MOTORS FAULT RECOGNITION USING DISTRIBUTED CURRENT SIGNATURE ANALYSIS

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INDUSTRIAL FAULT RECOGNITION USING DISTRIBUTED CURRENT SIGNATURE ANALYSIS

ABSTRACT

Immediate detection and diagnosis of existing faults and faulty behaviour of electrical motors using electrical signals is one of the important interests of the power industry. Motor current signature analysis is a modern approach to diagnose faults of induction motors. This thesis investigates the significance of propagated fault signatures through distributed power systems, aiming at explaining and quantifying different observations of faults signals and hence diagnoses machine faults with a higher accuracy.

Electrical indicators of faults, unlike other fault indicators, (e.g. vibration signals), propagate all over the network. Therefore fault signals may be manipulated by operation of neighbouring motors and the system's environmental noise. Both simulation and practical results clearly demonstrate the signal interference and hence confusion in diagnosis due to presence of a faulty motor nearby. Thus a knowledge based system is necessary to understand the meaning of the signals manifested at various parts of the distributed power system. On another side, taking into account that fault signals are travelling all over the network, several observations can be made for events in the network. In this thesis the idea of cross evaluation of fault signals considering signal propagation will be discussed and analysed. The research attempts to improve diagnosis reliability with a simple and viable framework of decision making.

The thesis scope is limited to monitoring behaviour of induction motors in distributed power systems. These types of electrical motors are the main load of most industries. In this thesis, existing formulations of fault signatures would not be significantly disturbed, as distributed diagnosis can fit into an existing framework of current signature analysis. The research takes advantage of multiple areas of study to formulate propagation of fault signals while they are travelling in a scaled down distributed power system.

At the beginning, a systematic approach has been employed to estimate influence of fault signals in currents of neighbouring electrical motors. Further analysis in attenuation of electrical signals leads to a technical framework that evaluates propagation of fault signals in power networks. The framework has been developed to estimate origin of fault signal by employing propagation patterns and estimating anticipated fault representatives around the network. An analytical process has been proposed to take advantage of multiple observations in order to diagnose the type and identify origin of fault signals. This can help maximize the number of independent observations and thus improve the accuracy of traditional approaches to current signature analysis. In general, this provides a better monitoring of behaviour of electrical motors at a given site. A rewarding system has been used to identify and track the signals caused by motors and quantify association of current signals with known industrial faults.

An example of a scaled down distributed power system has been simulated to describe behaviour of distributed power systems with faulty components. The simulation model is carefully compared with the practical results to validate the simulation results thoroughly. Type and strength of faults and size, speed, load and placement of electrical motors are acting variables in propagation patterns of fault signals. These variables have been simulated in a scaled down industrial power network to examine distributed diagnosis in the new environment. In addition a number of scaled-down experiments have been employed to verify results of simulation models and confirm the accuracy of results.

Analytical results demonstrate significant improvement in describing interference amongst electrical motors that work together in an electrical network. This leads to a simple strategy for identifying the ownership of fault signals and hence having more accurate diagnostic results. Further developments in modelling the propagation of fault indicators emerged for improving the reliability and efficiency of fault diagnosis in industrial systems. On the other hand, a number of shortcomings have been observed in implementing strategy of distributed diagnosis including confusion among many similar faults in the power network and malfunctioning of the diagnosis system due to non-linear interferences of noise signals. Some of these problems are believed to be solvable by using a proper numerical solution (e.g. Artificial Neural Network, Bayesian, etc.) to process fault indices and propagation patterns before and after occurrence of each fault.

In conclusion, the thesis does not claim to provide a complete solution of fault diagnosis in electrical motors. But it is an attempt to provide a more dependable industry solution for fault diagnosis in induction motors. Distributed diagnosis is a framework which takes advantage of multiple observations of a single fault and hence it is dependent on quality of acquired signals among individual observations.

Publications

[1] Gheitasi, A. and Al-Anbuky, A., “Industrial Fault Signals Propagation and Current Signature Analysis”, Journal of Energy and Power Engineering (ISSN1934-8975), Vol 7, No 2, Feb 2013, pp361-369

[2] Gheitasi, A.; Al-Anbuky, A.; Tek Tjing Lie "Impact of propagation of fault signals on industrial diagnosis using current signature analysis", Australasian Universities Power Engineering Conference, 2011, pp 1 - 6

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FFT:	Fast Fourier Transform
IEEE:	Institute of Electrical and Electronics Engineers
IPA	Instantaneous Power Analysis
MCSA:	Motor Current Signature Analysis
FFT:	Fast Fourier Transform
STFT:	Short Time Fourier Transform
ANN:	Artificial Neural Networks
SCADA:	Supervisory Control And Data Acquisition
AUT:	Auckland University of Technology

