF is a nonlinear Bayesian filter which recursively estimates current posterior PDF through two steps, the prediction step to estimate the prior PDF, and the update step to estimate the posterior PDF using the current output measurements. In the PF approach, a PDF is represented by a set of random particles with associated weights such as

$$p(z(k)|y(1:k)) \approx \sum_{i=1}^N w^{(i)}(k) \delta(z(k) - z^{(i)}(k)), \quad (4.18)$$

where $z^{(i)}(k), i = 1, 2, \dots, N$ denotes a set of random particles drawn from $p(z(k)|y(1:k))$, N is the number of particles, $w^{(i)}(k)$ is the weight associated with particle $z^{(i)}(k)$, and $\delta(\cdot)$ is the Dirac delta function. Hence, the prediction and update steps of a PDF become that of particles and weights in PF approach. The particles and weights are chosen using the principle of importance sampling [237], and hence the corresponding filter is called sequential importance sampling (SIS) particle filter. In this kind of filter, the particles are sampled from a so called importance PDF, instead of directly sampled from a target PDF, and the weights need to be determined from the relationship between these two PDF. A common problem with the SIS PF is the degeneracy phenomenon. That is, after in few recursions, most particles converge to negligible weights. Other types of particle filter such as auxiliary sampling importance resampling [238], regularized PF [239], and sequential importance resampling (SIR) [240] have been proposed to overcome this problem. Fig. 4.4 illustrates the different steps in SIR technique, which is applied in this chapter due to its intuitive and simple implementation.

SIR particle filter algorithm

1. Initialize $z^{(i)}(0)$ and associated weights $w^{(i)}(0) = 1/N$, $i = 1:N$, and set $k = 0$.
2. Predict next state variables using the process model

$$z^{(i)}(k+1|k) \sim p(z(k+1)|z^{(i)}(k)),$$

i.e., $z^{(i)}(k+1|k) = f(z^{(i)}(k|k), u(k)) + v^{(i)}(k)$, where v is process noise

3. Calculate likelihood

$$w^{(i)}(k+1) = p(y(k)|z^{(i)}(k+1|k)).$$

4. Normalize weights

$$w^{(i)}(k+1) = \frac{w^{(i)}(k+1)}{\sum_{i=1}^N w^{(i)}(k+1)}.$$

5. Resample

$$index = resampling(w^{(i)}(k+1))$$

$$w^{(i)}(k+1) = 1/N, i = 1:N$$

$$z^{(i)}(k+1|k+1) = z^{(i)}(k+1|k)(index).$$

6. $k = k + 1$, and start the iteration process again from Step 2 above.

Figure 4.4: Illustration of sequential steps in SIR particle filter.

4.6 Experimental Prototype and Design of Degradation Process

4.6.1 Designed degradation process

Usually, motor life depends on many factors such as mechanical, thermal, electrical, and environmental stresses. Here, the motor life is defined as the stator winding insulation life under thermal stress. That is, it is characterized by the insulation life of the shorted turns, and hence the motor is considered reach the end of life if the fault loop insulation resistance is below its failure threshold. Accordingly, the fault development process is represented by the decrease of the fault loop resistance over time, and the percentage of shorted turns is kept constant. The degradation model can take various forms, for example, exponential, polynomial, etc. In this chapter, the exponential decay is assumed for validation of prognosis method. As discussed in [241], common degradation models, Arrhenius model, Coffin-Mason mechanical crack growth model, and Eyring model, have the form of exponential decay. Also, the leakage current under inter-turn fault has an exponential form [242]. Therefore, it can be suitably assumed for the inter-turn fault considered in this chapter. Inter-turn fault causes the circulating current and generates

thermal stress, which creates higher fault loop current and accelerates the degradation process. The resistance drop results in the higher circulating current. The degradation process designed in the chapter is the decrease of the fault loop resistance, equivalent to the increase of the magnitude of the circulating current in the degradation process. The exponential degradation model has the following mathematical form

$$r_f = ae^{-bt}. \quad (4.19)$$

As shown in the next chapter, the current i_f is inversely proportional to r_f , so the assumption of exponential decay is actually corresponding to the exponential increase of i_f .

This thesis proposes a methodology, by which the prognosis and RUL estimation can be possible using model based prognostic parameters, which are not measurable, and slowly varying compared to the electrical frequency of the system. They can be estimated using the measured terminal quantities. The degradation process in the experiment is considered as the “accelerated version” of the actual RUL, which may be a few hours or days [243, 244]. Firstly, with such type of accelerated model, this chapter aims to illustrate the capability of the proposed method. Secondly, in the real case, if the degradation process is longer, the method is still applicable since the only difference here is a longer time for estimation and prediction. If suppose the time for failure is very short, then the method can be still applied. Since the fault can be detected at the incipient stage, it has a significant role to prevent catastrophic damage to the machine and the associated systems, which can develop from the early stage to the complete failure.

The chosen values for a and b in the tests are $a = 30 \, \Omega$ and $b = 0.0489 \, (\text{time unit})^{-1}$. By this choice, the designed value of RUL, assuming the threshold value is $r_f = 0.8 \, \Omega$, is obtained as 54.86 (time unit). The degradation curve is shown in Fig. 4.5.

The same experimental setup for model validation in the previous chapter is employed here. The experimental test rig allows to customize only certain values of r_f , so in the test, the degradation process is emulated by changing r_f in steps according to the following values: 25 Ω , 11.7 Ω , 5.4 Ω , 2.5 Ω , 1.5 Ω , and 0.8 Ω , which are highlighted in red color in the figure.

Figure 4.5: The designed degradation model.

4.6.2 Estimation of RUL

The steps to estimate RUL is presented in Fig. 4.6.

Figure 4.6: Steps for estimating RUL.

In the experimental test rig, the values of r_f are changed in fixed steps. As discussed, not only its values, but also the instants at which the values are changed need to be estimated. The detection process can detect any step changes in r_f so that the instants can be recorded. Both the estimates of r_f and the instants t_1, t_2 are utilized to obtain the parameters a and b of the exponential model. The estimates of r_f are in PDF form, represented by the particles and its associated weights. A point estimate of r_{f1} and r_{f2} , the mean of their PDF, can be used for RUL estimation. However, correspondingly, only a single estimated degradation curve and RUL value is determined. Instead, in this work,

the estimates $r_{f1}^{(i)}$ and $r_{f2}^{(i)}$ of each particle are exploited to estimate parameters a and b and RUL, as shown below. The advantage of this approach is that the PDF of particles can be used to quantify the estimation performance.

Parameter $b^{(i)}$, corresponding to the i -th particle, can be estimated as

$$b^{(i)} = \frac{\ln \frac{r_{f1}^{(i)}}{r_{f2}^{(i)}}}{t_2 - t_1}. \quad (4.20)$$

The estimated $a^{(i)}$ is

$$a^{(i)} = \frac{1}{2} \left(\frac{r_{f1}^{(i)}}{e^{-b^{(i)}t_1}} - \frac{r_{f2}^{(i)}}{e^{-b^{(i)}t_2}} \right). \quad (4.21)$$

Define $t_e^{(i)}$ as the failure time, which is corresponding to a predefined threshold value of 0.8Ω for r_f , t_e can be found as

$$t_e^{(i)} = \frac{\ln \frac{a^{(i)}}{0.8}}{b^{(i)}}. \quad (4.22)$$

The $RUL^{(i)}$ is determined as

$$RUL^{(i)} = t_e^{(i)} - t_2. \quad (4.23)$$

That is, each particle will converge to a certain value of r_{f1} and r_{f2} , while t_1 and t_2 , provided from the diagnosis process, are unchanged. Therefore, there will be different RUL estimates corresponding to each of the particles. In other words, RUL estimates are in a range instead of a point estimate. This is explained in more details in the experimental result section.

The point estimate of RUL can be taken as the mean of the weights of all particles.

$$RUL_{Point \quad Estimate} = \frac{1}{N} \sum_{i=1}^N RUL^{(i)}. \quad (4.24)$$

4.7 Results and Discussion

The same motor and test rig used in Chapter 3 is adopted here. The experiments are conducted under different load conditions, no-load, half-load, and full-load, $T_L = 10.2$

N.m. Three different voltage conditions are tested, balanced-voltage (BL), three-phase under-voltage (UV), and three-phase over-voltage (OV), as depicted in Table 4.1. The two later voltage imbalance conditions are selected so that both have VUF=1% according to the IEC standard definition, but their magnitudes and phases are different. This allows to test the robustness of the proposed technique against different load and voltage imbalance conditions.

Table 4.1: Different voltage conditions used in experiment

Type	RMS- phase a	RMS- phase b	RMS- phase c	Angle- phase a	Angle- phase b	Angle- phase c
BL	240.0V	240.0V	240.0V	0°	-120°	120°
OV	253.1V	248.7V	244.4V	0°	-120°	120°
UV	227.9V	231.9V	236.0V	0°	-120°	120°

4.7.1 Fault detection and commencing of prognosis

Case 1 is a normal case when the supply voltage is balanced, and Case 2 and Case 3 are to check whether the scheme works in case of any voltage imbalance.

The fault progression indicator Δ_n is synchronous with the change in fault (step change), as shown in Fig. 4.7. Therefore, both the instants of fault occurrence and fault progression can be identified. Also, the magnitude of Δ_n increases with higher fault severity levels, as depicted in Fig. 4.8, indicating that it can reliably track the fault progression. In addition, it does not change with load appreciably, or has very less variation as the machine is loaded, for both balanced voltage and under-voltage conditions. The over-voltage imbalance condition can occur, and the fault has to be diagnosed under such conditions. The indicator does not show up with the fault due to inherent asymmetrical machine construction. This kind of phenomenon is observed during low levels of fault in Fig. 4.9. The presence of second indicator supplements the first indicator by detecting the fault and its time of occurrence more reliably. It shows that the multiple-indicator approach can improve the reliability and robustness of fault diagnosis at the incipient stage of fault development.

Figure 4.7: Closely depicting change in fault progression indicator with the synchronous signal (Case 1).

Figure 4.8: Load variation and indicator values for fault progression (Case 3).

4.7.2 Parameter estimation and RUL estimation

The fault parameter estimation method using the PF algorithm is employed for predicting the RUL. The predicted value is compared with the designed RUL, to check the performance of parameter estimation and prognosis algorithm. Since the estimates of two different values of fault loop resistances are sufficient to identify the degradation

Figure 4.9: Over-voltage condition where the multiple indicators are necessary (Case 2).

model, only the estimation for the first two instants, corresponding to fault occurrence, healthy state to faulty state with $r_f = 25 \Omega$, and progression, $r_f = 25 \Omega$ to $r_f = 11.7 \Omega$, are required.

a) Case 1

The estimate of r_f is shown in Fig. 4.10 and Fig. 4.11 for its designed values of 25Ω and 11.7Ω , respectively. In Fig. 4.10(a), it is the estimated particles and its associated weights at the 2-nd, 4-th, 6-th, 8-th, 10-th, 12-th estimation steps. Fig. 4.10(b) represents the estimates in term of histogram, by which the number of particles corresponding to each estimated value is shown. The mean of the estimate of r_f and the 95% confident level is depicted in Fig. 4.10(c). The distance between the lower and upper bounds is smaller after each estimation step, which shows the reliability of the estimated results. μ is estimated in Fig. 4.12. Rotor speed is accurately obtained, as shown in Fig. 4.13, showing that the method is sensorless. Fig. 4.14 is the estimated parameters a and b . They are depicted in weighted form of particles, which project the degradation process into the future and predict RUL. Fig. 4.15 shows the estimation of the degradation curve. Fig. 4.16 is the histogram, which is the distribution of the RUL. Each particle converges to a particular value of the estimates of r_{f1} and r_{f2} , which

calculates the corresponding estimated parameters of a and b , t_e , and RUL. The point estimate of RUL, calculated as the mean of this RUL distribution by equation (4.24), is 63.24 (time unit). The estimation error is nearly 15.27%. The estimated results show the suitability of parameter estimation and RUL prediction based on PF technique.

Figure 4.10: Estimate of r_f for BL-No load, $r_f = 25 \Omega$ (Case 1).

b) Case 2

The case of OV imbalance is investigated since it can occur due to the inherent imbalance of the voltage supply. The machine is partially loaded (half-load). Fig. 4.17 shows the estimates of parameter r_f , for which the 95% confident level has smaller bound, consistently observed in Case 1. Fig. 4.18 provides the estimated values of parameters a and b . Fig. 4.19 shows the estimation of the degradation process, and Fig. 4.20 shows the distribution of the RUL estimation. The mean of this RUL distribution is 60.73 (time unit), and the corresponding RUL estimation error is about 10.70%.

c) Case 3

This case is also discussed showing the robustness of the approach against voltage imbalance. Fig. 4.21 and Fig. 4.22 depict the estimates of fault loop resistance and the corresponding parameters a and b . Fig. 4.23 shows the estimation of the degradation curve, and Fig. 4.24 presents the distribution of the RUL estimation. The mean of RUL

Figure 4.11: Estimate of r_f for BL-No load, $r_f = 11.7 \Omega$ (Case 1).

Figure 4.12: Estimate of μ for BL-No load. (a) $r_f = 25 \Omega$. (b) $r_f = 11.7 \Omega$ (Case 1).

Figure 4.13: Estimate of rotor speed for BL-No load (Case 1).

distribution is 49.19 (time unit), and the corresponding RUL estimation error is about

 Figure 4.14: Estimated parameters a and b for BL-No load (Case 1).

Figure 4.15: Estimated degradation curve for BL-No load (Case 1).

10.33%.

4.7.3 Discussion

The noted differences in RUL mean values between the different cases are due to the influence of voltage imbalances on the prediction process, which is expected. The differences can be explained due to the stochastic nature of the PF-based approach, and also the specific voltage conditions. Considering the PF-based approach, the data of

Figure 4.16: RUL estimation for BL-No load (Case 1).

 Figure 4.17: Estimate of r_f for OV-Half load (Case 2).

input and output, and the stochastic characteristics of each case are different, then the estimates are also different. However, taking into account all particles, the 95% confident levels in all cases are close to the designed curves. Even though the mean values of the estimated RULs under different cases are different, they follow the designed values, which is as desired. The experimental results show that the proposed method can reliably work under various conditions of voltages and loads.

Inter-turn fault causes the circulating current, which in turn creates the local thermal

 Figure 4.18: Estimated parameters a and b for OV-Half load (Case 2).

Figure 4.19: Estimated degradation curve for OV-Half load (Case 2).

effect, speeding up the degradation process. This process, aided by the thermal stress, generates higher fault loop current. The decrease of r_f , equivalent to the higher circulating current, corresponds to the progression of the degradation process. The emulation system is reasonable to consider the diagnosis and prognosis method. The present work is first of this kind to estimate RUL during inter-turn fault using two estimated fault parameters. The basic methodology is in place now. In real situations, the inter-turn

Figure 4.20: RUL estimation for OV-Half load (Case 2).

 Figure 4.21: Estimate of r_f for UV-Full load (Case 3).

insulation breakdown can contain the capacitance effect, which can be detected by an offline method using the impedance analyzer [54]. In future work, it is possible to consider other effects such as dielectric capacitance to investigate the effect in RUL estimation due to these parasitic parameters.

This chapter proposes a diagnosis and prognosis method using the estimated values of two fault parameters. Parameter estimation forms the core of the process. It links between the diagnosis and prognosis, and also enables RUL estimation. Any form for

Figure 4.22: Estimated parameters a and b for UV-Full load (Case 3).

degradation process can be envisaged, since the estimation process can be applied to any of the functions. As long as a model structure is available, the degradation model can be identified, and RUL can be estimated.

4.8 Conclusion

In this chapter, a technique for winding failure prognosis of induction machines has been proposed and validated. This includes a fault diagnosis system using multiple indicators, and a parameter estimation and RUL estimation method using PF-based algorithm. The validation of the methodology has been performed under inter-turn fault for no load, half load, full load, and different voltage conditions of balanced voltage, over-voltage, and under-voltage. The fault diagnosis using multiple indicators is found to perform well in cases where single indicator does not show any significant change, and multiple-indicator approach can improve fault diagnosis at the early stage of fault development. The validation results show that the fault parameter estimation method can work under voltage imbalance and loaded conditions. The reason is that the faulty model takes into account the imbalance of voltage supply and load condition. In addition, for different voltage conditions, the estimates of parameters and RUL prediction is comparably accurate. The statistical nature of prognosis method based on PF technique

Figure 4.23: Estimated degradation curve for UV-Full load (Case 3).

Figure 4.24: RUL estimation for UV-Full load (Case 3).

helps quantify the performance of the estimation results. Since the methodology and algorithm is generic in nature, it can be applied to any other machines such as wound field or PM machines.

Chapter 5

Incipient Fault Detection Insensitive to Inherent Asymmetry and Voltage Imbalance

5.1 Introduction

Induction machines have been applied to marine propulsions, aerospace actuators, and traction in electric vehicles/hybrid electric vehicles [5–7]. Despite their rugged construction, they are subject to fault due to aging, severe operating conditions, and harsh environments. Industrial surveys have shown that stator winding accounts for a significant portion of failures in electrical machines [232]. The research on diagnosis of this fault has a long history of several decades along with tremendous research. Based on the applied techniques, diagnosis methods can be classified into the sequence component-based [12, 27, 28, 63–66, 70, 245], signature-based [55, 56, 60, 71, 72, 76, 82, 83, 85, 86, 89, 104–107], model-based [29–31, 75, 150], and artificial intelligence (AI)-based [162, 165, 170, 246, 247] approaches. The details of these methods have been presented in Chapter 2. Survey papers [13, 248, 249] also provide good summary of these techniques.

The main challenge in fault diagnosis is the effect of ambiguous factors, especially at the early stage of fault development. For SWITSF, the inherent asymmetry and voltage imbalance have been identified as the major ambiguous factors. As reported in [12, 27, 63, 65, 66, 72, 107], this issue is significant for the incipient fault detection. In addition, fault severity estimation is another important part of diagnosis, for tracking the degradation process after fault has been occurred. An effective diagnostic method, therefore, should be

able to detect the early fault and concurrently estimate the fault severity levels. Methods, considering the effect of inherent asymmetry, based on negative sequence currents, off-diagonal elements of sequence impedance matrix, or voltage mismatch detectors have been proposed in [12, 63], and [66], respectively. These methods require an offline process to collect data under various operating conditions. In [72], a method, considering the voltage imbalance and inherent asymmetry, using the rotor-slot-related harmonics of the terminal voltage of the machine, has been proposed. The method is offline since the data is collected when the machine is switched off. A technique using the positive- and negative-sequence third harmonic components of line currents to identify the effect of inherent asymmetry is proposed in [27]. However, the estimated severity is not monotonic. The fault-dependent quantities, directly related to fault parameters, have been estimated in [28, 29]. Nonetheless, the treatment of the effect of both voltage imbalance and inherent asymmetry concurrently has been not considered.

In this chapter, the diagnosis of incipient inter-turn fault under the influence of voltage imbalance and inherent asymmetry, and its severity estimation pertaining to fault parameters, have been studied. The main contribution of this work is threefold. First, the contribution in the modeling part is to decouple the fault, inherent asymmetry and voltage imbalance effects. Second, exploiting the decoupling achieved in modeling part, a diagnosis method has been developed which aids in achieving incipient diagnosis, in presence of ambiguous factors such as inherent asymmetry and voltage imbalance. The diagnosis method has advantage of being independent of cross-impedance sequence components, and hence, can be implemented in a simple manner. Third, the novel indicators have been also developed, which directly represent the unmeasurable fault parameters, thereby contributing to the fault severity assessment. The decoupling achieved in modeling part, as well as indicator development has been analytically proven and experimentally verified. Besides that, a faulty phase identification method is also developed in this chapter. Due to the generic nature of the proposed method, it can be diversified to other types of electrical machines having winding inter-turn short fault.