LIST OF SYMBOLS

A_{i,m,k_X} :The anticipated magnitude of the fault signal x

D: The frequency of the suspected significant point

d: Fault distance

E: Voltage

E_1: Stator e.m.f generated by resultant air-gap flux

F: Matrix of fault indices

f_0: Fundamental frequency

f_{ra}: Fault frequencies associated with rotor asymmetry

f_{ru}: Fault frequencies associated with rotor unbalanced

f_{bq}: Fault frequencies associated with broken bars

f_i: Frequency components associated with the fault i

$F_{i,j,k}$ Symbol for fault indices

i: Type of the fault

I : Current

I_0: Sum of magnetizing current components

I_1: Stator current

I'_2: Rotor current referred to stator

I_a: a-phase current

I_{Bx}: is total current passing the Bus x in radial power networks

I_a: A-phase current

I': The remote-end current infeed on the faulted phase

i: Denotes the imaginary part

j: Speed band related to a group of electric motors with the same speed

k: Harmonic order of fault symptom; k=1,2,3,…

l: Number of measuring point

M_i: Amplitude of the frequency component in a given signature

N: Neural network

O: Matrix of outputs

p: Number of poles

R: Index of seriousness of fault

R_1: Stator effective resistance

$R_{m:}$ Iron core-loss resistance

$R'_{2:}$ Rotor effective resistance referred to stator

r : Denotes the real part

s: Motor slip

s: second

s_{ra}: Associated motor slip for rotor asymmetry frequencies

s_{ru}: Associated motor slip for rotor unbalance frequencies

s_{bq}: Associated motor slip for broken bar frequencies

U_1: Stator terminal voltage

$u_{rb:}$ e.m.f due to the saturable iron bridges in the rotor slots

V: Speed of the target motor

$V_{a:}$ a-phase voltage;

V_{Bx}: The nominal voltage measured in Bus x

V'_a: a-phase voltage at fault point;

V_e : The voltage at the end of the conductor

V_s: The voltage at the start of the conductor

vs: Synchronous speed of the target motor

$X_{1:}$ Stator leakage reactance

X_m: Magnetizing reactance

X'_2: Rotor leakage reactance referred to stator

$Z_{B1\rightarrow B0}$:The total impedance between Bus 1 and Bus 0

Z_{Bx}: The total impedance observed in Bus x

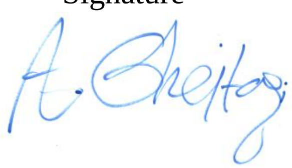
Z_l: Line impedance;

$\delta_{m\rightarrow k}$: The estimated propagated signal in electric motor k which is originally caused by the motor m

Attestation of Authorship

I Alireza Gheitasi, hereby declare that this submission is my own work and that to the best of my knowledge and belief, it contains no material previously published or written by another person or material which to a substantial extent has been submitted for the award of any other degree or diploma of a University or other institution of higher learning.

Signature



18 October 2012

Chapter 1:

INTRODUCTION

1.1 Industrial Fault Diagnosis

Diagnosis of the malfunctioning behaviours in power systems is a challenging research area. Many technologies have been implemented to protect electrical equipment and detect the cause of faults since establishment of power systems. Various types of protective equipment have been recommended to detect serious faults such as short circuit. Another type of fault is related to the malfunctioning and unhealthy operation of the network components. Such incidents have less impact on the operation of distributed power systems compared to electrical faults. Neglect of these faults can cause major and regular losses due to failure of electrical appliances and possible interruption in the continuity of the service.

Induction motors are the main load of most industrial power systems. Therefore special attention has to be paid to maintain the healthy operation of electric motors. For more than a century, regular protective maintenance was the main approach employed by industry to assure healthy operation of electric motors. Recent developments in processing technologies suggested using state monitoring to minimize the cost of maintenance and assess the condition of the operation of electrical motors, without interrupting the normal function. Several technologies have been introduced and valued in power industries. These developments have led to a continuous improvement in accuracy and effectiveness of diagnostic methodologies. A number of successful diagnostic approaches have been indicated in Figure 1.