This chapter is organized as follows. Section 5.2 presents the existing approach and the proposed approach to overcome the limitations of the existing approach. Section 5.3 describes the diagnosis method under the concurrent effects of inherent asymmetry and

voltage imbalance. Section 5.4 presents the experimental results. Section 5.5 gives the discussion on the method and results, and concludes the chapter.

5.2 Existing Approaches and the Proposed Approach

5.2.1 Existing models and approaches

As discussed in Chapter 3, a three-phase electrical motor can be considered as a system of three-phase voltages as input and three-phase currents as output, as in Fig. 5.1(a). Using the physical laws, the relationship between the voltages v_{as} , v_{bs} , and v_{cs} , and three currents i_{as} , i_{bs} , and i_{cs} can be established. For the analysis of fault effects and the generating fault indicators, the sequence component model, as shown in Fig. 5.1(b), is preferred because it can capture the imbalance effect, caused by fault.

Figure 5.1: *abc* and sequence component models of an electrical machine. (a) *abc* representation. (b). Sequence component representation.

5.2.1.1 Sequence component model and diagnostic approach for an ideal machine and balanced voltages

Assuming an ideal machine, i.e., symmetrical machine with balanced supply voltages, the corresponding sequence component model is described in Fig. 5.2(a). When the fault occurs, the machine is not symmetrical anymore, and hence the negative sequence current $\tilde{I}_{sn}$ can be used to detect the fault occurrence.

5.2.1.2 Sequence component model and diagnostic approach for a real machine under inherent asymmetry and voltage imbalance

However, in real situation, machines always have a certain level of asymmetry due to manufacturing imperfections. Also, supply voltages are never ideally balanced. There-

fore, the suitable model should include negative sequence quantities, as shown in Fig. 5.2(b). The equation below describes this model.

Figure 5.2: Existing models for fault diagnosis. (a). Ideal machine under ideal operational condition. (b). Real machine under inherent asymmetry and voltage imbalance.

$$\tilde{V}_{sp} = Z_{pp}\tilde{I}_{sp} + Z_{pn}\tilde{I}_{sn}, \quad (5.1)$$

$$\tilde{V}_{sn} = Z_{np}\tilde{I}_{sp} + Z_{nn}\tilde{I}_{sn}, \quad (5.2)$$

where Z_{pp} and Z_{nn} are positive sequence and negative sequence impedances, respectively. Z_{pn} and Z_{np} are the off-diagonal sequence impedances/cross-sequence impedances indicating the coupling effects of positive and negative sequence models. The imbalance of supply voltages is represented by the negative sequence voltage $\tilde{V}_{sn}$. On the other hand, the inherent asymmetry of the machine is represented by the sequence off-diagonal sequence impedances Z_{pn} and Z_{np} . Due to the relationship between the sequence component quantities, described by equations above, the inherent asymmetry is also reflected in the negative sequence current $\tilde{I}_{sn}$.

For the existing approach [29, 63, 66], it is mostly based on the equations (5.1) and (5.2) above, i.e., using the same model structure for a healthy machine and a faulty machine. When the fault occurs, it changes the asymmetry of the electrical machine. However, the challenge with the approach using the model above is that the effect of both inherent asymmetry and fault is mixed into the sequence impedances Z_{pn} and Z_{np} . Therefore, by detecting the non-zero value in these sequence component quantities will lead to the false fault alarm due to offset caused by the existence of inherent asymmetry and voltage imbalance. In [63], the approach is to compare the cross-sequence impedance Z_{np} under the healthy and faulty conditions. Since the value of this quantity depends

on the operational conditions, an offline stage is required to estimate and store its value. The actual Z_{np} is compared with the stored value to detect if a fault occurs. In [66], the method using the voltage mismatch under healthy and faulty conditions is proposed. It has the similar nature to that in [63], based on the change in the value of the cross-sequence impedances under fault. An offline stage is also required to estimate and store the necessary quantities under various operational conditions.

In order to overcome this limitation, instead of estimating the impedances, in this chapter, a method is proposed, which cancels out these quantities under the healthy and faulty conditions and extract only the fault-dependent quantity. The method is made possible by using a developed analytical model, decomposing the effects of inherent asymmetry, voltage imbalance, and fault. Fig. 5.3 explains the proposed model and method compared to the existing ones. The next section will discuss more about this.

Figure 5.3: Explanation of the proposed methodology.

5.2.2 Proposed model of induction machines under ambiguous factors and fault, and the introduction of the diagnostic method

The proposed model is symbolically represented by the equations below

$$\tilde{V}_{sp} = Z_{pp}\tilde{I}_{sp} + Z_{pn}\tilde{I}_{sn} + Z_{pf}\tilde{I}_f, \quad (5.3)$$

$$\tilde{V}_{sn} = Z_{np}\tilde{I}_{sp} + Z_{nn}\tilde{I}_{sn} + Z_{nf}\tilde{I}_f. \quad (5.4)$$

To be different from the existing approaches, the proposed approach is based on different model structures for a healthy machine and a faulty machine. That is, equations (5.1) and (5.2) are used for a healthy machine, and equations (5.3) and (5.4) are used for the faulty machine. Z_{pf} and Z_{nf} are the quantities, present to only the faulty machine, equivalent to the sequence impedances to describe the effect of fault in the positive and negative sequence models, respectively. They are, therefore, dependent on fault parameters. $\tilde{I}_f$ is the current in the fault loop portion. These quantities are written here in the generic form. For stator winding fault studied in this chapter, in the next section, Z_{pf} and Z_{nf} will be determined, which is shown to be an expression of fault parameters. Fig. 5.4 graphically summaries the models of a healthy machine and a faulty machine. In the figure, the superscripts h and f indicate the healthy machine and faulty machine, respectively. The components enclosed by the red dash dot boxes represent the effect of inherent asymmetry, and the components enclosed by the blue dash dot boxes are due to the effect of fault.

Figure 5.4: Sequence component model of a healthy machine and a faulty machine. (a) Healthy machine. (b) Faulty machine.

Fig. 5.5 provides the explanation of the attributes of the sequence component quantities depending on fault, inherent asymmetry, and voltage imbalance. The input is the

sequence component voltages $\tilde{V}_{sp}$ and $\tilde{V}_{sn}$. The main sequence impedances Z_{pp} and Z_{nn} represents the relationship between the voltages and currents of same rotating directions, i.e., positive or negative components. The sequence off-impedances Z_{pn} and Z_{np} shows the effect of inherent asymmetry. Along with the effect of fault-dependent quantities Z_{pf} , Z_{nf} , and I_f , the all effects are integrated and reflected in the output currents $\tilde{I}_{sp}$ and $\tilde{I}_{sn}$. Fig. 5.6 provides the viewpoint on the unknown and measurable properties of the sequence component quantities. Output $\tilde{V}_{sp}$, $\tilde{V}_{sn}$, and input $\tilde{V}_{sp}$, $\tilde{V}_{sn}$ are measured by voltage and current sensors. Z_{pp} and Z_{nn} can be found from motor parameters. Z_{pn} , Z_{np} , and I_f are unknown, but we need to estimate them to quantify the fault severity level under the challenge that Z_{pn} and Z_{np} are unknown. This chapter proposes a diagnostic method which exploits the decoupling advantage of the developed model to achieve incipient fault detection and direct fault severity estimation, in presence of ambiguous factors such as inherent asymmetry and voltage imbalance. As aforementioned, the proposed model is a generic model for different kinds of fault. In the next section, first, the sequence component model for in induction motor under stator winding inter-turn fault will be presented. Second, both the main sequence impedances Z_{pp} and Z_{nn} , and the impedances Z_{pn} , Z_{np} characterized for the stator winding inter-turn fault will be formulated. After that, the diagnostic method is presented.

Figure 5.5: Explanation of the attributes of the sequence component quantities.

Fig. 5.7 shows the steps from the model in abc reference frame to that in sequence component model and also the step to determine the sequence impedance quantities.

Figure 5.6: Explanation of the unknown and measurable properties of the sequence component quantities.

Figure 5.7: From *abc* model to determination of sequence component quantities.

5.2.3 Formulation of sequence component impedances

Equations (3.58), (3.59), (3.60), and (3.61) are written here again.

$$\tilde{V}_{sp} = (R_s + j\omega_e L_s)(\tilde{I}_{sp} - \frac{1}{3}\mu\gamma\tilde{I}_f) + j\omega_e L_m \tilde{I}_{rp}, \quad (5.5)$$

$$\tilde{V}_{sn} = (R_s + j\omega_e L_s)(\tilde{I}_{sn} - \frac{1}{3}\mu\gamma^*\tilde{I}_f) + j\omega_e L_m \tilde{I}_{rn}, \quad (5.6)$$

$$0 = (\frac{R_r}{s} + j\omega_e L_r)\tilde{I}_{rp} + j\omega_e L_m(\tilde{I}_{sp} - \frac{1}{3}\mu\gamma\tilde{I}_f), \quad (5.7)$$

$$0 = (\frac{R_r}{2-s} + j\omega_e L_r)\tilde{I}_{rn} + j\omega_e L_m(\tilde{I}_{sn} - \frac{1}{3}\mu\gamma^*\tilde{I}_f), \quad (5.8)$$

From equation (5.7), the quantity $\tilde{I}_{rp}$ can be expressed as

$$\tilde{I}_{rp} = -\frac{j\omega_e L_m}{\frac{R_r}{s} + j\omega_e L_r}(\tilde{I}_{sp} - \frac{1}{3}\mu\gamma\tilde{I}_f) \quad (5.9)$$

Substitute this expression into equation (5.5), it becomes

$$\tilde{V}_{sp} = ((R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{s} + j\omega_e L_r})\tilde{I}_{sp} - \frac{1}{3}\mu\gamma^* Z_{pp}\tilde{I}_f, \quad (5.10)$$

This equation is equivalent to equation (5.3), assuming there is non inherent asymmetry, i.e., $Z_{pn} = 0$. That is, under the ideal condition of no inherent asymmetry, the asymmetry is due to only the effect fault. The positive sequence impedance Z_{pp} , and the fault-dependent impedance Z_{pf} can be derived, by equaling the equivalent terms, as

$$Z_{pp} = (R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{s} + j\omega_e L_r}. \quad (5.11)$$

$$Z_{pf} = -\frac{1}{3}\mu\gamma^* Z_{pp}, \quad (5.12)$$

Similarly, the negative sequence impedance Z_{nn} can be found from equations (5.6), (5.8), and (5.4) as

$$Z_{nn} = (R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{2-s} + j\omega_e L_r}. \quad (5.13)$$

and the fault-dependent impedance Z_{nf} is

$$Z_{nf} = -\frac{1}{3}\mu\gamma Z_{nn}, \quad (5.14)$$

Once these sequence impedances terms are determined, they can be employed for the diagnostic method, presented in the next section.

5.3 Diagnosis Method for Early Fault Detection and Fault Severity Estimation

5.3.1 Diagnosis method under the effect of only voltage imbalance

In this section, the diagnosis method is studied for a symmetrical machine under voltage imbalance. That is, it is assumed that there is no inherent asymmetry, which actually is an ideal case. However, it established the basis for the method considering the effect of both inherent asymmetry and voltage imbalance, which is presented in the next section.

For an ideal healthy machine, its model is expressed by the equations (5.1) and (5.2) assuming that $Z_{pn} = 0$ and $Z_{np} = 0$.

$$\tilde{V}_{sp}^h = Z_{pp}\tilde{I}_{sp}^h, \quad (5.15)$$

$$\tilde{V}_{sn}^h = Z_{nn}\tilde{I}_{sn}^h, \quad (5.16)$$

Define quantities, calculated by the negative sequence components, Δ_p and Δ_n as

$$\Delta_p = \tilde{I}_{sp} - \frac{\tilde{V}_{sp}}{Z_{pp}}, \quad (5.17)$$

$$\Delta_n = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}}. \quad (5.18)$$

From equations (5.15) and (5.16), it can be derived that both Δ_p and Δ_n are equal to zero under healthy condition.

When the fault occurs, the equations (5.3) and (5.4), without the term regarding Z_{pn} and Z_{np} due to the assumption, are employed.

$$\tilde{V}_{sp}^f = Z_{pp}\tilde{I}_{sp}^f + Z_{pf}\tilde{I}_f, \quad (5.19)$$

$$\tilde{V}_{sn}^f = Z_{nn}\tilde{I}_{sn}^f + Z_{nf}\tilde{I}_f, \quad (5.20)$$

The quantities Δ_p and Δ_n becomes

$$\Delta_p^f = -\frac{Z_{pf}}{Z_{pp}}\tilde{I}_f, \quad (5.21)$$

$$\Delta_n^f = -\frac{Z_{nf}}{Z_{nn}}\tilde{I}_f. \quad (5.22)$$

Employing equation (5.12) and (5.14), we have

$$\Delta_p^f = \frac{1}{3}\mu\gamma^*\tilde{I}_f, \quad (5.23)$$

$$\Delta_n^f = \frac{1}{3}\mu\gamma\tilde{I}_f, \quad (5.24)$$

That is, when the machine is under healthy condition, both Δ_p and Δ_n have zero value. However, when the fault is present, they have fault-dependent values. Therefore, by tracking the values of Δ_p and Δ_n , the fault can be detected.

5.3.2 Diagnosis method under the effects of both inherent asymmetry and voltage imbalance

Under the effect of inherent asymmetry, the model of the healthy machine is expressed by equations (5.1) and (5.2), and that of the faulty machines is expressed by equations (5.3) and (5.4).

$$\tilde{V}_{sp}^h = Z_{pp}\tilde{I}_{sp}^h + Z_{pn}\tilde{I}_{sn}^h, \quad (5.25)$$

$$\tilde{V}_{sn}^h = Z_{np}\tilde{I}_{sp}^h + Z_{nn}\tilde{I}_{sn}^h, \quad (5.26)$$

$$\tilde{V}_{sp}^f = Z_{pp}\tilde{I}_{sp}^f + Z_{pn}\tilde{I}_{sn}^f + Z_{pf}\tilde{I}_f, \quad (5.27)$$

$$\tilde{V}_{sn}^f = Z_{np}\tilde{I}_{sp}^f + Z_{nn}\tilde{I}_{sn}^f + Z_{nf}\tilde{I}_f, \quad (5.28)$$

The quantity Δ_p under the healthy condition, derived from equations (5.17) and (5.25) becomes

$$\Delta_p^h = -\frac{Z_{pn}}{Z_{pp}}\tilde{I}_{sn}^h, \quad (5.29)$$

This simple equation explains for challenge of fault diagnosis. For an actual machine, Δ_p is no longer valid to detect the fault due to the offset at the healthy condition, caused by the effect of inherent asymmetry. However, considering Δ_p under the faulty condition, derived from equation (5.27),

$$\Delta_p^f = -\frac{Z_{pn}}{Z_{pp}}\tilde{I}_{sn}^f - \frac{Z_{pf}}{Z_{pp}}\tilde{I}_f, \quad (5.30)$$

This relation shows the fault-dependent term is distinguished from the inherent asymmetry term. Therefore, the difference of Δ_p between the faulty and healthy conditions can be used to cancel out the effect of inherent asymmetry and generate a term sensitive to only fault. It is defined as

$$\delta_p = \Delta_p - \Delta_p^h. \quad (5.31)$$

That is, by tracking the change of Δ_p , the fault can be detected. Under the healthy condition δ_p is zero, and when the fault occurs, take the difference between equations (5.29) and (5.30), and the definition of δ_p in equation (5.31), the value of δ_p under fault is

$$\delta_p^f = -\frac{Z_{pf}}{Z_{pp}}\tilde{I}_f. \quad (5.32)$$

That is,

$$\delta_p^f = \frac{1}{3}\mu\gamma^*\tilde{I}_f. \quad (5.33)$$

as adopted from equations (5.12).

Similarly, for the quantity Δ_n

$$\Delta_n^h = -\frac{Z_{np}}{Z_{nn}}\tilde{I}_{sp}^h, \quad (5.34)$$

$$\Delta_n^f = -\frac{Z_{np}}{Z_{nn}}\tilde{I}_{sp}^f - \frac{Z_{nf}}{Z_{nn}}\tilde{I}_f. \quad (5.35)$$

And define the quantity

$$\delta_n = \Delta_n - \Delta_n^h, \quad (5.36)$$

Using equations (5.34), (5.35), and (5.36), the value of δ_n under fault is

$$\delta_n = -\frac{Z_{nf}}{Z_{nn}}\tilde{I}_f. \quad (5.37)$$

Also, using the formula for Z_{nf} in equation (5.14), then

$$\delta_n^f = \frac{1}{3}\mu\gamma\tilde{I}_f. \quad (5.38)$$

This analysis shows that both δ_p and δ_n can be used for fault diagnosis. The diagnosis method is able to detect the incipient fault since it can compensate the effects of both voltage imbalance and inherent asymmetry, which cause the challenge of early fault detection. It is also able to estimate the fault severity since δ_p and δ_n have fault-dependent values when the fault occurs, as shown by equations (5.33) and (5.38), respectively.

In the next section, the suitability of the proposed indicators for representing the fault severity is further discussed.

5.3.3 Relationship between the proposed indicators and fault parameters

From equations (5.33) and (5.38), and noticing that the factor γ and γ^* has the magnitude of one, and is only the phase component, the magnitude of δ_p and δ_n are equal to magnitude of $\frac{1}{3}\mu\tilde{I}_f$. That is,

$$|\delta_p| = |\delta_n| = \left| \frac{1}{3}\mu\tilde{I}_f \right| \quad (5.39)$$

Also, from equation (3.62), written again here

$$\left(j\omega_e\mu\left(1 - \frac{2\mu}{3}\right)L_{ls} + \mu\left(1 - \frac{2\mu}{3}\right)R_s + r_f\right)\tilde{I}_f = \mu(\gamma\tilde{V}_{sp} + \gamma^*\tilde{V}_{sn}), \quad (5.40)$$

Since incipient fault detection is the focus, either μ is small or r_f is large. Also, considering applications, in which ω_e is not high, $\omega_e\mu L_{ls}$ and μR_s is negligible compared to r_f . $\tilde{V}_{sn}$ is negligible compared to $\tilde{V}_{sp}$. As a result, equation (3.62) can be approximated to

$$r_f\tilde{I}_f \approx \gamma\mu\tilde{V}_{sp}. \quad (5.41)$$

That is,

$$\frac{1}{3}\mu\tilde{I}_f \approx \gamma\frac{\mu^2\tilde{V}_{sp}}{3r_f}. \quad (5.42)$$

In term of magnitude, then

$$\left|\frac{1}{3}\mu\tilde{I}_f\right| \approx \frac{\mu^2}{r_f} \times \left|\frac{\tilde{V}_{sp}}{3}\right| \quad (5.43)$$

As indicated by equation (5.39), the magnitudes of the proposed indicators δ_p and δ_n are equal to that of $\frac{1}{3}\mu\tilde{I}_f$. Using also the relationship between $\frac{1}{3}\mu\tilde{I}_f$ and the fault parameters μ and r_f , shown in equation (5.43), the magnitudes of the proposed indicators are proportional to the square of μ , and inversely proportional to r_f . Therefore, it is higher when fault severity is higher, represented by either μ increased or r_f decreased. Also, it can be normalized by using the rated voltage, represented by the factor $\tilde{V}_{sp}$, as a scaling factor so that it is applicable for machines of different power ratings. In other words, δ_p and δ_n are very suitable fault severity estimates since they are directly related to fault parameters μ and r_f .

5.3.4 A method for faulty phase identification

Faulty phase identification has been proposed in some other works. In this section, a method to identify the faulty phase, based on the developed quantity, is discussed. This is equivalent to estimate the faulty phase angle γ , which can take only the values of 0° , -120° , or 120° for fault occurring in phase a , b , or c , respectively.