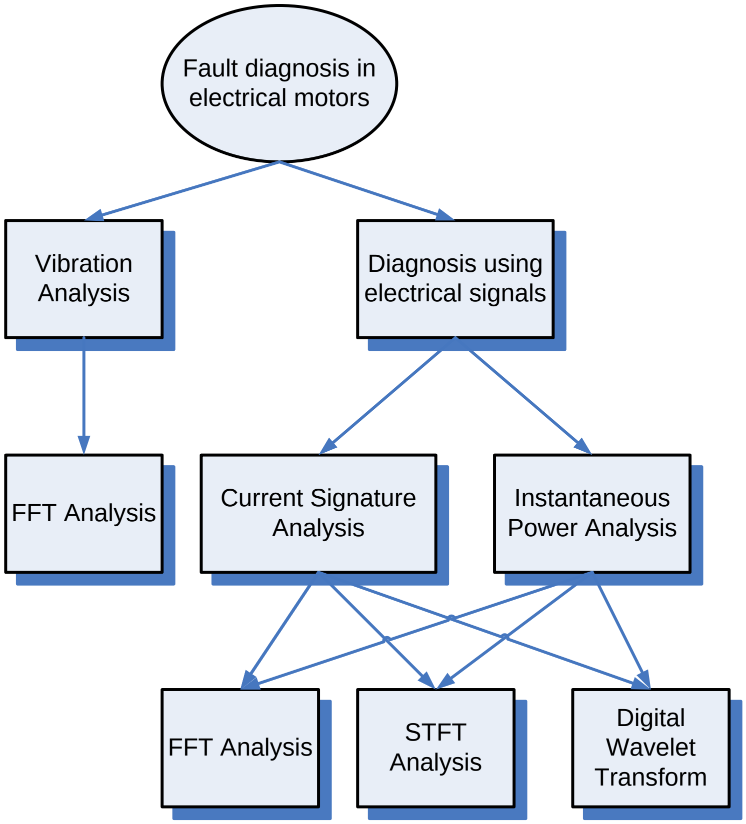


Figure 1 Diagnostic approaches for induction motors

As shown in Figure 1, diagnostic technologies can be categorized into two groups of vibration analysis and analysis of electric signals. Fault diagnosis using electric signals offers a remote judgment while direct access to vibration sensors is required for vibration analysis. A number of technologies have been proposed to diagnose motor faults by analysing electric signals.

Various types of motor faults are frequently associated with electric drives and rotating components. Many methods have been published and are commercially available to observe the behaviour of electric motors. However, most industries are still complaining about regular unpredicted faults. Moreover, there are always some faults that are difficult to detect and their effects would appear as they accelerate motor aging and reduce the useful lifetime of system components [1].

Vibration analysis, thermal monitoring, noise monitoring and finally monitoring electric signals are the most common approaches of fault diagnosis in electric motors. Among all these methods, monitoring the behaviour of electric motors using electric signals is the most viable and interesting for industries due to the following reasons:

- Direct access to the motor is not required
- It is easier to simplify electric signals
- There is the possibility of remote monitoring
- Use of current and voltage sensors for other monitoring purposes (e.g. power monitoring)

However, despite these benefits, fault diagnosis using electric signals usually offers lower reliability compared to other established methods of diagnosis such as vibration analysis. Reliability issues are mainly caused because of the interference of noise signals due to the normal operation of electric motors and also other sources of noises on the site. Therefore there is a high demand from industry to provide more robust solutions for fault diagnosis using electric signals.

1.2 Diagnosis of faults in electric motors using electrical signals

Current and voltage of electric motors are available indicators to judge the proper functioning of electric motors. Current is a function of voltage and characterises the operation of the electric motor. But, the voltage of the terminals of a motor is a function of its supply voltage and the topography of the power network. Therefore voltage cannot be considered as indicative of behaviour of electric motors. Since the supplied voltage is dependent on generated voltage and network topography, it cannot be considered as an indicator of functioning performance of the electric motor. But a combination of current and voltage as the instantaneous power can be considered as another method of diagnosis. Instantaneous power analysis requires measurement of two signals and hence is more expensive compared to current monitoring. On the other hand it does not provide a major improvement in reliability of diagnosis where a signal processing algorithm is set to categorize significant fault signals [2].

Motor current signature analysis is one of the most successful diagnostic approaches proposed for rotating components. This strategy utilizes pattern recognition over current signals of electric motors to estimate the presence of pre-recorded faults. Recently there have been a number of studies that reported successful applications of motor current signature analysis for various types of electric machines. A recent meta- analysis classified and evaluated a number of investigations which reported successful employment of fault diagnosis techniques for inter-turn faults [4].

The main challenge in diagnosis of motor faults using signature analysis is interference among components of distributed power systems. Some approaches have been proposed to improve the reliability and reduce conflict. However, a significant amount of interference due to operation of parallel motors causes frequency signals similar to patterns of suspected faults. In addition, for most low power or less important electric components these techniques are too expensive. A survey found that for many low and medium powered electrical component, an individual monitoring system is not viable in terms of cost [1]. This paradox demonstrates the need to develop a strategy that provides the necessary technology for effective and less expensive fault detection and diagnosis in distributed power systems [2, 3].

1.3 Diagnosis framework using motor current signature analysis

The general framework of diagnosis using MCSA has been shown in Figure 2.

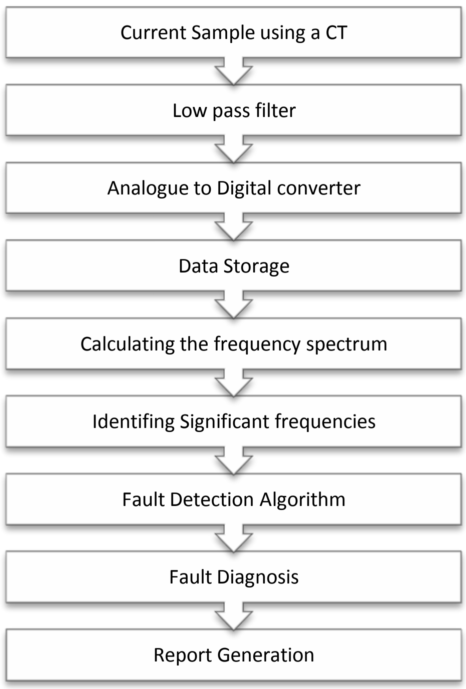


Figure 2 Single-phase current monitoring scheme

As shown in Figure 2 any process of diagnosis is involved in data acquisition, categorizing fault signals, pattern recognition and report generation. There are several data acquisition components to capture and store electric signals. In all technologies, initially the signal should be converted and sampled via a current or voltage transformer or transducer. Then the 50Hz frequency will be removed to exclude the normal operation of the electric motor. The next stage is to exclude high frequency components of the wave that are not contributing toward the process of diagnosis. Analogue current signals will then be sampled and converted to digital signals using an analogue to digital converter. Digitization processes are followed by calculating the frequency spectrum of the waveform and categorizing significant components of the wave using a data processing transformer such as Fast Fourier Transform or Discrete Wavelet Transform. Then a fault detection algorithm is required to process fault indicators and a post processing system will be needed to generate a diagnostic report and announce required warnings.

1.4 Motivation

Motor current signature analysis provides good results in laboratory environments when the approach is used on isolated motors. In a real life situation, electric machines are connected to the same Bus and work in groups for handling a given industrial operation. They usually share voltage and current from common terminals and would easily influence each other. This means that signals picked up at any point within the distributed power system would contain information on the local motor as well as components relevant to other motors in the neighbourhood. This will result in a significant amount of interference among motors and hence a reduction in the degree of confidence in the diagnosis. A diagnosis based on analysis of multiple test points may help in easing out this issue.

The aim of this research is the development of a distributed, and in-network data-processing algorithm based on analysis of signals available at various test points within the network. Each test point reveals its view on the potential fault at the various physical locations within the neighbourhood. These will then be processed to identify the type and physical location of the fault with a higher degree of confidence. The concept is based on collaborative diagnosis and may reveal faults relevant to motors with or without sensing points within the neighbourhood.

A clear understanding of the infrastructure of distributed power systems is required. Any industrial site is a combination of several types of clusters of equipment. These components include the different size of electrical drives, static loads and nonlinear equipment. Clusters are connected to each other via cables and electrical connections. Most electric motors are equipped with voltage and current measuring points. Some components have an individual monitoring system while many components do not have a direct monitoring system.

Fault signals travel over the network from one bus to another, thus they may be detected in theory wherever a physical link generates a path between sources of fault signals and a measuring point. Theoretically, fault patterns may be detected if a typical link exists between the sources of the remotely detected signal. In the real situation, noise interference degrades the quality of the signal and makes diagnosis difficult. Considering this limitation, there will still be some selected points that may have a clear view of the fault. Some fault signals may travel without a major change and others may have major changes. The modified signal may still be detectable in the remote location.

1.5 Contributions and Thesis Outline

In this thesis, existing formulations of fault signatures would not be significantly disturbed, as distributed diagnosis can fit into the existing framework of current signature analysis. The research takes advantage of multiple areas of study to formulate propagation of fault signals while they are travelling in a scaled down distributed power system.

In the research, a systematic approach has been employed to estimate the influence of fault signals in currents of in-network electric motors. Further analysis in attenuation of electric signals has led to a technical framework that evaluates the propagation of fault signals in power networks. The framework has been developed to estimate the origin of the fault signal by employing propagation patterns and estimating anticipated fault representation around the network. A technical process has been proposed to take advantage of multiple observations in order to diagnose the type and identify the origin of fault signals. This can help maximize the number of independent observations and thus improve the accuracy of traditional approaches to current signature analysis. In general, this provides a better monitoring of behaviour of electrical components in a given site. A rewarding system has been used to identify and track the signals caused by motors and quantify the association of current signals with known industrial faults.

The main contributions of this thesis are:

- A framework of fault diagnosis is proposed for automated fault diagnosis for individual induction motors
- Inherent shortcomings of individual diagnosis due to the propagation of fault signals have been demonstrated

- An in-network solution has been proposed to improve the reliability and dependability of fault diagnosis when a direct monitoring system is available and to provide a preliminary diagnosis whenever a direct measuring point is not available.

The thesis is organized into 8 chapters which include the introduction, literature review, theory of the distributed signature analysis concept, a distributed power system behavioural simulation model, results, performance evaluation and analysis, conclusion and future scope.