It is observed from equation (5.42) that the phase of $\frac{1}{3}\mu\tilde{I}_f$ is leading γ the phase of $\tilde{V}_{sp}$. Combining it with equation (5.38),

$$\delta_p^f = \frac{\mu^2 \tilde{V}_{sp}}{3r_f}, \quad (5.44)$$

$$\delta_n^f \approx \gamma^2 \frac{\mu^2 \tilde{V}_{sp}}{3r_f}. \quad (5.45)$$

It means that the phase of δ_n^f is leading 2γ the phase of $\tilde{V}_{sp}$. That is, γ , the angle of faulty phase, can be directly inferred from the phase of δ_n^f . If the faulty phase is a , b , or c , the phase of δ_n^f after shifted the negation of the phase of $\tilde{V}_{sp}$, will be equal to 0° , 120° , or -120° , respectively.

5.3.5 Summary of the proposed diagnosis method

Fig. 5.8 summarizes the method to extract the fault-dependent quantity under the effects of both voltage imbalance and inherent asymmetry, used for early fault detection and severity estimation. Some main points are summarized and analyzed here.

Figure 5.8: Method to extract the fault-dependent quantity.

- Positive sequence quantities $\tilde{V}_{sp}$, $\tilde{I}_{sp}$ and negative sequence quantities $\tilde{V}_{sn}$, $\tilde{I}_{sn}$ are calculated from measured stator voltages and stator currents.
- Positive sequence impedance Z_{pp} and negative sequence Z_{nn} are calculated from equation (5.11) and (5.13) using the motor parameters. The motor parameters can be found from the data-sheet of the motor, or can be determined from standard tests, such as DC test, locked-rotor test, and no-load test.

- Since the supply voltages can change anytime during the operation of the motor, it needs to be detected separately. The continuous measurement and calculation of voltage sequence components or other methods, such as that presented in [107] can be used for this purpose.
- Both δ_n and δ_p can be used for fault diagnosis. However, for applications in which motors are operated near the rated speed, s is small, and hence δ_n can be considered to be independent of slip, as shown by equation (5.13) for Z_{nn} with $2 - s \approx 2$. On the other hand, δ_p is shown to be dependent on slip value, depicted in equation (5.11) for Z_{pp} , and hence speed measurement/estimation is required. This is the reason δ_n can be applied for sensor-less applications, even though δ_p can provide the similar results.

5.4 Experimental Result

The same experimental setup and electrical machine for model validation in Chapter 3 is employed here. In order to test the robustness of the proposed method to voltage imbalance, more different voltage conditions are tested, as shown in Table 5.1. They are balance (BL), three-phase undervoltage (3UV), three-phase overvoltage (3OV), two-phase undervoltage (2UV), two-phase overvoltage (2OV), one-phase undervoltage (1UV), one-phase overvoltage (1OV), and one-phase angular deviation (1AD).

In this validation part, the diagnosis method is validated through the main points as follows.

- The method to compensate the effect of inherent asymmetry and voltage imbalance is validated by showing the early fault detection and fault severity estimation for a real machine with inherent asymmetry and supplied by various imbalanced voltages, as in Table 5.1, and under different load conditions.
- Early fault detection is validated as the increasingly monotonic change in the indicator δ_n from the healthy condition to the healthy condition, i.e., from healthy to $r_f = 25 \Omega$. As in the theoretical analysis, the indicator changes from zero to a certain positive value, validated in the next section.

Table 5.1: Different voltage conditions used in experiment

Type	RMS-phase a (V)	RMS-phase b (V)	RMS-phase c (V)	phase a	phase b	phase c
BL	240	240	240	0°	-120°	120°
3UV	227.9	231.9	236.0	0°	-120°	120°
3OV	253.1	248.7	244.4	0°	-120°	120°
2UV	240	231.8	235.9	0°	-120°	120°
2OV	240	248.5	244.3	0°	-120°	120°
1UV	240	240	232.8	0°	-120°	120°
1OV	240	240	247.3	0°	-120°	120°
1AD	240	240	240	0°	-118°	120°

- Fault severity estimation is validated as the increasingly monotonic change in an indicator when the fault is changed from a condition ($r_f = 25 \Omega$) to its higher severity conditions ($r_f = 11.7 \Omega$, $r_f = 5.4 \Omega$, then $r_f = 2.5 \Omega$). Also, it will be validated that the indicator is proportional to the square of fraction of shorted turn and inversely proportional to fault loop resistance, and hence, it is found to be an appropriate fault severity estimate. In order to validate this relation, first, equation (5.43) is validated using the measured $\frac{1}{3}\mu\tilde{I}_f$ compared with the value calculated by $\frac{\mu^2}{r_f} \times \frac{\tilde{V}_{sp}}{3}$. Second, equation (5.39) is tested by comparing δ_n and δ_p with the measured $\frac{1}{3}\mu\tilde{I}_f$.
- The faulty phase identification method is validated by identifying the correct angle γ when the fault is occurred to the stator winding a , b , or c .

5.4.1 Validation of the fault-dependent quantity $\frac{1}{3}\mu\tilde{I}_f$

First, the fault-dependent quantity is validated since it is necessary condition for an effective severity estimation. That is, the equation (5.43) will be verified. In order to verify that equation, the magnitude of the measured $\frac{1}{3}\mu\tilde{I}_f$, and the value calculated by equation (5.43) is compared. The data is measured and calculated as described in Fig. 5.9.

Figure 5.9: The measured and calculated value of $\frac{1}{3}\mu\tilde{I}_f$.

Since the magnitudes of $\tilde{V}_{sp}$ under different voltage conditions has the largest variance of only 8.2%, only one voltage condition needs to be verified. The results in Table 5.2 verify the accuracy of the equation (5.43). The magnitude of the actual $\frac{1}{3}\mu\tilde{I}_f$ is close to the value calculated as $\frac{\mu^2 \tilde{V}_{sp}}{3r_f}$. It verifies the accuracy of the equation (5.43). Therefore, once the fault indicator δ_n can estimate the magnitude of $\frac{1}{3}\mu\tilde{I}_f$, it will be suitable and accurate estimate of the fault severity level.

Also, Fig. 5.10 shows the magnitude of $\frac{1}{3}\mu\tilde{I}_f$ for different voltage and loading conditions and fault severity levels in which $\mu = 10\%$ and $r_f = 25 \Omega, 11.7 \Omega, 5.4 \Omega$, and 2.5Ω . The fault loop current is measured in the test. It is observed that the fault loop current is insensitive to both voltage conditions and load variations. Therefore, if $\frac{1}{3}\mu\tilde{I}_f$ can be estimated accurately, the indicators will be robust to load and voltage conditions.

In the next section, the estimation of $\frac{1}{3}\mu\tilde{I}_f$ by δ_n and δ_p along with early fault detection under the effects of voltage imbalance and inherent asymmetry will be tested.

Figure 5.10: Magnitudes of $\frac{1}{3}\mu\tilde{I}_f$ under different voltage conditions a) BL b) 3UV c) 3OV d) 2UV e) 2OV f) 1UV g) 1OV h) 1AD i) all conditions.

5.4.2 Experimental investigation for negative sequence-based indicator

5.4.2.1 Validation of fault detection and severity estimation

In this section, first, the effects of voltage imbalance and inherent asymmetry will be investigated. After that, the compensation method is evaluated. In order to achieve this, in this section, besides Δ_n and δ_n , negative sequence current I_{sn} is also tested. It is sensitive to both inherent asymmetry and voltage imbalance, and hence is a suitable benchmark to validate the proposed diagnosis method. In addition, $\tilde{I}_{sn}$ can be used for observing the combined effects of fault and all ambiguous factors. Δ_n is under effect of inherent asymmetry and fault, and is less affected by the voltage imbalance, as shown in equation (5.18) with the second term relating the negative sequence voltage $\tilde{V}_{sn}$ in its expression. On the other hand, δ_n is the proposed indicator that is only sensitive to fault and independent of both inherent asymmetry and voltage imbalance. In Table 5.3, the tested signals and also the voltage conditions are listed again.

Table 5.2: Magnitudes of directly measured $\frac{1}{3}\mu\tilde{I}_f$ and its calculated value by equation (5.43)

μ	10%	10%	10%	10%
r_f (Ω)	25	11.7	5.4	2.5
Magnitude of $\tilde{V}_{sp}$ (V)	339	339	339	339
Magnitude of $\frac{1}{3}\mu\tilde{I}_f$ calculated as $\frac{\mu^2\tilde{V}_{sp}}{3r_f}$ based on equation (5.43) (A)	0.045	0.097	0.209	0.452
Magnitude of measured $\frac{1}{3}\mu\tilde{I}_f$ (A)	0.047	0.097	0.200	0.380

Table 5.3: The quantities and voltage conditions investigated in the test

Signals	$\tilde{I}_{sn}, \Delta_n = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}}, \text{ and } \delta_n = \Delta_n - \Delta_n^h$
Voltage conditions	Balanced voltage (BL) and imbalanced voltages 3UV, 3OV, 2UV, 2OV, 1UV, 1OV, 1AD

Fig. 5.11 shows the experimental result for balanced voltages. The balanced voltage and no-load condition is tested since under this condition, the influence of voltage imbalance and load condition is negligible, and hence, the single effect of inherent asymmetry can be investigated. The magnitudes of I_{sn} (blue color) and Δ_n (green color), shown in Fig. 5.11(a), are close to each other, as expected. This can be explained by the definition of Δ_n as in Table 5.3, then when the voltages are balanced, $\Delta_n = \tilde{I}_{sn}$. The slight discrepancy is due to the fact that the actual voltages are not ideal balanced. Also, it can be observed that there is offset in $\tilde{I}_{sn}$ and Δ_n under healthy condition (before 5 sec.). In addition, the deviation of I_{sn} and Δ_n from the $\frac{1}{3}\mu\tilde{I}_f$ (cyan color) is larger when the fault is at the incipient stage ($r_f = 25 \Omega$) and smaller for higher fault severity ($r_f = 11.7 \Omega, 5.4 \Omega$, and 2.5Ω), highlighting the significant effect of inherent asymmetry at the incipient stage ($r_f = 25 \Omega$) and the challenge for early fault detection. In both loaded cases in Fig. 5.11(b) and Fig. 5.11(c), the influence of inherent asymmetry is still present, causing the difference in magnitude between Δ_n (green color) and the measured quantity $\frac{1}{3}\mu\tilde{I}_f$ (cyan color).

Fig. 5.12 shows the experimental result of the imbalanced voltage case, 3UV voltage condition. I_{sn} (blue color) is significantly deviated from the fault-dependent quantity

Figure 5.11: Magnitudes of Δ_n , δ_n , and I_{sn} under BL voltage. (a) No-load. (b) Half-load. (c) Full-load.

$\frac{1}{3}\mu\tilde{I}_f$ (cyan color). This is because under 3UV voltage condition, both the effects of voltage imbalance and inherent asymmetry are present, and negative sequence current $\tilde{I}_{sn}$ is sensitive to both these ambiguous factors. Δ_n (green color) is less deviated from $\frac{1}{3}\mu\tilde{I}_f$, since as in the theoretical analysis, Δ_n is less effected by voltage imbalance. However, Δ_n has non-zero value under the healthy condition (before 5 sec.), and when the fault occurs at 5 sec., the magnitude of Δ_n is decreased, making it not possible to detect the incipient fault. On the other hand, δ_n (red color) has zero value at the healthy condition. When the fault occurs (at 5 sec.), the machine is changed from the healthy condition to $r_f = 25 \Omega$, its value is increased. In addition, its magnitude is equal to the magnitude of the measured $\frac{1}{3}\mu\tilde{I}_f$, for any severity levels ($r_f = 25 \Omega$, $r_f = 11.7 \Omega$, 5.4Ω , and 2.5Ω). This is true for both cases of balanced (Fig. 5.11) and 3UV (Fig. 5.12) imbalanced voltages. Therefore, the inherent asymmetry and voltage imbalance has been properly

compensated by using δ_n , which is crucial for incipient fault occurrence and its severity assessment.

Figure 5.12: Magnitudes of Δ_n , δ_n , and I_{sn} under 3UV, full-load condition.

Fig. 5.13 and Fig. 5.14 depict I_{sn} and Δ_n , respectively, under various voltage conditions, indicated in the legend. It can be observed that both of them are not monotonic and unpredictable. The range of Δ_n under different voltage cases is smaller than that of I_{sn} since again, it is less effected by voltage imbalance. However, due to the variance of I_{sn} and Δ_n under different voltage conditions, i.e., highly dependent on voltage imbalance, either of them cannot be used for reliable fault indicators.

Fig. 5.15 compares Δ_n and δ_n . The deviations of Δ_n (green color) from $\frac{1}{3}\mu\tilde{I}_f$ (cyan color) are noticed in all different voltage cases, Fig. 5.15(a), 3OV, Fig. 5.15(b), 2UV, Fig. 5.15(c), 2OV, Fig. 5.15(d), 1UV, Fig. 5.15(e), 1OV, and Fig. 5.15(f), 1AD. Also, the magnitudes of Δ_n are monotonic for only 1OV and 1AD voltage conditions. In contrast, the value of δ_n (red color) for healthy and faulty states (the transition between two states is at 5 sec.) are distinguishable under all tested conditions. It also increases proportionally to all different severity levels, corresponding to $r_f = 25 \Omega$, $r_f = 11.7 \Omega$, $r_f = 5.4 \Omega$, then $r_f = 2.5 \Omega$. In 3OV, 2UV, 2OV, and 1UV cases, the magnitudes of Δ_n for the healthy conditions are larger than that under faulty conditions, but after the compensation, the magnitudes of δ_n are always monotonic and correctly estimate

Figure 5.13: Magnitudes of I_{sn} under various voltage conditions.

Figure 5.14: Magnitudes of Δ_n under various voltage conditions.

the quantity $\frac{1}{3}\mu\tilde{I}_f$ for fault severity evaluation. This is due to the fact that quantities in sequence component models are phasors/complex quantities, which actually is one advantage of sequence component approach.

Figure 5.15: Magnitudes of Δ_n , δ_n under different voltage conditions, full-load. (a) 30V. (b) 20V. (c) 20V. (d) 10V. (e) 10V. (f) 1AD.

5.4.2.2 Validation of faulty phase identification method

In order to test the fault occurring in phase a , b , or c , a different phase notation (a' , b' , c') is considered. For faulty phases a , or b , or c , $a' \equiv a$, $b' \equiv b$, $c' \equiv c$, or $a' \equiv c$, $b' \equiv a$, $c' \equiv b$, or $a' \equiv b$, $b' \equiv c$, $c' \equiv a$, respectively, and the fault indicators are calculated in this a' , b' , c' system. The phase of δ_n is estimated under high voltage imbalance condition 30V, depicted in Fig. 5.16. For fault occurring in phases a , or b , or c , the estimated angle γ^2 is approximately 0° , 120° , and -120° , corresponding to γ approximately equaling to 0° , -120° , and 120° , as described in Section 5.3.4, showing that the faulty phases can be identified for any of their cases.

Figure 5.16: Phase of δ_n under 30V voltage, different faulty phases.

5.4.3 Experimental result for positive sequence-based indicator

The values of Δ_p (blue color) and δ_p (red color) are displayed in Fig. 5.17 for balanced voltages and under different loads. The machine is changed from healthy condition to faulty condition with $\mu = 10\%$ and $r_f = 25 \Omega$, and then fault is progressed in steps to 11.7Ω , 5.4Ω , and 2.5Ω . It is shown that the effect of inherent asymmetry is significant, causing the large deviations between the magnitude of Δ_p (blue color) and that of the

measured $\frac{1}{3}\mu\tilde{I}_f$ (cyan color) in all cases, Fig. 5.17(a), no-load, Fig. 5.17(b), half-load, and Fig. 5.17(c), full-load. In addition, the value of Δ_p varies with different load conditions. On the other hand, δ_p (red color) can accurately estimate the fault severity, i.e., the measured $\frac{1}{3}\mu\tilde{I}_f$ in all load conditions.

Figure 5.17: The values of Δ_p and δ_p under BL voltage. (a) No-load. (b). Half-load (c). Full-load.

Similarly, Fig. 5.18 and Fig. 5.19 show the results of Δ_p and δ_p for imbalanced voltages, 3UV and 3OV voltage conditions, respectively. Once again, they show the dependence of Δ_p on load. The magnitude of Δ_p (blue color) in Fig. 5.18(a), Fig. 5.18(b), and Fig. 5.18(c), corresponding to no-load, half-load, and full-load, are different. For 3OV case, the dependence is not proportional to load, as shown in Fig. 5.19(b) and Fig. 5.19(c), in which its value is almost similar for healthy condition at half-load and

full-load. More importantly, Δ_p also depends upon voltage conditions nonlinearly. For 3UV case, which has the magnitudes of supplied voltages smaller than that of 3OV case, Δ_p is even higher than 3OV case (Compare Δ_p in Fig. 5.18(b) with that in Fig. 5.19(b) for half-load, and Δ_p in Fig. 5.18(c) with that in Fig. 5.19(c) for full-load). Once again, δ_p (red color) is still able to estimate accurately the measured $\frac{1}{3}\mu\tilde{I}_f$ (cyan color). They are not only independent of load, but also independent of voltage imbalance.

Figure 5.18: The values of Δ_p and δ_p under 3UV imbalanced voltages. (a) No-load. (b) Half-load. (c) Full-load.

Fig. 5.20 shows the results of Δ_p and δ_p for other voltage conditions: 2UV, 2OV, 1UV, 1OV, and 1AD. Only full-load case is shown. The same observation is drawn from experimental results and δ_p is verified to be reliable indicator under various voltage imbalance conditions.

Figure 5.19: The values of Δ_p and δ_p under 30V imbalanced voltages. (a) No-load. (b) Half-load. (c) Full-load.

5.4.4 Validation for a lower fault severity level

In this section, the robustness of the proposed method is investigated for a lower fault severity level, $\mu = 5\%$. The challenge is that, as described in equation (5.43), for a same value of r_f , the magnitude of $\frac{1}{3}\mu\tilde{I}_f$ under $\mu = 5\%$ is four times smaller than that of $\mu = 10\%$. Fig. 5.21 shows the experimental result. The magnitudes of Δ_n under all fault severity levels are even smaller than that under healthy condition, showing the significant effect of inherent asymmetry and the challenge to detect the fault. However, using the method based on δ_n , the fault signature is still able to captured and the fault progression is closely tracked.

Figure 5.20: The values of Δ_p and δ_p under different voltage conditions. (a) 2UV. (b) 2OV. (c) 1UV. (d) 1OV. and (e) 1AD.

Figure 5.21: Magnitudes of Δ_n , δ_n under $\mu = 5\%$, full-load.

5.5 Discussion and Conclusion

A technique is proposed for compensating inherent asymmetry using two different indicators. Theoretical and experimental results are matching and show that each indicator has its own advantages and limitations.

δ_n does not require speed measurement/estimation. Since the magnitude of δ_n is significantly smaller than δ_p , it may be more sensitive to noise or any factors causing deviation in measurement and hence requires higher accurate measurement equipment. Also, experiment result shows that Δ_p itself has monotonic characteristic. Its value is higher when machine is changed from the healthy state to the faulty state, or and fault progresses to higher severity levels. However, its magnitude is not equal to the magnitude of $\frac{1}{3}\mu\tilde{I}_f$ due to the effect of inherent asymmetry, load variation, and voltage imbalance. When fault severity estimation is needed, δ_p must be used instead of Δ_p .

The experimental result for the case $\mu = 5\%$ is encouraging. As mentioned, for the similar value of r_f , the corresponding magnitude of $\frac{1}{3}\mu\tilde{I}_f$ for $\mu = 5\%$ is four times smaller than that of $\mu = 10\%$. However, the proposed method is still able to detect early fault and concurrently obtain the severity information.

The indicators can be normalized to determine the severity level represented by both fault parameters and machine rating. As in (5.43), δ_p and δ_n include the factor of fault parameters and supplied voltages. If only fault parameters are required, they need to be normalized by the rated voltage.

The technique is feasible for real-time implementation. The proposed technique can be adopted to inter-turn fault diagnosis of other kinds of machines as long as winding is included in their construction.

Chapter 6

Estimation of Fault Parameters Using Phasor Quantities

In Chapter 3, the model of an induction machine under fault has been experimentally validated. In Chapter 4, the model-based framework has been proposed. A generic approach, using multiple fault indicators for diagnosis and particle filter for estimation of fault parameters, and RUL prediction, have been proposed and experimentally validated. In Chapter 5, a diagnosis method, decoupling the fault and the effects of ambiguous factors, thereby, aiding incipient fault detection, has been proposed and experimentally validated. The fault severity information, which represents the two fault parameters in a single quantity, is also obtained in the chapter.

In this chapter and the next chapter, the other methods for parameter estimation of fault parameters are discussed. Electrical machines possesses unique characteristics which will be proven that they can be employed to develop different estimation approaches. In this chapter, a characteristic of electrical machines under sinusoidal input voltages is exploited. Using this characteristic, the differential equation of fault quantities can be transformed to trigonometry equation, and thereby, a closed-form solution of fault parameters can be obtained. In the next chapter, the multiple forms of models of induction machines are exploited. The sequence component model can be used to find out an equality constraint on fault parameters, which is utilized to simplify the other model form, the state-space model. In the simplified state-space model, only one fault parameter is needed to be estimated. The other parameter will be determined from the equality constraint.

6.1 Introduction

Induction machines are widely used in modern industries. They are subject to faults due to aging, severe operating conditions, and harsh environments. Among various kinds of component faults such as bearing fault, stator fault, broken rotor bar, etc., SWITSF is among the most concerned ones. It is a common fault [232] and usually occurs first and leads to further severe faults such as phase-to-phase and phase-to-ground [12]. In addition, inter-turn fault is difficult to detect and identify.

Various fault indicators have been proposed to detect SWITSF. Negative sequence stator currents [12, 64, 67, 69], sequence impedances [63, 65], faulty parameters [29, 73–75], electrical parameters [75], fluxes [78, 79, 82, 83], vibrations [87], torques [88], and the others [66, 89–93] calculated from stator current and voltage measurements have been proposed as different fault indicators. They have demonstrated certain effectiveness in various scenarios and under certain conditions.

However, these indicators are only for fault detection purpose, and there are just a few works proposed for fault parameter estimation and faulty phase identification. The output-error technique is proposed in [75] to identify faulty phase and estimate the fraction of shorted turns. In [29], positive and negative sequence analysis are applied to localize the faulty phase. The observer technique is employed in [73, 74] in order to estimate the fraction of shorted turns. Nonetheless, these works focus only on faulty phase identification and/or fault parameter estimation of complete shorted fault. That is, only the fraction of shorted turns is estimated assuming zero fault loop resistance. Fault loop resistance is a direct parameter for indicating fault severity. In addition, it can be an indicator representing the evolution of degradation process and hence can be utilized for prognosis purpose. Consequently, a method to estimate not only the fraction of shorted turns but also the fault loop resistance before complete inter-turn fault is necessary.

In this chapter, a fault parameter estimation and faulty phase identification method is proposed for single but unknown faulty phase. The method is based on steady-state analysis and sequence component analysis of induction machines under stator winding inter-turn fault. The method provides a closed-form solution to the fraction of shorted

turns and the fault loop resistance. As a result, it can be applied to online fault detection and identification. This chapter is divided into the sections as follows. Section 6.2 presents the method for fault parameter estimation and faulty phase identification. Section 6.3 provides the simulation result and section 6.4 concludes the chapter.

6.2 Fault Parameter Estimation and Faulty Phase Identification

6.2.1 Fault parameter estimation

Fault parameter estimation method is developed here for any given faulty phase. Firstly, consider the case of faulty phase a . Denote $z_5 = \frac{2}{3}\mu i_f$, and $z_6 = \frac{\mu}{1-\frac{2}{3}\mu}$, then equation (3.42) can be written again as

$$\frac{dz_5}{dt} = -\frac{R_f}{L_f}z_5 + \frac{2}{3L_{ls}}z_6v_{qs}, \quad (6.1)$$

Assume balanced voltage supplies, that is,

$$v_{as}(t) = V_s \sin(\omega t), \quad (6.2)$$

$$v_{bs}(t) = V_s \sin(\omega t - \frac{2\pi}{3}), \quad (6.3)$$

$$v_{cs}(t) = V_s \sin(\omega t + \frac{2\pi}{3}), \quad (6.4)$$

then $v_{qs}(t) = v_{as}(t) = V_s \sin(\omega t)$.

Under steady-state condition, z_5 has sinusoidal expression as

$$z_5 = I_5 \sin(\omega t + \varphi). \quad (6.5)$$

Consequently, equation (6.1) is equivalent to

$$I_5\omega \cos(\omega t + \varphi) = -\frac{R_f}{L_f}I_5 \sin(\omega t + \varphi) + \frac{2}{3L_{ls}}z_6V_s \sin(\omega t). \quad (6.6)$$

Now let $\omega t + \varphi = k2\pi$, equation (6.6) is reduced to

$$I_5\omega = -\frac{2}{3L_{ls}}z_6V_s \sin(\varphi). \quad (6.7)$$

Therefore, z_6 can be estimated as

$$\hat{z}_6 = \frac{3I_5\omega L_{ls}}{2V_s \sin(-\varphi)}, \quad (6.8)$$

As a result, the estimated fraction of shorted turns is

$$\hat{\mu} = \frac{\hat{z}_6}{1 + \frac{2}{3}\hat{z}_6}. \quad (6.9)$$

Now let $\omega t = k2\pi$, then equation (6.6) becomes

$$I_5\omega \cos(\varphi) = -\frac{R_f}{L_f} I_5 \sin(\varphi). \quad (6.10)$$

That is,

$$\frac{R_f}{L_f} = \omega \cot(-\varphi). \quad (6.11)$$

Therefore, the fault loop resistance is estimated as

$$\hat{r}_f = (\omega \cot(-\varphi) - \frac{R_s}{L_{ls}}) \hat{\mu} (1 - \frac{2}{3}\hat{\mu}) L_{ls}. \quad (6.12)$$

I_5 and φ are the magnitude and phase of z_5 . They can be determined from the error of negative sequence stator currents (defined as e_{Isn} in [29]). The relationship between z_5 and e_{Isn} for faulty phase a is

$$z_5 = I_5 \sin(\omega t + \varphi) = \frac{2}{3} \mu i_f = 2e_{Isn}. \quad (6.13)$$

To generalize the estimation method for the case of single faults in phase b and c and imbalanced voltage supplies, define new variable ζ equaling to $0, -120^\circ$, or 120° for the fault in phase a, b or c , respectively. z_5 has leading phase or lagging phase of 120° to e_{Isn} for the faulty phase of b or c , respectively. The equation for the faulty loop current becomes

$$\frac{dz_5}{dt} = -\frac{R_f}{L_f} z_5 + \frac{2}{3L_{ls}} z_6 \boldsymbol{\gamma}^T \mathbf{v}_{qds}. \quad (6.14)$$

Assume $\boldsymbol{\gamma}^T \mathbf{v}_{qds}$ has the expression

$$\boldsymbol{\gamma}^T \mathbf{v}_{qds} = V_\gamma \sin(\omega t + \eta), \quad (6.15)$$

then the estimate of z_6 is

$$\hat{z}_6 = \frac{3I_5\omega L_{ls}}{2V_\gamma \sin(-\varphi + \zeta + \eta)}. \quad (6.16)$$

The estimate of fault loop resistance is

$$\hat{r}_f = (\omega \cot(-\varphi + \zeta + \eta) - \frac{R_s}{L_{ls}}) \hat{\mu} (1 - \frac{2}{3}\hat{\mu}) L_{ls}. \quad (6.17)$$

6.2.2 Faulty phase identification

A possible method to localize the faulty phase is to determine the angle of faulty phase as half of the difference between the phases of the errors of the negative and positive sequence stator currents, respectively. More details about these errors are presented in [29]. However, this method is sensitive to motor parameter variation.

In this section, a new faulty phase identification method is proposed to overcome this drawback. In [29], the faulty phase angle ϕ_μ is determined as

$$\phi_\mu = \phi_{\tilde{V}_{sp}} - \phi_{Z_f} - \phi_{e_{Isn}}, \quad (6.18)$$

where $\phi_{\tilde{V}_{sp}}$, ϕ_{Z_f} , and $\phi_{e_{Isn}}$ are the angle of positive sequence component of stator phasor voltage, the angle of Z_f , and the angle of e_{Isn} , respectively, and Z_f is the faulty impedance defined as

$$Z_f = (R_s + j\omega_e L_{ls})(1 - \frac{2}{3}\mu) + \frac{r_f}{\mu} \quad (6.19)$$

Because the fault impedance Z_f is a function of stator resistor, stator leakage induction and fault parameters, the angle ϕ_μ depends on unknown fault parameters. Therefore, the fault parameter estimation can be employed to identify the faulty phase. The proposed scheme to identify the angle of the faulty phase ϕ_μ and concurrently estimate the fault parameters is presented as follows.

- Assume the faulty phase is phase a , b , or c .
- Estimate μ and r_f .
- Employ estimated μ and r_f to calculate Z_f from equation (6.19) .
- Calculate the faulty phase ϕ_μ from equation (6.18).
- Check if the assumption is true based on the condition that if fault phase is phase a , b , or c , then $\phi_\mu \approx 0^\circ$, or -120° , or 120° , respectively, and both estimated μ and r_f are positive values.
- If the faulty phase is not the assumed phase, assume the faulty phase is one of the other.

- Repeat from step 2 until finding the true faulty phase or concluding there is no single faulty phase.

Fig. 6.1 is a block diagram for finding z_5 and Fig. 6.2 is a flowchart diagram integrating fault parameter estimation and faulty phase identification.

Figure 6.1: A block diagram for finding z_5 .

Figure 6.2: A flowchart diagram integrating fault parameter estimation and faulty phase identification.

6.3 Simulation Result

Simulation is performed for the motor with the same parameters as the real one in Chapter 3. The proposed method is simulated for different constant load levels, both balanced supply voltages and imbalanced supply voltages, and motor parameter variation (i.e., there is deviation between parameters of real and modeled motors) in order to investigate the method under various operating conditions. The faulty severity is represented by fault parameters as $\mu = 5\%$ (severity level I), 10% (severity level II), and 20% (severity level III), and $r_f = 50\ \Omega, 45\ \Omega, 40\ \Omega, 35\ \Omega, 30\ \Omega, 25\ \Omega, 20\ \Omega, 15\ \Omega, 10\ \Omega, 5\ \Omega, 3\ \Omega, 1\ \Omega, 0.1\ \Omega, 0.01\ \Omega$, and $0.001\ \Omega$, changed in steps. The supply voltage imbalance is corresponding to $VUF = 1\%$, which is three-phase imbalanced voltages 30V. The supply excitation frequency is 50 Hz and the sampling period is 0.00001 sec. MATLAB[®] and Simulink[®] software is used in the simulation.

6.3.1 Estimation performance against different severity levels

In this section, the estimation method is tested under balanced supply voltages, and no motor parameter variation under different fault severity levels. Fig 6.3 and Fig. 6.4 show the estimates of r_f and μ with simulated $\mu = 10\%$ and simulated r_f gradually reduced from $50\ \Omega$ to $0.001\ \Omega$. They show that the estimation results are independent of load variation. This is reasonable since the proposed method is based on sequence component analysis, which is insensitive to load variation. Fig. 6.5 and Fig. 6.6 show the estimates of r_f and μ for different fault severity levels III, II, and I. The estimation error is smaller for higher severity levels, as expected. That is the estimation error is smaller from severity levels III to lower fault severity levels II and I. The estimated accuracy increases if the fraction of shorted turns is increased and the fault loop resistance is decreased, corresponding to higher fault severity levels.

There is deviation between the estimates and true values, as shown in Fig 6.3, Fig. 6.4, Fig. 6.5 and Fig. 6.6. In order to find out the reason, the magnitudes of estimated z_5 is compared with that generated from the model, shown in Fig. 6.7 for a typical case $\mu = 10\%$. It shows that the magnitude of z_5 is estimated accurately by the method. Fig. 6.8 depicts the estimate of the angle of z_5 . Since the angle of z_5 is small, it implies that

 Figure 6.3: Estimate of r_f under balanced voltages and different loads.

 Figure 6.4: Estimate of μ under balanced voltages and different loads.

 Figure 6.5: Estimate of r_f under different fault severity levels and balanced voltages.

Figure 6.6: Estimate of μ under different fault severity levels and balanced voltages.

the deviation can be due to the error in the estimation of this angle. In order to check if this error is due to the method or due to the simulation configuration, the sampling time is reduced to 0.000001 sec., assuming that the estimate of the phase angle of z_5 can be sensitive to digitized calculation. Fig. 6.9 and Fig. 6.10 show the estimation results of r_f and μ , respectively, for this case. It is significantly improved. The estimates of r_f and μ are close to their true values. It implies that the proposed method is able to estimate the fault parameters accurately. It requires the sampling time to be small in order to reduce the effect of digitized calculation. This is a challenge to real applications.

Figure 6.7: Estimate of magnitude of z_5 under balanced voltages and full-load.

Figure 6.8: Estimate of phase of z_5 under balanced voltages and full-load.

Figure 6.9: Estimate of r_f under balanced voltages and full-load with small sampling frequency.

6.3.2 Estimation performance against voltage imbalance and motor parameter variation

Fig. 6.11 and Fig. 6.12 depict the simulation results of r_f and μ , respectively, for 30V imbalanced voltages and full-load condition with simulated $\mu = 10\%$ and simulated r_f gradually reduced from 50Ω to 0.001Ω . The results are almost same with that of balanced voltages, in Fig 6.3 and Fig. 6.4. It shows that the method is robust to voltage imbalance.

The motor parameter variation is tested assuming the motor parameters R_s and R_r are 1.2 times higher than the counterparts in the model. It simulates the case the parameters of the real motor can change, and the online motor parameter estimation, if installed,

Figure 6.10: Estimate of μ under balanced voltages and full-load with small sampling frequency.

Figure 6.11: Estimate of r_f under 3OV imbalanced voltages.

estimates the real parameters with certain errors. Fig. 6.13 and Fig. 6.14 show the estimates of r_f and μ , respectively, under motor parameter variation with simulated $\mu = 10\%$ and simulated r_f gradually reduced from 50Ω to 0.001Ω . The estimates at low fault severity levels (before 4 sec., r_f is larger or equal to 15Ω) fluctuate around the simulated values. In order to explain this, the estimated magnitude and phase of z_5 are investigated in Fig. 6.15 and Fig. 6.16, respectively. The magnitude of z_5 is estimated accurately. In Fig. 6.16, the estimated angle of z_5 is zoomed in. There is fluctuation in this value. Even though this fluctuation is small, the corresponding change in sinusoidal function of $\sin(\varphi)$ can be large, as observed from equation (6.8). This causes the corresponding fluctuation on the estimated r_f and μ . This indicates the challenge of the application of

 Figure 6.12: Estimate of μ under 3OV imbalanced voltages.

the proposed method for the circumstance of parameter deviation in motor parameters between the real motor and modeled motor.

 Figure 6.13: Estimate of r_f under motor parameter variation, balanced voltages.

Also, inferred from equation (6.8), when the excitation frequency ω_e is higher, the φ is larger, and the calculation of $\hat{z}_6$ is probably less sensitive to the error in the estimate of the phase angle of z_5 . In order to test that, a simulation case with excitation frequency of 500 Hz is presented. The test is under both 3OV imbalanced voltages and parameter deviation, and the estimates of r_f and μ are shown in Fig. 6.17 and Fig. 6.18, respectively. The improved results, shown by the less fluctuation in the estimated values (compared to that in Fig. 6.13 and Fig. 6.14 under 50 Hz excitation frequency), show that the proposed method is favorable for high excitation frequency applications.

 Figure 6.14: Estimate of μ under motor parameter variation, balanced voltages.

 Figure 6.15: Estimate of magnitude of z_5 under motor parameter variation, balanced voltages.

6.3.3 Validation of faulty phase identification method

First, the faulty phase identification method is tested for motor parameter variation with balanced voltages. This is the case the fault parameters are able to be estimated but the estimates fluctuate around the true values. The estimation of the faulty phase is applied to the true $r_f = 30 \Omega$, $\mu = 0.1$, corresponding to the estimated magnitude of z_5 is 0.074 A and the estimated angle of z_5 is between -1° and -0.6° , as shown in Fig. 6.16 after 2 sec. moment. The respective estimate of the faulty phase angle for fault occurring to phase a is depicted in Fig. 6.19.

Similarly, for the case the fault occurs to phase b or c , the estimated results of the faulty phase angle is shown in Fig. 6.20 and Fig. 6.21, respectively.

Figure 6.16: Estimate of phase of z_5 under motor parameter variation, balanced voltages.

Figure 6.17: Estimate of r_f under motor parameter variation, 30V imbalanced voltages with high excitation frequency.

The simulation is also performed for the case of 30V imbalanced voltage condition, motor parameter variation with the parameters R_s and R_r are 1.1 times higher than the counterparts in the model. In this case, the fault parameters are not accurately estimated with excitation frequency 50 Hz, but as shown here, the faulty phase are still estimated accurately. The magnitude of the estimated z_5 is not close to the simulated one as in the other simulation cases, as it is shown in Fig. 6.22 for the case of faulty phase b , and Fig. 6.23 for the case of faulty phase c . For the former case, the magnitude of z_5 is underestimated, while for the other case, it is overestimated. Also, the estimated angle of z_5 fluctuates. Fig. 6.24 and Fig. 6.25 show the estimation results for the cases of faulty phase b and phase c , respectively. The faulty phases are still able to estimated,

Figure 6.18: Estimate of μ under motor parameter variation, 3OV imbalanced voltages with higher excitation frequency.

```
>> calculate_muyrfloc(Van,Vbn,Vcn,phian,phibn,phicn,freq,0.074,-1)
First, assume the faulty phase is phase a
Estimated fault location is: 0
i.e., estimated faulty phase is: a
>> calculate_muyrfloc(Van,Vbn,Vcn,phian,phibn,phicn,freq,0.074,-0.6)
First, assume the faulty phase is phase a
Estimated fault location is: -1.1102e-16
i.e., estimated faulty phase is: a
```

Figure 6.19: Estimate of the faulty phase angle for the fault in phase a , balanced voltages and motor parameter variation.

proving that the faulty phase identification method is insensitive to the discrepancy in the estimates of the magnitude of z_5 .

6.4 Conclusion

This chapter proposes a method for fault parameter estimation and faulty phase identification of stator winding inter-turn fault in induction machines. The fault parameter estimation method is able to estimate not only the fraction of shorted turns but


```
>> calculate_muyrfloc(Van,Vbn,Vcn,phian,phibn,phicn,freq,0.073,-240.)
First, assume the faulty phase is phase a
Faulty phase is not phase a, then assume the faulty phase is phase b
Estimated fault location is: -120
i.e., estimated faulty phase is: b
```

Figure 6.20: Estimate of the faulty phase angle for the fault in phase b , balanced voltages and motor parameter variation.

```
>> calculate_muyrfloc(Van,Vbn,Vcn,phian,phibn,phicn,freq,0.073,239.3)
First, assume the faulty phase is phase a
Faulty phase is not phase a, then assume the faulty phase is phase b
Faulty phase is not phase a or b, then assume the faulty phase is phase c
Estimated fault location is: 120
i.e., estimated faulty phase is: c
```

Figure 6.21: Estimate of the faulty phase angle for the fault in phase c , balanced voltages and motor parameter variation.

also the fault loop resistance, and the faulty phase identification method can identify the true faulty phase under voltage imbalance and motor parameter variation. The proposed method provides a closed-form solution, and hence is applicable to online fault detection and identification. However, it has challenge to apply in real situations, since it requires high excitation frequency or small sampling time to reduce the error in discretized

Figure 6.22: Estimate of magnitude of z_5 for the fault in phase b , 3OV imbalanced voltage and motor parameter variation.