Chapter 1 describes the process of fault diagnosis in general and current signature analysis in particular in terms of motivation, state-of-the-art, background information, and finally the thesis outline.

Chapter 2 presents the literature review in relevant areas followed by the problem statement, research objectives, and contributions. In both chapters one and two, great attention is given to those techniques applied so far for the diagnosis of electric motor faults. This attempts to give an overview of currently used methods for current signature analysis and to estimate the progress made towards an implementation of these techniques in typical industrial situations.

Chapter 3 describes tools, equipment and software that have been used to accomplish thesis tasks.

Chapter 4 presents the theory of distributed fault diagnosis and related formulations of propagation of fault signals and patterns recognition strategy developed in the thesis.

Chapter 5 describes the research materials, simulation tools and scaled down test-beds, their capability and any limiting effect they might have on the results obtained. Details of the simulation model and essential key factors of simulations are also described in this chapter.

Chapter 6 simulates several types of faults by changing acting variables of distributed fault diagnosis. Attenuated fault signals and propagation patterns through the network are discussed in the chapter.

Chapter 7 implements the theory of distributed signature analysis by employing the simulation results which are described in the previous chapter. This chapter also evaluates the performance, and analysis is based on the final results generated by the strategy of distributed signature analysis.

Chapter 8 summarizes the conclusion drawn in the thesis along with discussing future research directions.

There are three appendices. Appendix I provides essential MCSA formulation to analyse a number of motor faults in electrical motors. Details of components of simulation models are provided by Appendix II. Finally all MATLAB functions and m-files developed to diagnose motor faults given by Appendix III.

Chapter 2:

LITERATURE SURVEY

Several studies have been done in the area of fault monitoring and diagnosis. Vibration monitoring and current signature analysis are two well-known successful methodologies to identify industrial faults. There are a number of engineering areas that contribute to the improvement of accuracy and interpretation of fault detection and diagnosis. Associated research and investigations can be classified into the following groups:

- Fault diagnosis using pattern recognition
- Motor current signature analysis
- Application of smart processing strategies in fault diagnosis
- Propagation of fault signals throughout the distributed power system
- Distributed processing and data synthesis

In this chapter, significant developments and contributions of the listed areas toward fault detection and diagnosis will be discussed in detail.

2.1 Traditional Fault monitoring and diagnosis

Fault detection and risk management is a complex problem. Today it is claimed that most of the sharp and high risk faults can be detected by modern digital relays. Traditional protection devices are not able to detect slow nature faults particularly at early stages of manifestation of faults. Therefore another protection method is required to monitor slow nature faults based on vibration and current trends. Fault trends caused by change of magnetic flux as a result of the change of mechanical characteristics of electric motors.

Generally, any increment in the level of vibration signals is considered as a primary illustrator of a mechanical fault. Moreover by analysing vibration signals, the nature of most of mechanical faults can be detected. Vibration itself may damage mechanical components and must be controlled. If the effective value of machine vibrations becomes more than the tolerance of the mechanical equipment, protection systems must stop operation of the machine to avoid further damages. Generally, the average vibration speed of bearings are compared with a standard set-point such as the international IS0 2372, the British BS 4675, or the German VDI 2056, as shown in Table 1. These standards recommend a set of vibration limitations of machines which were developed as an indication of a serious mechanical fault in the target motor [6].

Table 1 Vibration Severity (10 Hz–1 kHz) VDI 2056, ISO, 2372, BS 4675. This information has been summarised from Reference “[7]” in [6].

	Group K	**Group M**	**Group G**
Types of Machines	Small machines up to 15KW	Medium Machines 15-75 kW or up to 300kW on special foundation	Large machines with rigid and heavy foundations whose natural frequency exceeds machines speed
Good	Up to 0.71m/s	Up to 1.12 m/s	Up to 1.8 m/s
Allowable	0.71 to 1.8 m/s	1.12 m/s to 2.8 m/s	1.8 m/s to 4.5 m/s
Just tolerable	1.8 to 4.5 m/s	2.8 m/s to 7.1 m/s	4.5 m/s to 11.2 m/s
Not permissible	More than 4.5 m/s	More than 7.1 m/s	More than 11.2 m/s

In the last few decades strategies of applying vibration waveforms to analyse the nature of fault signals have been developed and widely accepted. This method is based on the fact that any kind of fault has a specific frequency response. Hence by analysing frequency responses of vibration sensors, the nature of the fault may be differentiated. By employing digital processing and pattern recognition methods, a number of effective diagnostic methods have been proposed. These methods mainly concentrate on amplitude of a range of frequency components of vibration signals. Nowadays vibration motoring is an established industrial tool in fault detection and diagnosis. The effects of vibrations in current waveform are clearly tested in several studies. These studies prove that mechanical faults can be diagnosed by detecting unexpected changes in the frequency spectrum of current waveforms.