Figure 6.23: Estimate of magnitude of z_5 for the fault in phase c , 30V imbalanced voltage and motor parameter variation.

```
>> calculate_muyrfloc(Van,Vbn,Vcn,phian,phibn,phicn,freq,0.05,-265)
First, assume the faulty phase is phase a
Faulty phase is not phase a, then assume the faulty phase is phase b
Estimated fault location is: -119.4215
i.e., estimated faulty phase is: b
```

Figure 6.24: Estimate of the faulty phase angle for the fault in phase b , 30V imbalanced voltage and motor parameter variation.

```
>> calculate_muyrfloc(Van,Vbn,Vcn,phian,phibn,phicn,freq,0.11,230.4)
First, assume the faulty phase is phase a
Faulty phase is not phase a, then assume the faulty phase is phase b
Faulty phase is not phase a or b, then assume the faulty phase is phase c
Estimated fault location is: 119.7048
i.e., estimated faulty phase is: c
```

Figure 6.25: Estimate of the faulty phase angle for the fault in phase c , 30V imbalanced voltage and motor parameter variation.

calculation.

Chapter 7

Estimation of Fault Parameters using Equality Constraint

7.1 Introduction

In this chapter, another method to estimate fault parameters is proposed. It is based on the observation that an electrical machine can be modeled in different forms, such as *abc* reference frame, *qd0* reference frame, sequence component representation, or state-state representation. These models can provide supplementary information, and this is exploited in this chapter. Using the state-space model, a filter-based approach such as NKF can be applied to estimate unknown parameters. The improvement here is that the sequence component model is applied to simplify that model, thereby simplifying also the parameter estimation process. As shown in the next section, the sequence component analysis provides an equality constraint on fault parameters. As a result, only one unknown parameter is present in the state-space model, and the other parameter is determined using the constraint after the first parameter is estimated. The simulation and experimental results demonstrate the effectiveness of the proposed method.

7.2 An Equality Constraint on Fault Parameters

The equality constraint on fault parameters is derived from the sequence component model of the faulty induction machine. The *qd* model of a faulty machine is transformed into that the sequence component model as [29]. The equations (3.58), (3.59), (3.60), (3.61), and (3.62) are written here again for the fault occurring to phase *a*.

$$\tilde{V}_{sp} = (R_s + j\omega_e L_s)(\tilde{I}_{sp} - \frac{1}{3}\mu\tilde{I}_f) + j\omega_e L_m \tilde{I}_{rp}, \quad (7.1)$$

$$\tilde{V}_{sn} = (R_s + j\omega_e L_s)(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f) + j\omega_e L_m \tilde{I}_{rn}, \quad (7.2)$$

$$0 = (\frac{R_r}{s} + j\omega_e L_r)\tilde{I}_{rp} + j\omega_e L_m(\tilde{I}_{sp} - \frac{1}{3}\mu\tilde{I}_f), \quad (7.3)$$

$$0 = (\frac{R_r}{2-s} + j\omega_e L_r)\tilde{I}_{rn} + j\omega_e L_m(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f), \quad (7.4)$$

$$(j\omega_e \mu(1 - \frac{2}{3}\mu)L_{ls} + \mu(1 - \frac{2}{3}\mu)R_s + r_f)\tilde{I}_f = \mu(\tilde{V}_{sp} + \tilde{V}_{sn}), \quad (7.5)$$

where $\tilde{V}_{sp}, \tilde{V}_{sn}$ are positive and negative components of stator voltage, $\tilde{I}_{sp}, \tilde{I}_{sn}$ are positive and negative components of stator current, $\tilde{I}_{rp}, \tilde{I}_{rn}$ are positive and negative components of rotor current, $\tilde{I}_f$ is fault loop current phasor, ω_e is excited electrical frequency, and s is motor slip.

From equations (3.59) and (3.61), $\frac{1}{3}\mu\tilde{I}_f$ can be estimated as

$$\frac{1}{3}\mu\tilde{I}_f = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}}, \quad (7.6)$$

where

$$Z_{nn} = (R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{2-s} + j\omega_e L_r}. \quad (7.7)$$

For applications in which motors are operated near the rated speed, s is small, and hence $\frac{1}{3}\mu\tilde{I}_f$ can be calculated assuming it is independent of slip.

The equality constraint is directly derived from equation (7.5). Since incipient fault detection is the focus, either μ is small or r_f is large. Also, considering applications, in which ω_e is not high, $\omega_e \mu L_{ls}$ and μR_s is negligible compared to r_f . $\tilde{V}_{sn}$ is negligible compared to $\tilde{V}_{sp}$ as well. As a result,

$$r_f \tilde{I}_f = \mu \tilde{V}_{sp}. \quad (7.8)$$

That is,

$$\frac{1}{3}\mu\tilde{I}_f = \frac{\mu^2 \tilde{V}_{sp}}{3r_f}, \quad (7.9)$$

hence,

$$r_f = \frac{\tilde{V}_{sp}}{3(\frac{1}{3}\mu\tilde{I}_f)}\mu^2. \quad (7.10)$$

Therefore, an equality constraint of fault parameters can be described as

$$r_f = k_f \mu^2, \quad (7.11)$$

where k_f is determined from

$$k_f = \left| \frac{\tilde{V}_{sp}}{3\Delta_n} \right|, \quad (7.12)$$

where Δ_n is defined as

$$\Delta_n = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}}. \quad (7.13)$$

This Δ_n is the same as that proposed in Chapter 5. In this chapter, it is applied to application of parameter estimation.

7.3 Proposed Fault Severity Estimation Technique

In order to estimate fault severity level, two fault parameters are directly estimated. This has a significant advantage over other techniques using indirect features. The quantification process, the mapping of measured/calculated features to direct severity quantities, is not required. The block diagram of the proposed method is shown in Fig. 7.1.

Figure 7.1: Block diagram of the proposed fault parameter estimation method.

The stator voltage and currents are measured, and negative sequence component voltages and currents are calculated. They are used to estimate $\mu\tilde{I}_f/3$ based on equation (7.6). The magnitude of $\mu\tilde{I}_f/3$ is compared with a pre-defined threshold to diagnose whether the fault is present. If inter-turn fault is identified, coefficient k_f is calculated, and the equality constraint based on equation (7.11) is formed. A parameter is substituted as an expression of the other parameter in the state-space model. The single unknown parameter in the state-space model is estimated by augmentation technique, which considers the parameter as a state variable. The augmentation process results in the nonlinearity in the considered system. However, it can be handled using nonlinear filter approach. Either EKF or UKF can be used. EKF is proposed in this chapter due to its less expensive computation.

In order to commence the estimation process, the magnitude of $\mu\tilde{I}_f/3$ is compared with a certain threshold. Therefore, the threshold needs to be updated so that whenever a fault progresses to a higher severity level, the estimation process is triggered again. A convenient choice of this threshold is the magnitude of $\mu\tilde{I}_f/3$, after each of its new value is estimated. The approach here has two significant advantages. Firstly, only the sequence component calculation process is implemented continuously, and the computationally extensive process, nonlinear filter, is triggered only a change in severity condition is detected. Secondly, the state-space model is simplified so that the estimation process is less computation.

In the block diagram, one step to estimate i_f is also added. It is a direct consequence from parameter estimation of μ and r_f . i_f is applied mainly for checking condition to stop machine. It can happen that the magnitude of $\mu\tilde{I}_f/3$ is small, but the magnitude of i_f is too high so that it can deteriorate the coils seriously. In this case, the machine needs to be stopped.

7.4 State-Space Model Induction Machines under Fault

7.4.1 State-space model without using equality constraint

The state-space model of a faulty model can be derived from its qd model. Define $x_1 = i_{qs}$, $x_2 = i_{ds}$, $x_3 = -i_{qs} + \frac{a}{c}\lambda_{qr}$, $x_4 = -i_{ds} + \frac{a}{c}\lambda_{dr}$, $x_5 = \frac{2}{3}\mu i_f$, where $a = \left(-\frac{R_r L_m^2}{L_r \nabla} - \frac{R_s L_r}{\nabla}\right)$,

$c = \frac{R_r L_m}{L_r}$, and the state vector $\mathbf{x} = [x_1 \ x_2 \ x_3 \ x_4 \ x_5]^T$, input $\mathbf{u} = [v_{qs} \ v_{ds}]^T$, output $[i_{qs} \ i_{ds}]^T$, then the state equations are

$$\frac{d\mathbf{x}}{dt} = (\mathbf{A} + \omega_r \mathbf{A}_{\omega_r})\mathbf{x} + \mathbf{B}\mathbf{u}, \quad (7.14)$$

$$\mathbf{y} = \mathbf{C}\mathbf{x}, \quad (7.15)$$

where

$$\mathbf{A} = \begin{bmatrix} (a + \frac{bc}{a})\mathbf{I}_{2 \times 2} & \frac{bc}{a}\mathbf{I}_{2 \times 2} & \begin{bmatrix} -a - \frac{R_f}{L_f} \\ 0 \end{bmatrix} \\ (d - \frac{bc}{a})\mathbf{I}_{2 \times 2} & (d - \frac{bc}{a})\mathbf{I}_{2 \times 2} & \begin{bmatrix} \frac{R_f}{L_f} \\ 0 \end{bmatrix} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & -\frac{R_f}{L_f} \end{bmatrix}, \quad (7.16)$$

$$\mathbf{A}_{\omega_r} = \begin{bmatrix} \frac{ce}{a}\mathbf{J} & \frac{ce}{a}\mathbf{J} & \mathbf{0}_{2 \times 1} \\ -(1 + \frac{ce}{a})\mathbf{J} & -(1 + \frac{ce}{a})\mathbf{J} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & 0 \end{bmatrix}, \quad (7.17)$$

$$\mathbf{B} = \begin{bmatrix} g\mathbf{I}_{2 \times 2} \\ -g\mathbf{I}_{2 \times 2} \\ \mathbf{0}_{1 \times 2} \end{bmatrix} + \begin{bmatrix} \frac{2\mu^2}{3L_f} & 0 \\ 0 & 0 \\ -\frac{2\mu^2}{3L_f} & 0 \\ 0 & 0 \\ \frac{2\mu^2}{3L_f} & 0 \end{bmatrix}, \quad (7.18)$$

$$\mathbf{C} = [\mathbf{I}_{2 \times 2} \ \mathbf{0}_{2 \times 3}], \quad (7.19)$$

and $\mathbf{I}_{n \times n}$ is the n -by- n identify matrix, $\mathbf{0}_{n \times m}$ is the n -by- m zero matrix. $\mathbf{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$, $b = \frac{R_r L_m}{L_r \nabla}$, $d = -\frac{R_r}{L_r}$, $e = \frac{L_m}{\nabla}$, $g = \frac{L_r}{\nabla}$, $\nabla = L_s L_r - L_m^2$, $L_f = \mu(1 - \frac{2}{3}\mu)L_{ls}$, and $R_f = \mu(1 - \frac{2}{3}\mu)R_s + r_f$.

In order to estimate fault parameters μ and r_f , a system augmentation technique can be utilized by considering these parameters as additional state variables. The resultant system becomes seventh-order system.

7.4.2 State-space model using equality constraint

Before applying EKF for parameter estimation, the model is simplified using the equality constraint. The term $\frac{R_f}{L_f}$ and $\frac{2\mu^2}{3L_f}$ in matrices $\mathbf{A}$ and $\mathbf{B}$ can be expressed as

$$\frac{R_f}{L_f} = \frac{R_s}{L_{ls}} + \frac{k_f \mu}{(1 - \frac{2}{3}\mu)L_{ls}}. \quad (7.20)$$

$$\frac{2\mu^2}{3L_f} = \frac{2\mu}{3(1 - \frac{2\mu}{3})L_{ls}}. \quad (7.21)$$

Therefore, if defining new state variable $x_6 = \frac{\mu}{(1 - \frac{2\mu}{3})L_{ls}}$, then the augmented model can be reduced to sixth-order system. The estimation of x_6 is equivalent to that of μ , and r_f is estimated from the estimate of μ based on equation (7.11).

The new state vector becomes $\mathbf{x}_a = [\mathbf{x}^T \ x_6]^T$ and its associated state equations are

$$\frac{d\mathbf{x}_a}{dt} = (\mathbf{A}_a + \omega_r \mathbf{A}_{\omega_{ra}} + v_{qs} \mathbf{A}_{v_{qs}}) \mathbf{x}_a + \mathbf{B}_a \mathbf{u}, \quad (7.22)$$

$$\mathbf{y} = \mathbf{C}_a \mathbf{x}_a, \quad (7.23)$$

where

$$\mathbf{A}_a = \begin{bmatrix} (a + \frac{bc}{a})\mathbf{I}_{2 \times 2} & \frac{bc}{a}\mathbf{I}_{2 \times 2} & \begin{bmatrix} -a - \frac{R_s}{L_{ls}} & -k_f x_5 \\ 0 & 0 \end{bmatrix} \\ (d - \frac{bc}{a})\mathbf{I}_{2 \times 2} & (d - \frac{bc}{a})\mathbf{I}_{2 \times 2} & \begin{bmatrix} \frac{R_s}{L_{ls}} & k_f x_5 \\ 0 & 0 \end{bmatrix} \\ \mathbf{0}_{2 \times 2} & \mathbf{0}_{2 \times 2} & \begin{bmatrix} -\frac{R_s}{L_{ls}} & -k_f x_5 \\ 0 & 0 \end{bmatrix} \end{bmatrix}, \quad (7.24)$$

$$\mathbf{A}_{\omega_{ra}} = \begin{bmatrix} \frac{ce}{a}\mathbf{J} & \frac{ce}{a}\mathbf{J} & \mathbf{0}_{2 \times 2} \\ -(1 + \frac{ce}{a})\mathbf{J} & -(1 + \frac{ce}{a})\mathbf{J} & \mathbf{0}_{2 \times 2} \\ \mathbf{0}_{2 \times 2} & \mathbf{0}_{2 \times 2} & \mathbf{0}_{2 \times 2} \end{bmatrix}, \quad (7.25)$$

$$\mathbf{A}_{v_{qs}} = \begin{bmatrix} \mathbf{0}_{2 \times 5} & [\frac{2}{3} & 0]^T \\ \mathbf{0}_{2 \times 5} & [-\frac{2}{3} & 0]^T \\ \mathbf{0}_{2 \times 5} & [\frac{2}{3} & 0]^T \end{bmatrix}, \quad (7.26)$$

$$\mathbf{B}_a = \begin{bmatrix} g\mathbf{I}_{2 \times 2} \\ -g\mathbf{I}_{2 \times 2} \\ \mathbf{0}_{2 \times 2} \end{bmatrix}, \quad (7.27)$$

$$\mathbf{C}_a = [\mathbf{I}_{2 \times 2} \ \mathbf{0}_{2 \times 4}]. \quad (7.28)$$

7.5 EKF for Estimation of Fault Parameters

7.5.1 EKF for estimation in nonlinear systems

EKF is the extension of KF to handle nonlinear systems by linearizing state equations and output equations around current estimates of state variables' mean and covariance [250]. The nonlinear system is

$$\mathbf{x}(k) = \mathbf{f}(\mathbf{x}(k-1), \mathbf{u}(k-1)) + \boldsymbol{\nu}(k-1), \quad (7.29)$$

$$\mathbf{y}(k) = \mathbf{h}(\mathbf{x}(k), \mathbf{u}(k)) + \boldsymbol{\omega}(k), \quad (7.30)$$

where both $\mathbf{f}(\mathbf{x}(k), \mathbf{u}(k))$ and $\mathbf{h}(\mathbf{x}(k), \mathbf{u}(k))$ can be nonlinear functions of state and output variables, $\boldsymbol{\nu}(k)$ and $\boldsymbol{\omega}(k)$ are the process and output noises, respectively. $\boldsymbol{\nu}(k)$ and $\boldsymbol{\omega}(k)$ are assumed to be multivariate Gaussian noises having zero means and covariance matrices $\mathbf{Q}(k)$ and $\mathbf{R}(k)$, respectively. The initial mean and covariance of $\mathbf{x}$ are assumed known as $\mathbf{x}(0|0) = \mathbf{x}_0$ and $\mathbf{P}(0|0) = \mathbf{P}_0$. In addition, the system is assumed to be a Markov process, in which the next state is dependent solely on its present state.

EKF includes two steps, prediction step and update step. The prediction step estimates the mean and covariance of the current state from the previous state based on the process model. The update step, also called correction step, employs the current measurement to update the predicted mean and covariance in the prediction step. The prediction and update steps are described by equations below [250]

$$\hat{\mathbf{x}}(k|k-1) = \mathbf{f}(\hat{\mathbf{x}}(k-1|k-1), \mathbf{u}(k-1)), \quad (7.31)$$

$$\hat{\mathbf{P}}(k|k-1) = \mathbf{F}(k-1)\hat{\mathbf{P}}(k-1|k-1)\mathbf{F}^T(k-1) + \mathbf{Q}(k-1). \quad (7.32)$$

$$\hat{\mathbf{x}}(k|k) = \hat{\mathbf{x}}(k|k-1) + \mathbf{K}(k)(\mathbf{y}(k) - \mathbf{h}(\hat{\mathbf{x}}(k|k-1))), \quad (7.33)$$

$$\hat{\mathbf{P}}(k|k) = (\mathbf{I} - \mathbf{K}(k)\mathbf{H}(k))\hat{\mathbf{P}}(k|k-1), \quad (7.34)$$

where $\mathbf{K}(k)$ is the near-optimal gain determined from residual covariance $\mathbf{S}(k)$. They are defined as

$$\mathbf{S}(k) = \mathbf{H}(k)\hat{\mathbf{P}}(k|k-1)\mathbf{H}^T(k) + \mathbf{R}(k), \quad (7.35)$$

$$\mathbf{K}(k) = \hat{\mathbf{P}}(k|k-1)\mathbf{H}^T(k)\mathbf{S}^{-1}(k). \quad (7.36)$$

The linearized state transition matrix $\mathbf{F}(k-1)$ and the linearized output matrix $\mathbf{H}(k)$ are defined from Jacobian matrix of $\mathbf{f}(\mathbf{x}(k), \mathbf{u}(k))$ and $\mathbf{h}(\mathbf{x}(k), \mathbf{u}(k))$ as

$$\mathbf{F}(k-1) = \frac{\partial \mathbf{f}(\hat{\mathbf{x}}(k-1|k-1), \mathbf{u}(k-1))}{\partial \mathbf{x}}, \quad (7.37)$$

$$\mathbf{H}(k) = \frac{\partial \mathbf{h}(\hat{\mathbf{x}}(k|k-1), \mathbf{u}(k))}{\partial \mathbf{x}}. \quad (7.38)$$

7.5.2 EKF for fault parameter estimation

The system under state vector $\mathbf{x}_a$ can be discretized with sample time Δt using the Euler method presented in [251].

$$\mathbf{x}_a(k) = \mathbf{x}_a(k-1) + \Delta t \mathbf{q}(\mathbf{x}_a(k-1), \omega_r(k-1), \mathbf{u}(k-1)), \quad (7.39)$$

where

$$\begin{aligned} \mathbf{q}(\mathbf{x}_a(k-1), \omega_r(k-1), \mathbf{u}(k-1)) = \\ (\mathbf{A}_a(\mathbf{x}_a(k-1)) + \omega_r(k-1)\mathbf{A}_{\omega_r a} + v_{qs}(k-1)\mathbf{A}_{v_{qs}})\mathbf{x}_a(k-1) + \mathbf{B}_a\mathbf{u}(k-1). \end{aligned} \quad (7.40)$$

As a result, the matrix $\mathbf{F}$ can be derived as

$$\mathbf{F}(k-1) = \mathbf{I}_{6 \times 6} + \Delta t(\mathbf{A}_a(\mathbf{x}_a(k-1)) + \omega_r(k-1)\mathbf{A}_{\omega_r a} + v_{qs}(k-1)\mathbf{A}_{v_{qs}}) + \Delta t \mathbf{p}(\mathbf{x}_a(k-1)), \quad (7.41)$$

where

$$\mathbf{p}(\mathbf{x}_a(k-1)) = \begin{bmatrix} \mathbf{0}_{2 \times 4} & \begin{bmatrix} -k_f x_6(k-1) & 0 \\ 0 & 0 \end{bmatrix} \\ \mathbf{0}_{2 \times 4} & \begin{bmatrix} k_f x_6(k-1) & 0 \\ 0 & 0 \end{bmatrix} \\ \mathbf{0}_{2 \times 4} & \begin{bmatrix} -k_f x_6(k-1) & 0 \\ 0 & 0 \end{bmatrix} \end{bmatrix}. \quad (7.42)$$

Matrix $\mathbf{H}(k)$ simply equals to $\mathbf{C}_a$.

7.6 Simulation Results

7.6.1 Simulation design

The machine used in the simulation is a squirrel cage induction motor having the same parameters as the real one in Chapter 3.

The physics of degradation process based on the fault parameters has not been completely studied by research community. Even though it is not the focus of this chapter, some assumptions are given here to put parameter estimation in a certain context. Firstly, it is assumed that the degradation process is a monotonic trend. Secondly, the degradation process is faster when fault severity is higher. Also, two cases of fault degradation process are assumed. Case 1 is when both parameters change independently. Case 2 is

when the degradation is progressed in the way that μ is unchanging, and r_f decreases to lower values. Fig. 7.2 and Fig. 7.3 illustrate the former and later cases, respectively. In both cases, the fault is commenced with $\mu = 10\%$, $r_f = 20 \Omega$.

Also, to check the robustness of the proposed method against voltage imbalance, a three-phase overvoltage condition, shown in Table 7.1, is tested. In the model, it is assumed that there is no model error and there are only measurement noises in the voltages and currents. Hence, matrices Q and R can be derived from the simulated Gaussian noise characteristics of measurement devices.

Table 7.1: 3OV voltage imbalance condition used in simulation and experiment

Type	RMS-phase a	RMS-phase b	RMS-phase c	Angle-phase a	Angle-phase b	Angle-phase c
3OV	253.1V	248.7V	244.4V	0°	-120°	120°

Figure 7.2: Assumed development of fault parameters for Case 1.

MATLAB[®] and Simulink[®] software is used in the simulation. The simulations blocks are depicted in Fig. 7.4.

7.6.2 Fault detection and equality constraint

In order to test the fault detection, the simulated $\frac{1}{3}\mu\tilde{I}_f$ is compared with its estimated value through Δ_n . The equality constraint is checked by comparing the simulated $\frac{1}{3}\mu\tilde{I}_f$

Figure 7.3: Assumed development of fault parameters for Case 2.

Figure 7.4: MATLAB blocks for simulation of parameter estimation technique.

with $\frac{\mu^2 \tilde{V}_{sp}}{3r_f}$ as in equation (7.9). The results in Fig. 7.5 and Fig. 7.6 show the matching of the magnitude of $\frac{1}{3}\mu \tilde{I}_f$, Δ_n and $\frac{\mu^2 \tilde{V}_{sp}}{3r_f}$, for Case 1 and Case 2, respectively. That is, fault can be properly detected and tracked, and the constraint can be estimated accurately.

7.6.3 Fault parameter estimation

After the fault is detected and equality constraint is established, the fault parameters can be estimated using EKF, as shown in Fig. 7.7, and Fig. 7.8 for Case 1 and Case 2, respectively. They are accurately estimated, and hence fault severity can be tracked using the proposed method.

 Figure 7.5: Estimates of $\frac{1}{3}\mu\tilde{I}_f$ for fault detection and equality constraint, Case 1.

 Figure 7.6: Estimates of $\frac{1}{3}\mu\tilde{I}_f$ for fault detection and equality constraint, Case 2.

7.7 Experimental Result

The experimental result is tested for an early fault with $r_f = 25 \Omega$ and $\mu = 10\%$ for the same motor in Chapter 3. The value of $\tilde{V}_{sp}$ for 3OV condition can be calculated as 354 V, and the estimated of $\frac{1}{3}\mu\tilde{I}_f$ from Table 5.2 and Fig. 5.15, estimated k_f is $\frac{354}{3 \times 0.047} = 2510.64$. Substitute this value in the state-space equation, the estimation result

Figure 7.7: Estimates of fault parameters for Case 1.

Figure 7.8: Estimates of fault parameters for Case 2.

for x_6 is depicted in Fig. 7.9. From this estimate, the fraction of shorted turns can be estimated in Fig. 7.10. Using this estimate and the relationship between r_f and μ as in equation (7.11), r_f is estimated in Fig. 7.11. x_5 is estimated accurately, as expected, in Fig. 7.12. Even though there is slight deviation in the estimate of μ and r_f , the result is fairly acceptable.

 Figure 7.9: Real and estimated values of x_6 .

 Figure 7.10: Real and estimated values of μ , found from the estimate of x_6 .

7.8 Conclusion

A method to estimate two fault parameters of stator winding inter-turn short circuit is proposed in this chapter. The sequence component model analysis is utilized to generate an equality constraint on fault parameters, which is exploited to simplify the state-space model. The EKF approach is applied to estimate one parameter based on this model,

Figure 7.11: Real and estimated values of r_f . Figure 7.12: Real and estimated values of x_5 .

and the other is determined using the equality constraint. Fault parameter estimation can support maintenance planning, by which a right time and suitable maintenance policy can be properly proposed. The proposed technique, based on the combination of sequence component model and state-space model, can be considered to extend to study fault severity estimation of the same fault in other electrical machines and other types of faults in electrical machines.

Chapter 8

Conclusions and Future Work

8.1 Conclusions

In this thesis, the research problem is identified, and the proposed methods contribute to the domain of diagnosis and prognosis of component faults in engineering systems in general, and model-based approach for stator winding fault of induction machines in particular. The literature survey shows the lack of an investigation on model-based approach for prognosis using direct fault parameters and early diagnosis of SWITSF. This thesis tackles these problems using various techniques based on different forms of models of induction machines under the fault.

For the early fault detection, two methods are proposed. In the first approach, the multiple-indicator methodology is proposed. The fundamental idea is to use few indicators simultaneously. These indicators have supplementary effects so that they can improve the robustness and reliability of fault detection compared to the case using each indicator separately. During the incipient stage of fault progression, the fault develops slowly, and hence the robustness of fault detection would be more important than the time taken to detect the fault. Therefore, using several indicators is appropriate as long as the performance is improved. In addition, for such systems having multi-physics nature like electrical machines, it is very much possible that multiple indicators are available and they can supplement to each other.

The second approach is based on sequence component of electrical machines. The advantage of sequence component approach is that it is able to model the voltage imbalance and the inherent asymmetry in simple equations. In this thesis, the approach is employed

to incorporate the fault effect and decompose it from that of voltage imbalance and inherent asymmetry, which is a novel contribution. Since the voltage imbalance and inherent asymmetry are the main factors causing the challenge of early fault detection, the approach helps detect the fault at its incipient stage of degradation process. In addition, the proposed approach has the capability of fault severity identification and faulty phase identification.

The early fault detection capability brings out the necessary condition for an effective prognosis process. The proposed prognostic method is able to estimate the RUL using the electrical fault parameters, which is another contribution. These fault parameters are both unknown and unmeasurable in real situations. Since the problem associated with RUL prediction requires the quantity to represent the uncertainty of prediction results, in this thesis, particle filter is proposed due to its statistical nature very suitable to quantify the prediction performance. Experimental validation proves the advantage and suitability of particle filter-based parameter estimation and RUL prediction.

The model-based approach is further exploited through the study of two other approaches for fault parameter estimation. The first approach is based on a unique characteristic of a system under sinusoidal excitation. Under steady state and with sinusoidal applied voltages, the differential equations of the fault-dependent quantities can be transformed to the trigonometry equations. This property is employed to propose a closed-form solution to estimates of fault parameters. The other approach is based on different model forms of electrical machines. It uses the sequence component to derive an equality constraint on fault parameters, which helps reduce the order of the state-space model. The nonlinear filter such as extended Kalman filter is applied to the simplified state-space model to estimate one of the parameters, and the other parameter is determined by using the equality constraint.

In overall, the value of this thesis is, it sets up a design and methodology for diagnosis and subsequent prognosis for stator inter-turn fault. It is also flexible to be applied to different functions and time scales. This has got substantial value in CBM operations for time critical applications, for example in aerospace and marine. In addition, this can be, in future, extended to other component faults using fault specific parameters. The fundamental methodology is in place, by this work, and so future possibilities to diversify

the work to include other faults/ machines is very much possible. This work will have its importance for future research planning to pursue in this direction and also for industries working on tangible solutions to prognosis problem of engineering systems.

8.2 Recommendations for Future Work

There is substantial research in diagnosis and prognosis of engineering systems. However, there is a lot to be investigated in this topic. Based on the research in this thesis, some future work is recommended as follows.

Fault isolation of multiple faults

In this thesis, the challenge of the effect of ambiguous factors to early fault detection of SWITSF has been addressed. The approach is to decompose the fault effect from that of ambiguous factors, thereby aiding incipient fault detection. There are other component faults as well such as bearing and broken rotor bar faults. Considering that, a diagnosis method to identify the true fault, and distinguish it from other component faults is also necessary. This will have value in diagnosis at system level, when multiple faults are considered.

Hybrid approach using multiple prognostic indicators

There is huge amount of indicators proposed for diagnosis, but diagnostic indicators are not necessarily prognostic parameters. In this thesis, the two electrical parameters are explored for prognostic purpose. From the thermal effect point of view, the SWITSF results in the circulating current in the faulty winding portion, which in turn generates the local thermal heat. This process, aided by the thermal stress, generates higher fault loop current, and hence, accelerates the degradation process. Therefore, the hot spot temperature can be another prognostic parameter. Once it can be estimated or measured, a combination of both electrical and thermal prognostic parameters will be possible, and the hybrid approach will be well suited to multi-physics systems such as electrical machines.

Hybrid approach combining model-based and data driven methods

The fault parameter estimation and RUL prediction are based on model-based approach using PF in this thesis. These processes are actually affected by the uncertainty

of the diagnostic and prognostic models, the unknown nature of future inputs, and the noise in the measurements. Even though the knowledge of the fault model and degradation process are available for systems such as electrical machines, the historical data collected during operation of the systems can help define the uncertainty and improve the RUL result, as shown in [181, 252, 253]. Therefore, it is promising to consider hybrid approach combining both model-based and data driven methods if both physical model and operational data are available.

Degradation modelling

In this thesis, it is assumed that the degradation process has exponential structure. This assumption is fit to physical laws such as Arrhenius model, Coffin-Manson model, and Eyring model. The effect of voltage imbalance, load conditions, and other degradation factors are reflected in the parameters of the model. However, a detail of physical model to express the effect of these factors and their correlation would be useful. In addition, exponential form is a kind of deterministic model. Considering the temporal variability of deterioration due to the influence of changing operating conditions, a model based on stochastic processes would be needed [254]. Markov processes are stochastic processes with independent increments and can be considered. Some examples of Markov processes are Brownian motion with drift, the compound Poisson process, and the gamma process. Further study on the application of these stochastic models for degradation process will be beneficial.

Other recommendations

The thesis proposes a diagnosis and prognosis framework and the associate techniques for electrical machines. The H_-/H_∞ presented in [14, 15] can be explored to study the sensitivity of the fault indicators, and hence, to be used as in performance metric. Also, PF has been experimentally verified as an effective tool for parameter estimation and RUL prediction, through parameters of mean and 95% confidence level. Other PF algorithms, such as that in [182–184] can be considered to improve the RUL estimation performance. It will be an important future direction of this thesis relating to prognostic process. At that stage, the performance metrics in [255] can be applied to evaluate the prognostic performance for the comparison with standard PF in this thesis. In addition, as shown in Chapter 7, the two prognostic parameters are actually not independent, but dependent

on each other by an equality constraint, a performance index suiting to this specific situation maybe beneficial and necessary.

Appendix

Derivation of the Model of Induction Machine under SWITSF in abc Reference Frame

The stator winding includes two portions, as_h is in healthy condition, and the other as_f is under SWITSF. Therefore, the set of equations for voltages and fluxes in the four winding structure, including the stator windings as_h and as_f , and the windings in other phases bs and cs , will be described. After that, it is derived to three winding structure, as in Chapter 3.

The set of equations in the four winding structure is

$$\mathbf{v}'_s = \mathbf{R}'_s \mathbf{i}'_s + \frac{d\boldsymbol{\lambda}'_s}{dt} \quad (8.1)$$

$$\mathbf{0} = \mathbf{R}_r \mathbf{i}_r + \frac{d\boldsymbol{\lambda}_r}{dt} \quad (8.2)$$

$$\boldsymbol{\lambda}'_s = \mathbf{L}'_{ss} \mathbf{i}'_s + \mathbf{L}'_{sr} \mathbf{i}_r \quad (8.3)$$

$$\boldsymbol{\lambda}_r = \mathbf{L}_{sr}^T \mathbf{i}'_s + \mathbf{L}_{rr} \mathbf{i}_r \quad (8.4)$$

where

$$\mathbf{v}'_s = [v_{as_h} \quad v_{as_f} \quad v_{bs} \quad v_{cs}]^T \quad (8.5)$$

$$\mathbf{i}'_s = [i_{as_h} \quad i_{as_f} \quad i_{bs} \quad i_{cs}]^T \quad (8.6)$$

$$\boldsymbol{\lambda}'_s = [\lambda_{as_h} \quad \lambda_{as_f} \quad \lambda_{bs} \quad \lambda_{cs}]^T \quad (8.7)$$

$$\mathbf{i}_r = [i_{ar} \quad i_{br} \quad i_{cr}]^T \quad (8.8)$$

$$\boldsymbol{\lambda}_r = [\lambda_{ar} \quad \lambda_{br} \quad \lambda_{cr}]^T \quad (8.9)$$

$$\mathbf{R}'_s = \begin{bmatrix} (1-\mu)R_s & 0 & 0 & 0 \\ 0 & \mu R_s & 0 & 0 \\ 0 & 0 & R_s & 0 \\ 0 & 0 & 0 & R_s \end{bmatrix} \quad (8.10)$$

$$\mathbf{R}_r = \begin{bmatrix} R_r & 0 & 0 \\ 0 & R_r & 0 \\ 0 & 0 & R_r \end{bmatrix} \quad (8.11)$$

$$\mathbf{L}'_{ss} = \begin{bmatrix} (1-\mu)L_{ls} & 0 & 0 & 0 \\ 0 & \mu L_{ls} & 0 & 0 \\ 0 & 0 & L_{ls} & 0 \\ 0 & 0 & 0 & L_{ls} \end{bmatrix} + L_{ms} \begin{bmatrix} (1-\mu)^2 & \mu(1-\mu) & -\frac{1-\mu}{2} & -\frac{1-\mu}{2} \\ \mu(1-\mu) & \mu^2 & -\frac{\mu}{2} & -\frac{\mu}{2} \\ -\frac{1-\mu}{2} & -\frac{\mu}{2} & 1 & -\frac{1}{2} \\ -\frac{1-\mu}{2} & -\frac{\mu}{2} & -\frac{1}{2} & 1 \end{bmatrix} \quad (8.12)$$

$$\mathbf{L}'_{sr} = L_{ms} \begin{bmatrix} (1-\mu)\cos(\theta_r) & (1-\mu)\cos(\theta_r + \frac{2\pi}{3}) & (1-\mu)\cos(\theta_r - \frac{2\pi}{3}) \\ \mu\cos(\theta_r) & \mu\cos(\theta_r + \frac{2\pi}{3}) & \mu\cos(\theta_r - \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \quad (8.13)$$

$$\mathbf{L}_{rr} = \begin{bmatrix} L_{lr} + L_{ms} & -L_{ms}/2 & -L_{ms}/2 \\ -L_{ms}/2 & L_{lr} + L_{ms} & -L_{ms}/2 \\ -L_{ms}/2 & -L_{ms}/2 & L_{lr} + L_{ms} \end{bmatrix} \quad (8.14)$$

Equations of voltage quantities

The equation for voltage v_{as_h} can be found from equation (8.1) with λ_{as_h} found from equation (8.3), $\mathbf{R}'_s$, $\mathbf{L}'_{ss}$, and $\mathbf{L}'_{sr}$ found from equation (8.10), (8.12), and (8.13), respectively. Also, notice that $i_{as_h} = i_{as}$ and $i_{as_f} = i_{as} - i_f$, then the voltage v_{as_h} can be expressed as

$$\begin{aligned} v_{as_h} = & \begin{bmatrix} (1-\mu)R_s & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} \\ & + \frac{d}{dt} \left(\begin{bmatrix} (1-\mu)L_{ls} + (1-\mu)^2 L_{ms} & \mu(1-\mu)L_{ms} & -\frac{1-\mu}{2}L_{ms} & -\frac{1-\mu}{2}L_{ms} \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) \\ & + \frac{d}{dt} \left((1-\mu)L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right) \end{aligned} \quad (8.15)$$

That is,

$$\begin{aligned}
 v_{as_h} = & (1 - \mu)R_s i_{as} + \frac{d}{dt} \left(\begin{bmatrix} (1 - \mu)(L_{ls} + L_{ms}) & -\frac{1-\mu}{2}L_{ms} & -\frac{1-\mu}{2}L_{ms} \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) + \\
 & \frac{d}{dt} \left((1 - \mu)L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right) - \frac{di_f}{dt} \mu(1 - \mu)L_{ms}
 \end{aligned} \tag{8.16}$$

Similarly, for the voltage v_{as_f} and using λ_{as_f} from the 2-nd element of flux vector expressed in equation (8.3).

$$\begin{aligned}
 v_{as_f} = & \begin{bmatrix} 0 & \mu R_s & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} \\
 & + \frac{d}{dt} \left(\begin{bmatrix} \mu(1 - \mu)L_{ms} & \mu L_{ls} + \mu^2 L_{ms} & -\frac{\mu}{2}L_{ms} & -\frac{\mu}{2}L_{ms} \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) \\
 & + \frac{d}{dt} \left(\mu L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right)
 \end{aligned} \tag{8.17}$$

That is,

$$\begin{aligned}
 v_{as_f} = & \mu R_s i_{as} + \frac{d}{dt} \left(\begin{bmatrix} \mu(L_{ls} + L_{ms}) & -\frac{\mu}{2}L_{ms} & -\frac{\mu}{2}L_{ms} \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) + \\
 & \frac{d}{dt} \left(\mu L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right) - \mu R_s i_f - \frac{di_f}{dt} (\mu L_{ls} + \mu^2 L_{ms})
 \end{aligned} \tag{8.18}$$

Therefore, the voltage can be found from the sum of v_{as_h} and v_{as_f} , and hence

$$\begin{aligned}
 v_{as} = v_{as_h} + v_{as_f} = & R_s i_{as} + \frac{d}{dt} \left(\begin{bmatrix} L_{ls} + L_{ms} & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) + \\
 & \frac{d}{dt} \left(\mu L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right) - \mu R_s i_f - \frac{di_f}{dt} \mu(L_{ls} + L_{ms})
 \end{aligned} \tag{8.19}$$

For the voltage v_{bs} ,

$$\begin{aligned}
 v_{bs} = & \begin{bmatrix} 0 & 0 & R_s & 0 \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} \\
 & + \frac{d}{dt} \left(\begin{bmatrix} -\frac{1-\mu}{2}L_{ms} & -\frac{\mu}{2}L_{ms} & L_{ls} + \mu^2L_{ms} & -\frac{1}{2}L_{ms} \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) \\
 & + \frac{d}{dt} \left(\begin{bmatrix} \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right)
 \end{aligned} \tag{8.20}$$

and hence,

$$\begin{aligned}
 v_{bs} = & R_s i_{bs} + \frac{d}{dt} \left(\begin{bmatrix} -\frac{1}{2}L_{ms} & L_{ls} + L_{ms} & -\frac{1}{2}L_{ms} \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) + \\
 & \frac{d}{dt} \left(\begin{bmatrix} \mu L_{ms} \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right) + \frac{\mu}{2} L_{ms} \frac{di_f}{dt}
 \end{aligned} \tag{8.21}$$

Similarly, for the voltage v_{cs} ,

$$\begin{aligned}
 v_{cs} = & R_s i_{cs} + \frac{d}{dt} \left(\begin{bmatrix} -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ls} + L_{ms} \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) + \\
 & \frac{d}{dt} \left(\begin{bmatrix} \mu L_{ms} \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right) + \frac{\mu}{2} L_{ms} \frac{di_f}{dt}
 \end{aligned} \tag{8.22}$$

Therefore, in vector form, we have

$$\begin{aligned}
 \begin{bmatrix} v_{as} \\ v_{bs} \\ v_{cs} \end{bmatrix} &= \begin{bmatrix} R_s & 0 & 0 \\ 0 & R_s & 0 \\ 0 & 0 & R_s \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \\
 &+ \frac{d}{dt} \left(\begin{bmatrix} (L_{ls} + L_{ms}) & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & L_{ls} + L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ls} + L_{ms} \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \right) \\
 &+ \frac{d}{dt} \left(L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \right) \\
 &+ \mu \begin{bmatrix} (L_{ls} + L_{ms}) \\ -\frac{\mu}{2}L_{ms} \\ -\frac{\mu}{2}L_{ms} \end{bmatrix} \frac{di_f}{dt} - \begin{bmatrix} \mu R_s \\ 0 \\ 0 \end{bmatrix} i_f
 \end{aligned} \tag{8.23}$$

This is equation (3.2) in Chapter 3.