A set of diagnostic recommendations has been published in reference [8] to provide guidance for industrial fault diagnosis using vibration signals.

In the early 1970s, the US Nuclear Regulatory Commission introduced the need to verify the condition of the motors that are located in nuclear reactors. There is no direct access to those electric motors and their accessories as they are located in a high radiation zone. Study on the assignment was initiated by Oak Ridge National Labs[9]. These experiments found a relationship between harmonics of current signals with vibrations of target motors. Further studies were advised to take advantage of current signals to estimate presence of abnormal vibration signals in electrical motors and then diagnose motor faults [6]. The research claimed that "For a known frequency, the current and vibration levels are monotonically (if not linearly) related." The authors advised that conditional operation of motor vibrations can be evaluated with frequency spectrum of one phase of stator current. Later on, several investigations advocated a sensorless vibration monitoring by analysing the frequency spectrum of current signals. Earlier on 1992, G. B. Kliman and J. Stein indicated the possibility to diagnose motor faults by monitoring the current of electric motors [9]. These two areas of research demonstrate the possibility to diagnose motors by observing abnormal frequencies in frequency spectrums of current signals.

2.2 Fault diagnosis using electric signals

During the past three decades, many studies have been published to improve maintenance of electric motors by early diagnosis of faults. There are several methodologies advised to employ electrical signals for fault diagnosis. This suggests motor current signature analysis is a more reliable and cost effective method of fault diagnosis [11].

Haynes, et al. registered one of the earliest patents in the area of fault diagnosis entitled "Motor Current Signature Analysis method for diagnosing motor operated devices" [12]. They suggested recording the current signature of motor operated devices and comparing the saved data with the known fault signatures. Dorrell et al. demonstrated the relationship between vibration signals and abnormalities in current waveform of electric motors in event of static and dynamic air-gap eccentricity" [13].In addition it has been advised to employ a set of formulations that relate the air-gap flux variation to the subsequent current vibrations for the diagnoses of eccentricity faults. In this paper and also in [14] a set of complex relationships between current harmonics and rotor eccentricity as an indirect effect of eccentrics was presented.

In 1997, the relationship between vibration signals and magnitude of current harmonics for known vibration frequencies has been investigated by Riley, Lin, Habetler, and Kliman [15]. This investigation mainly moves towards determining feasibility of setting a limit set-point or a "standard" on the current harmonics due to vibrations. They advised that, for a given known vibration frequency, the harmonic RMS vibration level and RMS current level are monotonically related [15]. This achievement eases out finding further formulations in current signals where the vibration pattern is available.

Later on, Riley et al. introduced a method for Sensorless On-Line Vibration Monitoring of Induction Machines [16]. They proposed to monitor high shunt induction motors in an online situation. In this method, it was necessary to install vibration sensors on target machines and do the mandatory adjustments and calibrations. Then all sensors could be removed. The strategy provided a good estimation for big sized induction motors. However it is not applicable for motors with unreachable body due to the process complexity. In addition, monitoring results are limited to the time and adjustment of the motor at the time of experiment. Major mechanical or electrical damages may change the motor specification.

Abdel-Malek, et al. proposed to use analogue subtraction in order to improve the quality and decrease the processing load of motor current signature analysis [17]. In this patent fault diagnosis using current waveforms extended to other types of faults. Dister, et al. proposed architecture for a data capturing system that collected trends, and analyse data by utilizing required processing stages in the computer [17]. This method can be a good reference for any diagnostic system that is operated by the concept of current signature analysis.

These investigations were sustained by further studies and development to extend the coverage and functionality of motor current signature analysis. Tavner, has published an up-to-date paper that reviews different techniques and aspects of condition monitoring for rotating machines. This paper compares fault diagnostic strategies and provides a set of recommendations to employ in fault detection and diagnosis of induction motors [1].

2.3 Signature analysis

Motor current signature analysis is an inexpensive diagnostic approach. This is because, unlike vibration analysis, vibration sensors are not the essential part of analysis in most diagnostic strategies. Motor current signature analysis strategies are considered as remote monitoring methods because there is no need to approach and physically access the motor during operation. See Figure 3.

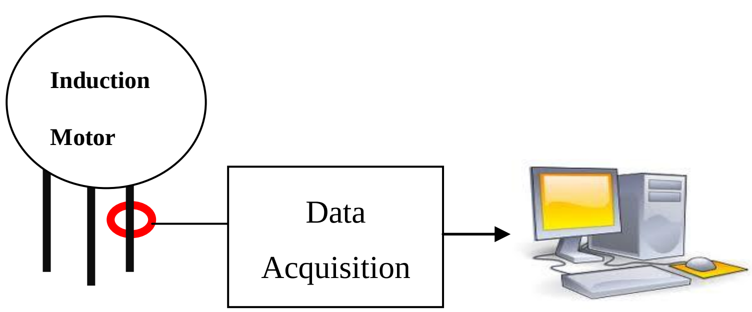


Figure 3 Basic MCSA instrumentation system

Signature analysis method has been successfully verified for various types of induction machines for both wound and squirrel cage electric motors. Despite of all advantages of current signature analysis, MCSA diagnosis has less accuracy than direct vibration measurements. Current signature analysis has some shortcomings that limit accuracy of diagnosis. It is very vulnerable to the environmental noise, voltage harmonics, operation of non-linear equipment and especially operation of another similar nearby motor and may result in wrong warnings being signalled. Also, relationships of current frequencies and vibration harmonics may be different from one frequency to another. As a result interpreting current signals usually requires extra calculation and considerations.