Equation (8.2) is equation (3.3) in Chapter 3.

Also,

$$v_{asf} = r_f i_f \tag{8.24}$$

and

$$v_{asf} = \mu R_s (i_{as} - i_f) + \frac{d\lambda_{asf}}{dt}, \tag{8.25}$$

These equations are combined into equation (3.14) in Chapter 3.

In order to derive equation (3.16), multiply two sides of equation (8.16) with μ , and multiply two sides of equation (8.18) with $-(1 - \mu)$, and take sum the side to side of the new equations, we have

$$\mu v_{as_h} - (1 - \mu) v_{asf} = -\frac{di_f}{dt} \mu^2 (1 - \mu) L_{ms} + \mu (1 - \mu) R_s i_f + \frac{di_f}{dt} (\mu L_{ls} + \mu^2 L_{ms}) (1 - \mu) \tag{8.26}$$

Notice $v_{as_h} + v_{asf} = v_{as}$ and $v_{asf} = r_f i_f$, then this equation becomes

$$\mu v_{as} - r_f i_f = \mu (1 - \mu) R_s i_f + \mu (1 - \mu) L_{ls} \frac{di_f}{dt} \tag{8.27}$$

This is equivalent to equation (3.16) in Chapter 3.

Equations of flux quantities

The flux equations can be written again in detail of elements as

$$\begin{aligned}
 & \begin{bmatrix} \lambda_{as_h} \\ \lambda_{as_f} \\ \lambda_{bs} \\ \lambda_{cs} \end{bmatrix} \\
 &= \begin{bmatrix} (1-\mu)L_{ls} + (1-\mu)^2L_{ms} & \mu(1-\mu)L_{ms} & -\frac{1-\mu}{2}L_{ms} & -\frac{1-\mu}{2}L_{ms} \\ \mu(1-\mu)L_{ms} & \mu L_{ls} + \mu^2L_{ms} & -\frac{\mu}{2}L_{ms} & -\frac{\mu}{2}L_{ms} \\ -\frac{1-\mu}{2}L_{ms} & -\frac{\mu}{2}L_{ms} & L_{ls} + L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1-\mu}{2}L_{ms} & -\frac{\mu}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ls} + L_{ms} \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} \\
 &+ L_{ms} \begin{bmatrix} (1-\mu)\cos(\theta_r) & (1-\mu)\cos(\theta_r + \frac{2\pi}{3}) & (1-\mu)\cos(\theta_r - \frac{2\pi}{3}) \\ \mu\cos(\theta_r) & \mu\cos(\theta_r + \frac{2\pi}{3}) & \mu\cos(\theta_r - \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \\
 & \tag{8.28}
 \end{aligned}$$

then, the vector of three elements $\lambda_{as_h} + \lambda_{as_f}$, λ_{bs} , and λ_{cs} is

$$\begin{aligned}
 & \begin{bmatrix} \lambda_{as_h} + \lambda_{as_f} \\ \lambda_{bs} \\ \lambda_{cs} \end{bmatrix} = \\
 & \begin{bmatrix} (1-\mu)L_{ls} + (1-\mu)L_{ms} & \mu L_{ls} + \mu L_{ms} & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1-\mu}{2}L_{ms} & -\frac{\mu}{2}L_{ms} & L_{ls} + L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1-\mu}{2}L_{ms} & -\frac{\mu}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ls} + L_{ms} \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} \\
 &+ L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \\
 & \tag{8.29}
 \end{aligned}$$

then,

$$\begin{aligned}
 & \begin{bmatrix} \lambda_{as_h} + \lambda_{as_f} \\ \lambda_{bs} \\ \lambda_{cs} \end{bmatrix} = \begin{bmatrix} L_{ls} + L_{ms} & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & L_{ls} + L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ls} + L_{ms} \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \\
 &+ L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} - \mu \begin{bmatrix} L_{ls} + L_{ms} \\ -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} \end{bmatrix} i_f \\
 & \tag{8.30}
 \end{aligned}$$

This is equation (3.7) in Chapter 3.

Also,

$$\lambda_{asf} = \mu \begin{bmatrix} L_{ls} + L_{ms} & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} + \mu L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r - \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} - (\mu L_{ls} + \mu^2 L_{ms}) i_f \quad (8.31)$$

This is equation (3.15) in Chapter 3.

For the rotor flux λ_r ,

$$\begin{bmatrix} \lambda_{ar} \\ \lambda_{br} \\ \lambda_{cr} \end{bmatrix} = L_{ms} \begin{bmatrix} (1-\mu)\cos(\theta_r) & \mu\cos(\theta_r) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r + \frac{2\pi}{3}) \\ (1-\mu)\cos(\theta_r + \frac{2\pi}{3}) & \mu\cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r - \frac{2\pi}{3}) \\ (1-\mu)\cos(\theta_r - \frac{2\pi}{3}) & \mu\cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \begin{bmatrix} i_{as_h} \\ i_{as} - i_f \\ i_{bs} \\ i_{cs} \end{bmatrix} + \begin{bmatrix} L_{lr} + L_{ms} & -L_{ms}/2 & -L_{ms}/2 \\ -L_{ms}/2 & L_{lr} + L_{ms} & -L_{ms}/2 \\ -L_{ms}/2 & -L_{ms}/2 & L_{lr} + L_{ms} \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \quad (8.32)$$

then

$$\begin{bmatrix} \lambda_{ar} \\ \lambda_{br} \\ \lambda_{cr} \end{bmatrix} = L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r - \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} + \begin{bmatrix} L_{lr} + L_{ms} & -L_{ms}/2 & -L_{ms}/2 \\ -L_{ms}/2 & L_{lr} + L_{ms} & -L_{ms}/2 \\ -L_{ms}/2 & -L_{ms}/2 & L_{lr} + L_{ms} \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} - \mu L_{ms} \begin{bmatrix} \cos(\theta_r) \\ \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) \end{bmatrix} i_f \quad (8.33)$$

This is equation (3.8) in Chapter 3.

Equation of electromagnetic torque

The electromagnetic torque is defined as

$$T_e = \frac{P}{2} \mathbf{i}_s'^T \frac{\partial \mathbf{L}'_{sr}}{\partial \theta_r} \mathbf{i}_r \quad (8.34)$$

$\mathbf{L}'_{sr}$ can be written as

$$\begin{aligned}\mathbf{L}'_{sr} &= \begin{bmatrix} 1-\mu & 0 & 0 \\ \mu & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} L_{ms} \begin{bmatrix} \cos(\theta_r) & \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r) & \cos(\theta_r - \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) & \cos(\theta_r + \frac{2\pi}{3}) & \cos(\theta_r) \end{bmatrix} \\ &= \begin{bmatrix} 1-\mu & 0 & 0 \\ \mu & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{L}_{sr}\end{aligned}\quad (8.35)$$

then, T_e can be expressed as

$$T_e = \frac{P}{2} \begin{bmatrix} i_{as} & i_{as} - i_f & i_{bs} & i_{cs} \end{bmatrix} \begin{bmatrix} 1-\mu & 0 & 0 \\ \mu & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \frac{\partial \mathbf{L}_{sr}}{\partial \theta_r} \mathbf{i}_r \quad (8.36)$$

i.e.,

$$\begin{aligned}T_e &= \frac{P}{2} \mathbf{i}_s^T \frac{\partial \mathbf{L}_{sr}}{\partial \theta_r} \mathbf{i}_r \\ &+ \frac{P}{2} \begin{bmatrix} -\mu i_f & 0 & 0 \end{bmatrix} \begin{bmatrix} -\sin(\theta_r) & -\sin(\theta_r + \frac{2\pi}{3}) & -\sin(\theta_r - \frac{2\pi}{3}) \\ -\sin(\theta_r - \frac{2\pi}{3}) & -\sin(\theta_r) & -\sin(\theta_r + \frac{2\pi}{3}) \\ -\sin(\theta_r + \frac{2\pi}{3}) & -\sin(\theta_r - \frac{2\pi}{3}) & -\sin(\theta_r) \end{bmatrix} \begin{bmatrix} i_{ar} \\ i_{br} \\ i_{cr} \end{bmatrix} \\ &= \frac{P}{2} \mathbf{i}_s^T \frac{\partial \mathbf{L}_{sr}}{\partial \theta_r} \mathbf{i}_r \\ &+ \frac{P}{2} \mu i_f L_{ms} \left[i_{ar} \sin(\theta_r) + i_{br} \left(-\frac{1}{2} \sin \theta_r + \frac{\sqrt{3}}{2} \cos \theta_r \right) + i_{cr} \left(-\frac{1}{2} \sin \theta_r - \frac{\sqrt{3}}{2} \cos \theta_r \right) \right]\end{aligned}\quad (8.37)$$

Note that $i_{ar} + i_{br} + i_{cr} = 0$, then $-i_{br} - i_{cr} = i_{ar}$, we have

$$T_e = \frac{P}{2} \mathbf{i}_s^T \frac{\partial \mathbf{L}_{sr}}{\partial \theta_r} \mathbf{i}_r + \frac{P}{2} \mu i_f L_{ms} \left[\frac{3}{2} i_{ar} \sin(\theta_r) + \frac{\sqrt{3}}{2} (i_{br} - i_{cr}) \cos(\theta_r) \right] \quad (8.38)$$

This is equation (3.19) in Chapter 3.

Derivation of the Model of Induction Machines under SWITSF in $qd0$ Reference Frame

The steps of derivation from abc to $qd0$ for a healthy induction machine is presented in detail in [256]. Since the key different of the model of a healthy machine and a faulty

machine is the additional terms representing the effect of fault. In this section, the derivation process is mostly for these additional terms.

The transformation matrix $\mathbf{K}_s$ is

$$\mathbf{K}_s = \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & -\frac{\sqrt{3}}{3} & \frac{\sqrt{3}}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \quad (8.39)$$

Equations of voltage quantities

For the stator voltage equation

$$\mathbf{v}_s = R_s \mathbf{i}_s + \frac{d\boldsymbol{\lambda}_s}{dt} - \mu R_s i_f \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad (8.40)$$

Multiply $\mathbf{K}_s$ to two sides of the equation then,

$$\mathbf{v}_{qdos} = R_s \mathbf{i}_{qdos} + \frac{d\boldsymbol{\lambda}_{qdos}}{dt} - \mu R_s i_f \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & -\frac{\sqrt{3}}{3} & \frac{\sqrt{3}}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad (8.41)$$

That is, we have equation (3.21) in Chapter 3.

Equation (3.22) for rotor in Chapter 3 is directly adopted from that in [256] since there is no fault-dependent term in this equation.

Since $i_{as} = i_{qs} + i_{os}$, equation (3.36) is adopted directly from equation (3.14).

Equations of flux quantities

For the stator flux linkage equation in abc reference frame

$$\boldsymbol{\lambda}_s = [(\lambda_{as_h} + \lambda_{as_f}) \quad \lambda_{bs} \quad \lambda_{cs}]^T = \mathbf{L}_{ss} \mathbf{i}_s + \mathbf{L}_{sr} \mathbf{i}_r - \mu i_f \mathbf{L}_{ss}(:, 1), \quad (8.42)$$

The fault-dependent term, which requires to be transformed to $qd0$ reference frame, is $-\mu i_f \mathbf{L}_{ss}(:, 1)$. In the $qd0$, it becomes

$$-\mu i_f \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & -\frac{\sqrt{3}}{3} & \frac{\sqrt{3}}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \begin{bmatrix} L_{ls} + L_{ms} \\ -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} \end{bmatrix} = -\mu i_f \begin{bmatrix} \frac{2}{3}(L_{ls} + \frac{3}{2}L_{ms}) \\ 0 \\ \frac{1}{3}L_{ls} \end{bmatrix} \quad (8.43)$$

That is, we have equation (3.23) and (3.24) in Chapter 3, written again below, with notation $L_m = \frac{3}{2}L_{ms}$ and $L_s = L_{ls} + \frac{3}{2}L_{ms}$.

$$\boldsymbol{\lambda}_{qds} = L_s \mathbf{i}_{qds} + L_m \mathbf{i}_{qdr} - \mu i_f \begin{bmatrix} \frac{2}{3}L_s & 0 \end{bmatrix}^T, \quad (8.44)$$

$$\lambda_{os} = L_{ls} i_{os} - \frac{1}{3} \mu L_{ls} i_f, \quad (8.45)$$

For the rotor flux linkage equation in abc reference frame

$$\boldsymbol{\lambda}_r = [\lambda_{ar} \quad \lambda_{br} \quad \lambda_{cr}]^T = \mathbf{L}_{sr}^T \mathbf{i}_s + \mathbf{L}_{rr} \mathbf{i}_r - \mu i_f \mathbf{L}_{sr}^T(:, 1), \quad (8.46)$$

The corresponding transformation matrix for the rotor quantities is $\mathbf{K}_r$, which is

$$\mathbf{K}_r = \frac{2}{3} \begin{bmatrix} \cos(-\theta_r) & \cos(-\theta_r - \frac{2\pi}{3}) & \cos(-\theta_r + \frac{2\pi}{3}) \\ \sin(-\theta_r) & \sin(-\theta_r - \frac{2\pi}{3}) & \sin(-\theta_r + \frac{2\pi}{3}) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \quad (8.47)$$

The fault-dependent term in the $qd0$ will be

$$\begin{aligned} & -\mu i_f \mathbf{K}_r \mathbf{L}_{sr}^T(:, 1) \\ &= -\frac{2}{3} \mu i_f L_{ms} \begin{bmatrix} \cos(-\theta_r) & \cos(-\theta_r - \frac{2\pi}{3}) & \cos(-\theta_r + \frac{2\pi}{3}) \\ \sin(-\theta_r) & \sin(-\theta_r - \frac{2\pi}{3}) & \sin(-\theta_r + \frac{2\pi}{3}) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} \cos(\theta_r) \\ \cos(\theta_r + \frac{2\pi}{3}) \\ \cos(\theta_r - \frac{2\pi}{3}) \end{bmatrix} \\ &= -\frac{2}{3} \mu i_f L_{ms} \begin{bmatrix} \cos^2(\theta_r) + \cos^2(\theta_r + \frac{2\pi}{3}) + \cos^2(\theta_r - \frac{2\pi}{3}) \\ -\sin(\theta_r) \cos(\theta_r) - \sin(\theta_r + \frac{2\pi}{3}) \cos(\theta_r + \frac{2\pi}{3}) - \sin(\theta_r - \frac{2\pi}{3}) \cos(\theta_r - \frac{2\pi}{3}) \\ \frac{1}{2}(\cos(\theta_r) + \cos(\theta_r + \frac{2\pi}{3}) + \cos(\theta_r - \frac{2\pi}{3})) \end{bmatrix} \\ &= -\frac{2}{3} \mu i_f L_{ms} \begin{bmatrix} \frac{1+\cos(2\theta_r)}{2} + \frac{1+\cos(2\theta_r + \frac{4\pi}{3})}{2} + \frac{1+\cos(2\theta_r - \frac{4\pi}{3})}{2} \\ -\frac{\sin(2\theta_r)}{2} - \frac{\sin(2\theta_r + \frac{4\pi}{3})}{2} - \frac{\sin(2\theta_r - \frac{4\pi}{3})}{2} \\ \frac{1}{2}(\cos(\theta_r) + \cos(\theta_r + \frac{2\pi}{3}) + \cos(\theta_r - \frac{2\pi}{3})) \end{bmatrix} \\ &= -\frac{2}{3} \mu i_f L_{ms} \begin{bmatrix} \frac{3}{2} \\ 0 \\ 0 \end{bmatrix} = -\frac{2}{3} \mu i_f \begin{bmatrix} L_m \\ 0 \\ 0 \end{bmatrix} \end{aligned} \quad (8.48)$$

In the equation, it use the property that for any θ_r ,

$$\cos(2\theta_r) + \cos(2\theta_r + \frac{4\pi}{3}) + \cos(2\theta_r - \frac{4\pi}{3}) = 0$$

$$\sin(2\theta_r) + \sin(2\theta_r + \frac{4\pi}{3}) + \sin(2\theta_r - \frac{4\pi}{3}) = 0 \quad (8.49)$$

$$\cos(\theta_r) + \cos(\theta_r + \frac{2\pi}{3}) + \cos(\theta_r - \frac{2\pi}{3}) = 0$$

then, we have the equations below as equation (3.25) and equation (3.26) in Chapter 3.

$$\boldsymbol{\lambda}_{qdr} = L_m \mathbf{i}_{qds} + L_r \mathbf{i}_{qdr} - \mu i_f \begin{bmatrix} \frac{2}{3} L_m & 0 \end{bmatrix}^T, \quad (8.50)$$

$$\lambda_{or} = L_{lr} i_{or}, \quad (8.51)$$

For the flux linkage in the faulty portion λ_{asf} ,

$$\lambda_{asf} = \mu \mathbf{L}_{ss}(1, :) \mathbf{i}_s + \mu \mathbf{L}_{sr}(1, :) \mathbf{i}_r - \mu (L_{ls} + \mu L_{ms}) i_f, \quad (8.52)$$

Substitute $\mathbf{i}_s = \mathbf{K}_s^{-1} \mathbf{i}_{qd0s}$ and $\mathbf{i}_r = \mathbf{K}_r^{-1} \mathbf{i}_{qd0r}$, then we have equation (3.37) in $qd0$ reference frame in Chapter 3. Here,

$$\mathbf{K}_s^{-1} = \begin{bmatrix} 1 & 0 & 1 \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} & 1 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} & 1 \end{bmatrix} \quad (8.53)$$

$$\mathbf{K}_r^{-1} = \begin{bmatrix} \cos(\theta_r) & -\sin(\theta_r) & 1 \\ \cos(\theta_r + \frac{2\pi}{3}) & -\sin(\theta_r + \frac{2\pi}{3}) & 1 \\ \cos(\theta_r - \frac{2\pi}{3}) & -\sin(\theta_r - \frac{2\pi}{3}) & 1 \end{bmatrix} \quad (8.54)$$

Equation of electromagnetic torque

With the same approach, from the equation of torque in abc reference frame

$$\begin{aligned} T_e &= \frac{P}{2} \mathbf{i}_s^T \frac{\partial \mathbf{L}_{sr}}{\partial \theta_r} \mathbf{i}_r \\ &+ \mu \frac{P}{2} L_{ms} i_f \left(\frac{3}{2} i_{ar} \sin \theta_r + \frac{\sqrt{3}}{2} (i_{br} - i_{cr}) \cos \theta_r \right). \end{aligned} \quad (8.55)$$

considering only the fault-dependent term $\mu \frac{P}{2} L_{ms} i_f \left(\frac{3}{2} i_{ar} \sin \theta_r + \frac{\sqrt{3}}{2} (i_{br} - i_{cr}) \cos \theta_r \right)$ and $\mathbf{i}_r = \mathbf{K}_r^{-1} \mathbf{i}_{qd0r}$ to represent i_{ar}, i_{br}, i_{cr} in term of i_{qr}, i_{dr}, i_{0r} , then we have equation (3.41) as in Chapter 3 in $qd0$ reference frame.

Derivation of the Model of Induction Machines under SWITSF in State-Space Representation

For a star-connection stator winding without neutral winding, the 0-component of voltage and current can be ignored. The equations in qd reference frame is written here for convenience.

$$\mathbf{v}_{qds} = R_s \mathbf{i}_{qds} + \frac{d\boldsymbol{\lambda}_{qds}}{dt} - \mu R_s i_f \begin{bmatrix} \frac{2}{3} \\ 0 \end{bmatrix} \quad (8.56)$$

$$\mathbf{0} = R_r \mathbf{i}_{qdr} + \frac{d\boldsymbol{\lambda}_{qdr}}{dt} + \omega_r \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \boldsymbol{\lambda}_{qdr} \quad (8.57)$$

$$\boldsymbol{\lambda}_{qds} = L_s \mathbf{i}_{qds} + L_m \mathbf{i}_{qdr} - \mu i_f \begin{bmatrix} \frac{2}{3} L_s \\ 0 \end{bmatrix} \quad (8.58)$$

$$\boldsymbol{\lambda}_{qdr} = L_m \mathbf{i}_{qds} + L_r \mathbf{i}_{qdr} - \mu i_f \begin{bmatrix} \frac{2}{3} L_m \\ 0 \end{bmatrix} \quad (8.59)$$

$$L_f \frac{di_f}{dt} = -R_f i_f + \mu v_{qs}, \quad (8.60)$$

First, the state-space equation for state variables of i_{qs} , i_{ds} , λ_{qr} , λ_{dr} , and i_f is derived. Define

$$\mathbf{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \quad (8.61)$$

and define $i'_{qs} = i_{qs} - \frac{2}{3}\mu i_f$ and $i'_{ds} = i_{ds}$, and vector $\mathbf{i}'_{qds} = [i'_{qs} \ i'_{ds}]^T$, then the set of equations above can be written to the new variable $\mathbf{i}'_{qds}$ as

$$\mathbf{v}_{qds} = R_s \mathbf{i}'_{qds} + \frac{d\boldsymbol{\lambda}_{qds}}{dt} \quad (8.62)$$

$$\mathbf{0} = R_r \mathbf{i}_{qdr} + \frac{d\boldsymbol{\lambda}_{qdr}}{dt} + \omega_r \mathbf{J} \boldsymbol{\lambda}_{qdr} \quad (8.63)$$

$$\boldsymbol{\lambda}_{qds} = L_s \mathbf{i}'_{qds} + L_m \mathbf{i}_{qdr} \quad (8.64)$$

$$\boldsymbol{\lambda}_{qdr} = L_m \mathbf{i}'_{qds} + L_r \mathbf{i}_{qdr} \quad (8.65)$$

From equation (8.64) and (8.65), we have

$$\mathbf{i}'_{qds} = \frac{L_r}{\nabla} \boldsymbol{\lambda}_{qds} - \frac{L_m}{\nabla} \boldsymbol{\lambda}_{qdr} \quad (8.66)$$

$$\mathbf{i}_{qdr} = \frac{L_s}{\nabla} \boldsymbol{\lambda}_{qdr} - \frac{L_m}{\nabla} \boldsymbol{\lambda}_{qds} \quad (8.67)$$

with $\nabla = L_s L_r - L_m^2$.

The derivative of $\mathbf{i}'_{qds}$ can be found as

$$\frac{d\mathbf{i}'_{qds}}{dt} = \frac{L_r}{\nabla} \frac{d\boldsymbol{\lambda}_{qds}}{dt} - \frac{L_m}{\nabla} \frac{d\boldsymbol{\lambda}_{qdr}}{dt} \quad (8.68)$$

From equation (8.62) and equation (8.63), we have

$$\begin{aligned} \frac{d\mathbf{i}'_{qds}}{dt} &= \frac{L_r}{\nabla} (\mathbf{v}_{qds} - R_s \mathbf{i}'_{qds}) - \frac{L_m}{\nabla} (-R_r \mathbf{i}_{qdr} - \omega_r \mathbf{J} \boldsymbol{\lambda}_{qdr}) \\ &= \frac{L_r}{\nabla} (\mathbf{v}_{qds} - R_s \mathbf{i}'_{qds}) - \frac{L_m}{\nabla} \left(-R_r \left(\frac{\boldsymbol{\lambda}_{qdr}}{L_r} - \frac{L_m}{L_r} \mathbf{i}'_{qds} \right) - \omega_r \mathbf{J} \boldsymbol{\lambda}_{qdr} \right) \\ &= - \left(\frac{L_r R_s}{\nabla} + \frac{R_r L_m^2}{L_r \nabla} \right) \mathbf{i}'_{qds} + \frac{L_m}{\nabla} \left(\frac{R_r}{L_r} + \omega_r \mathbf{J} \right) \boldsymbol{\lambda}_{qdr} + \frac{L_r}{\nabla} \mathbf{v}_{qds} \end{aligned} \quad (8.69)$$

For the derivative of λ_{qdr} is

$$\begin{aligned} \frac{d\lambda_{qdr}}{dt} &= -R_r \mathbf{i}_{qdr} - \omega_r \mathbf{J} \lambda_{qdr} \\ &= -R_r \left(\frac{\lambda_{qdr}}{L_r} - \frac{L_m}{L_r} \mathbf{i}'_{qds} \right) - \omega_r \mathbf{J} \lambda_{qdr} = \frac{R_r L_m}{L_r} \mathbf{i}'_{qds} - \left(\frac{R_r}{L_r} + \omega_r \mathbf{J} \right) \lambda_{qdr} \end{aligned} \quad (8.70)$$

Define $a = \left(-\frac{L_r R_s}{\nabla} - \frac{R_r L_m^2}{L_r \nabla} \right)$, $b = \frac{R_r L_m}{L_r \nabla}$, $c = \frac{R_r L_m}{L_r}$, $d = -\frac{R_r}{L_r}$, $e = \frac{L_m}{\nabla}$, $g = \frac{L_r}{\nabla}$, then the corresponding state-space equations for $[\mathbf{i}'_{qds} \quad \lambda_{qdr}]^T$ are

$$\begin{bmatrix} \frac{di'_{qs}}{dt} \\ \frac{di'_{ds}}{dt} \\ \frac{d\lambda_{qr}}{dt} \\ \frac{d\lambda_{dr}}{dt} \end{bmatrix} = \begin{bmatrix} a & 0 & b & -\omega_r e \\ 0 & a & \omega_r e & b \\ c & 0 & d & \omega_r \\ 0 & c & -\omega_r & d \end{bmatrix} \begin{bmatrix} i'_{qs} \\ i'_{ds} \\ \lambda_{qr} \\ \lambda_{dr} \end{bmatrix} + \begin{bmatrix} g & 0 \\ 0 & g \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{qs} \\ v_{ds} \end{bmatrix} \quad (8.71)$$

$$= \left(\begin{bmatrix} a\mathbf{I}_{2 \times 2} & b\mathbf{I}_{2 \times 2} \\ c\mathbf{I}_{2 \times 2} & d\mathbf{I}_{2 \times 2} \end{bmatrix} + \omega_r \begin{bmatrix} \mathbf{0}_{2 \times 2} & e\mathbf{J} \\ \mathbf{0}_{2 \times 2} & -\mathbf{J} \end{bmatrix} \right) \begin{bmatrix} i'_{qs} \\ i'_{ds} \\ \lambda_{qr} \\ \lambda_{dr} \end{bmatrix} + \begin{bmatrix} g\mathbf{I}_{2 \times 2} \\ \mathbf{0}_{2 \times 2} \end{bmatrix} \begin{bmatrix} v_{qs} \\ v_{ds} \end{bmatrix}$$

where $\mathbf{I}_{n \times n}$ is the n -order identity matrix, $\mathbf{0}_{n \times m}$ is the n -by- m matrix of all zero elements.

For the state variables $\mathbf{x} = [\mathbf{i}'_{qds} \quad \lambda_{qdr} \quad i_f]^T$, then the state-space equation is

$$\begin{aligned} \begin{bmatrix} \frac{di'_{qs}}{dt} \\ \frac{di'_{ds}}{dt} \\ \frac{d\lambda_{qr}}{dt} \\ \frac{d\lambda_{dr}}{dt} \\ \frac{di_f}{dt} \end{bmatrix} &= \left(\begin{bmatrix} a\mathbf{I}_{2 \times 2} & b\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ c\mathbf{I}_{2 \times 2} & d\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & -\frac{R_f}{L_f} \end{bmatrix} + \omega_r \begin{bmatrix} \mathbf{0}_{2 \times 2} & e\mathbf{J} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{2 \times 2} & -\mathbf{J} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & 0 \end{bmatrix} \right) \begin{bmatrix} i'_{qs} \\ i'_{ds} \\ \lambda_{qr} \\ \lambda_{dr} \\ i_f \end{bmatrix} \\ &+ \begin{bmatrix} g\mathbf{I}_{2 \times 2} \\ \mathbf{0}_{2 \times 2} \\ \frac{\mu}{L_f} & 0 \end{bmatrix} \begin{bmatrix} v_{qs} \\ v_{ds} \end{bmatrix} \end{aligned} \quad (8.72)$$

Define also $\mathbf{u} = [v_{qs} \quad v_{ds}]^T$, these equations can be written as

$$\frac{d\mathbf{x}}{dt} = (\mathbf{A}_o + \omega_r \mathbf{A}_{\omega_r}) \mathbf{x} + \mathbf{B} \mathbf{u}, \quad (8.73)$$

where

$$\mathbf{A}_o = \begin{bmatrix} a\mathbf{I}_{2 \times 2} & b\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ c\mathbf{I}_{2 \times 2} & d\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & -\frac{R_f}{L_f} \end{bmatrix}, \quad (8.74)$$

$$\mathbf{A}_{\omega_r} = \begin{bmatrix} \mathbf{0}_{2 \times 2} & e\mathbf{J} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{2 \times 2} & -\mathbf{J} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & 0 \end{bmatrix}, \quad (8.75)$$

$$\mathbf{B} = \begin{bmatrix} g\mathbf{I}_{2 \times 2} \\ \mathbf{0}_{2 \times 2} \\ [\frac{\mu}{L_f} \quad 0] \end{bmatrix}, \quad (8.76)$$

Because the measured currents are $\mathbf{i}_{qds}$, not $\mathbf{i}'_{qds}$, a transformation matrix $\mathbf{T}$ is applied to the state variables and equations. The transformation matrix is defined as

$$\mathbf{T} = \begin{bmatrix} \mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 2} & \begin{bmatrix} -1 \\ 0 \end{bmatrix} \\ \frac{c}{a}\mathbf{I}_{2 \times 2} & \frac{c}{a}\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & \frac{3}{2\mu} \end{bmatrix} \quad (8.77)$$

The transformed state variables $\mathbf{z} = \mathbf{T}^{-1}[\mathbf{i}'_{qds} \quad \lambda_{qdr} \quad i_f]^T = [z_1 \quad z_2 \quad z_3 \quad z_4 \quad z_5]^T$, where $z_1 = i_{qs}$, $z_2 = i_{ds}$, $z_3 = -i_{qs} + \frac{a}{c}\lambda_{qr}$, $z_4 = -i_{ds} + \frac{a}{c}\lambda_{dr}$, $z_5 = \frac{2}{3}\mu i_f$. Multiply $\mathbf{T}^{-1}$ to the two sides of the equation and substitute $[\mathbf{i}'_{qds} \quad \lambda_{qdr} \quad i_f]^T = \mathbf{T}\mathbf{z}$, then the state equation of state variables $\mathbf{z}$ is

$$\frac{d\mathbf{z}}{dt} = (\mathbf{T}^{-1}\mathbf{A}_o\mathbf{T} + \omega_r\mathbf{T}^{-1}\mathbf{A}_{\omega_r}\mathbf{T})\mathbf{z} + \mathbf{T}^{-1}\mathbf{B}\mathbf{u}, \quad (8.78)$$

where

$$\mathbf{T}^{-1}\mathbf{A}_o\mathbf{T} = \begin{pmatrix} (a + \frac{bc}{a})\mathbf{I}_{2 \times 2} & \frac{bc}{a}\mathbf{I}_{2 \times 2} & \begin{pmatrix} -a - \frac{R_f}{L_f} \\ 0 \end{pmatrix} \\ (d - \frac{bc}{a})\mathbf{I}_{2 \times 2} & (d - \frac{bc}{a})\mathbf{I}_{2 \times 2} & \begin{pmatrix} \frac{R_f}{L_f} \\ 0 \end{pmatrix} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & -\frac{R_f}{L_f} \end{pmatrix}, \quad (8.79)$$

$$\mathbf{T}^{-1}\mathbf{A}_{\omega_r}\mathbf{T} = \begin{pmatrix} \frac{ce}{a}\mathbf{J} & \frac{ce}{a}\mathbf{J} & \mathbf{0}_{2 \times 1} \\ -(1 + \frac{ce}{a})\mathbf{J} & -(1 + \frac{ce}{a})\mathbf{J} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & 0 \end{pmatrix}, \quad (8.80)$$

$$\mathbf{T}^{-1}\mathbf{B} = \begin{pmatrix} g\mathbf{I}_{2 \times 2} \\ -g\mathbf{I}_{2 \times 2} \\ \mathbf{0}_{1 \times 2} \end{pmatrix} + \begin{pmatrix} \frac{2\mu^2}{3L_f} & 0 \\ 0 & 0 \\ -\frac{2\mu^2}{3L_f} & 0 \\ 0 & 0 \\ \frac{2\mu^2}{3L_f} & 0 \end{pmatrix}, \quad (8.81)$$

Define $z_6 = r_f$, $z_7 = \mu$, $z_8 = \omega_r$, then

$$\frac{dz_6}{dt} = 0 \quad (8.82)$$

$$\frac{dz_7}{dt} = 0 \quad (8.83)$$

The state variable for ω_r is derived from

$$\frac{d\omega_r}{dt} = \frac{P}{2J}(T_e - T_L - B\omega_r). \quad (8.84)$$

with

$$T_e = \frac{3P}{4}L_m(i_{qs}i_{dr} - i_{ds}i_{qr}) - \frac{P}{2}\mu L_m i_f i_{dr}. \quad (8.85)$$

From equation (8.59)

$$\boldsymbol{\lambda}_{qdr} = L_m \mathbf{i}_{qds} + L_r \mathbf{i}_{qdr} - \mu i_f \begin{bmatrix} \frac{2}{3}L_m \\ 0 \end{bmatrix} \quad (8.86)$$

then

$$\mathbf{i}_{qdr} = \frac{\boldsymbol{\lambda}_{qdr}}{L_r} - \frac{L_m}{L_r} \mathbf{i}_{qds} - \frac{2}{3}\mu i_f \begin{bmatrix} \frac{L_m}{L_r} \\ 0 \end{bmatrix} \quad (8.87)$$

Also notice that $\boldsymbol{\lambda}_{qdr} = \frac{c}{a}[z_3 \quad z_4]^T + \mathbf{i}_{qds}$, then the state equation of ω_r can be derived as

$$\frac{d\omega_r}{dt} = \frac{P}{2J} \left(\frac{3cPL_m}{4aL_r} (z_1 z_4 - z_2 z_3 - z_2 z_5 - z_4 z_5) - B\omega_r - T_L \right) \quad (8.88)$$

then define $\mathbf{z} = [z_1 \quad z_2 \quad z_3 \quad z_4 \quad z_5 \quad z_6 \quad z_7 \quad z_8]^T$, input vector $\mathbf{u} = [v_{qs} \quad v_{ds} \quad T_L]^T$, and output vector $\mathbf{y} = [i_{qs} \quad i_{ds}]^T$, the corresponding state equations are

$$\frac{d\mathbf{z}}{dt} = (\mathbf{A}_z + \omega_r \mathbf{A}_{\omega_r})\mathbf{z} + \mathbf{B}_z + \mathbf{B}_{1z}\mathbf{u} + \mathbf{B}_2\mathbf{u}, \quad (8.89)$$

$$\mathbf{y} = \mathbf{C}_z \mathbf{z}, \quad (8.90)$$

where

$$\mathbf{A}_z = \begin{bmatrix} (a + bc/a)\mathbf{I}_{2 \times 2} & \frac{bc}{a}\mathbf{I}_{2 \times 2} & \begin{bmatrix} -a - \frac{R_s}{L_{ls}} - \frac{z_6}{z_7(1-\frac{2}{3}z_7)L_{ls}} \\ 0 \end{bmatrix} & \mathbf{0}_{2 \times 3} \\ (d - bc/a)\mathbf{I}_{2 \times 2} & (d - bc/a)\mathbf{I}_{2 \times 2} & \begin{bmatrix} \frac{r_s}{L_{ls}} + \frac{z_6}{z_7(1-\frac{2}{3}z_7)L_{ls}} \\ 0 \end{bmatrix} & \mathbf{0}_{2 \times 3} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & -\frac{r_s}{L_{ls}} - \frac{z_6}{z_7(1-\frac{2}{3}z_7)L_{ls}} & \mathbf{0}_{1 \times 3} \\ \mathbf{0}_{2 \times 2} & \mathbf{0}_{2 \times 2} & \mathbf{0}_{2 \times 1} & \mathbf{0}_{2 \times 3} \\ \mathbf{0}_{1 \times 2} & \mathbf{0}_{1 \times 2} & 0 & [0 \quad 0 \quad -\frac{BP}{2J}] \end{bmatrix}, \quad (8.91)$$

$$\mathbf{A}_{\omega_r} = \begin{bmatrix} \frac{ce}{a}\mathbf{J} & \frac{ce}{a}\mathbf{J} & \mathbf{0}_{2 \times 4} \\ -(1 + \frac{ce}{a})\mathbf{J} & -(1 + \frac{ce}{a})\mathbf{J} & \mathbf{0}_{2 \times 4} \\ \mathbf{0}_{4 \times 2} & \mathbf{0}_{4 \times 2} & \mathbf{0}_{4 \times 4} \end{bmatrix}, \quad (8.92)$$

$$\mathbf{B}_z = \begin{bmatrix} \mathbf{0}_{7 \times 1} \\ \frac{3cL_m P^2}{8aL_r J} (z_1 z_4 - z_2 z_3 - z_2 z_5 - z_4 z_5) \end{bmatrix}, \quad (8.93)$$

$$\mathbf{B}_{1z} = \begin{bmatrix} \frac{2z_7}{3(1-\frac{2}{3}z_7)L_{ls}} & \mathbf{0}_{1 \times 2} \\ 0 & \mathbf{0}_{1 \times 2} \\ -\frac{2z_7}{3(1-\frac{2}{3}z_7)L_{ls}} & \mathbf{0}_{1 \times 2} \\ 0 & \mathbf{0}_{1 \times 2} \\ \frac{2z_7}{3(1-\frac{2}{3}z_7)L_{ls}} & \mathbf{0}_{1 \times 2} \\ \mathbf{0}_{3 \times 1} & \mathbf{0}_{3 \times 2} \end{bmatrix}, \quad (8.94)$$

$$\mathbf{B}_2 = \begin{bmatrix} g\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ -g\mathbf{I}_{2 \times 2} & \mathbf{0}_{2 \times 1} \\ \mathbf{0}_{3 \times 2} & \mathbf{0}_{3 \times 1} \\ \mathbf{0}_{1 \times 2} & -\frac{P}{2J} \end{bmatrix}, \quad (8.95)$$

$$\mathbf{C}_z = [\mathbf{I}_{2 \times 2} \quad \mathbf{0}_{2 \times 6}]. \quad (8.96)$$

These are equations from (4.1) to (4.8) in Chapter 4.

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