2.3.1 Frequency patterns

The frequency components of any kind of faulty situations can be shown as a deviation from desirable healthy patterns. Any faulty event has a continuous consequence from appearance of the fault to stop by protection command or machine damage. In most situations, fault patterns can be detected by static snapshots; however estimation of fault development requires analysis of continuous frequency patterns.

Internal motor faults of induction machines were analysed and tested successfully in various investigations such as [18] to [23].

Patterns of faulty situations generally appear as exceeding from a given set-point. Also magnitude of fault signals can usually be considered as an indicator of the seriousness of the fault.

Locations of fault symptoms usually have a close relationship with synchronous speed where the magnitude of fault signals are dependent on type and characteristics of the motor and are proportional to the seriousness of the fault. Here, fault patterns of some major internal faults in induction machines will be investigated and formulated.

MCSA faults can be divided into two categories. In the first category, the fault can be detected using lower frequency components but the second category requires analysis of higher frequency points. Low frequency faults are: rotor bar degradation, misalignment, mechanical unbalance and foundation looseness [9]. Faults that can be diagnosed by using high frequency components are: static eccentricity, dynamic eccentricity, stator mechanical faults, stator electrical faults and bearing degradation [9].

Any of these faults have specific effects in current signals. By varying frequency components and their variation with respect to the time factor, the faulty components can be detected. In this method the frequency component of the captured current must be compared against those in the faulty categories.

2.3.2 Fault formulation

The MCSA formulations for some types of internal motor faults are given below. All formulation has been cited from reference [23]. A number of important MCSA formulations have been described in Appendix I.

There are a few studies that have been done to extend the motor current signature analysis to other machines. For example, Don Shaw employed current signature analysis to diagnose faults of a DC motor [25]. Given that most industrial loads are induction motors, diagnosis of faults in induction motors is more remarkable compared to other types of electrical motors.

2.4 Further development in motor current signature analysis

Fault formulations provide a guideline to diagnose industrial faults. However there are some shortcomings that limit applying MSCA in industrial situations.

Almost all fault patterns have some frequencies in common. Therefore an individual fault may not be detected if it is associated with more than one type of fault. Bonaldi, et al. advised using a rough set of identifiers to discriminate MCSA faults [23]. They have provided a table to discriminate between MCSA faults based on their possibility of occurrence and other criteria. This method is very helpful to discriminate signals that are coming from the same source. However, the method is not useful in a practical industrial situation where some fault signals may be caused by external sources.

Configurations of frequency patterns are dependent on motor velocity. This may change during any process such as induction motors with variable loading conditions. Some publications recommend recording of the motor speed of rotation as well [1]. Monitoring the shaft speed provides more accurate results but also involves extra instruments (i.e. sensors, data acquisition channels and a stronger processing unit) and a more complex processing algorithm.

A high level of noise is expected in industrial power networks due to the normal operation of distributed power systems including electrical motors and transformers. These types of noises occupy certain frequencies and hence may be eliminated partially by frequency filtration. Distributed power system transients including start-up of electric motors, inrush currents, operation of switches and also steady state operations of nonlinear equipment, filters and active components may cause electrical signals similar to fault indicators. This type of noise is more difficult to discriminate from the original signals.

Similar to any current signals, fault indicators and noises travel from one point to another point and may cause a wrong interpretation in the diagnostic system.

As a result an extra course of action is necessary to improve the reliability of MCSA diagnosis. There have been several studies towards improving reliability and applicability of motor current signature analysis. Some of these investigations have yielded acceptable and applicable results. Here a number of major improvements in employing current signals for fault diagnoses are described and discussed accordingly.

2.4.1 Improving data acquisition tools and signal resolution

There are many solutions provided to reduce the noise. Costa et al. collected a set of developments in data acquisition which contribute toward fault diagnostic techniques [23]. They also proposed a framework for data acquisition and signal processing.

By improving the quality of data acquisition tools and using appropriate data processing techniques, the major proportion of noises can be removed in large electric motors. These methods usually are not very successful where the motor is relatively small or is exposed to major noise sources in the same range of frequency.

Another development is to improve the quality and resolution of frequency spectrums and to try to acquire more useful information from the measured spectrum [27]. Wavelet Transform and short FFT are other attempts to analyse current signals and diagnose faults in varying conditions [18]. Devaney, et al. successfully detected rotor damage during the start-up process [28]. In the same year Hugh Douglas presented a technique to diagnose motor faults by using Wavelet Transform for broken bars of induction machines [29].

2.4.2 Numerical approaches to describing fault signals

Strategy of fault diagnosis, using AI (artificial intelligence) based methods has become very popular since 2000. There are many published papers with industry application which published demonstrate this application as an auxiliary way to finding damaged machines. Some of these investigations result in professional methods of diagnosing using current signals [18] and [30].

Many papers and technical reports have been published in application of different mathematical and logical methods to detect electrical problems and instant faults. Fuzzy logic, neural network and genetic algorithms have been widely used to improve accuracy of diagnostic techniques. A number of papers have reported successful application of artificial intelligence in current signature analysis [31]. Each method provides a unique solution to cancel the environmental noise and interpret captured information.

Examples of successful applications of MCSA are summarized in Table 2 below.

Table 2 Minimum fault severity detected by fault diagnosis techniques demonstrated in reference [31].

Nominal frequency	Motor size	Voltage	Loading	Cited in [31]	Severity as described in [31]	Method of Diagnosis
60	3hp	460	Full load	8	0.43%	MCSA
50	11kW	420	No load	10	20%	FFT
60	5hp	460	50% load	12	0.42%	MCSA-current envelop
50	15kW	400	No load	14	2.04%	MCSA- multiple reference frame theory
50	1kW	220/380	Nominal load	51	20%	Neural network-unsupervised
50	6hp	380	Nominal load	54	0.42%	Fuzzy neural network

As shown in Table 2, various types of experiments have successfully diagnosed the fault type using electrical signals. MCSA or a combination of MCSA and other diagnostic methods have been employed to diagnose faults with various severities and loading conditions. As demonstrated in Table 2, MCSA has outstanding diagnosis results in a full load situation where the fault signals are more observable in current waveforms. In light loading situations, field methodologies and voltage monitoring provide more accurate results.

A number of recent studies reported successful application of motor current signature analysis for synchronous and DC motors. Ilamparithi et al. reported a successful application of signature analysis to detect eccentricity of synchronous motors. However reported results are significantly less reliable compared to that of induction motors [32]. Another study has reported significant improvement of fault diagnosis using vibration signals by including results of current analysis [33]. This study does not recommend current signals as an independent method of diagnosis.

Torkaman et al. applied the pulse injection method to detect eccentricity faults in synchronous motors [34]. In this method a high frequency signal is injected to the supply waveform and the resultant current has been processed to diagnose eccentricity faults. Since the voltage frequency is much higher than the nominal frequency, all disturbances due to normal operation of the motor can be neglected. On the other hand the method does not have a significant disturbance on operation of the target motor as the pulse is rationally small and then inject is for a short duration.

Most diagnosis studies concentrate on the steady state operation of electrical motors to exclude the complex behaviour of electrical motors. However, there are a number of studies approaching fault diagnosis in transient situations [35, 36].

2.4.3 Data fusion and crosschecking

Electrical fault signals, unlike vibration signals, propagate all over the network. Therefore significant fault signals may be highly influenced by the operation of neighbouring motors and environmental noise. One possible solution to improving reliability of diagnosis is to collect more evidence to support a less dependable result. The idea of applying fusion of different signals in fault diagnosis is presented in a few research papers to improve redundancy and reliability of the diagnostic system. This data can be picked up from different sources of signals including current waveforms, electromagnetic field and vibration [37, 38]. There are a number of studies that widen the coverage of fault diagnosis using current signature analysis. Martínez-Morales et al. proposed a framework to diagnose motor faults in a variable operating condition using multiple vibration and current sensors [39]. Iorgulescu reported an improvement in detecting bearing faults using data fusion among current and vibration signals for DC motors [33].These methods are usually considerably more expensive compared to normal motor current signature analysis.

Taking into account that significant fault signals are travelling all over the network, several observations are achievable for a fault integrated in an electric motor. In this thesis the idea of cross evaluation of fault signals considering signal propagation will be discussed and analysed. The proposed method targets an improvement method in diagnostic reliability with a simple and viable framework of decision making.

2.5 Propagation of current signals in industrial power networks

There are a number of strategies that describe propagation of special signals throughout power systems. Power Line Carrier (PLC) is a well-known strategy to transfer control messages via power networks. By definition, “A PLC channel includes the signal path from the transmitting electronic equipment at one terminal, through its coupling equipment, over the power line, through the tuning equipment at the receiving end, and into the electronic equipment at the receiving terminal” [40].

Frequencies in the range of 30–500 kHz have been employed for PLC communication. This frequency range is high enough to be isolated from the normal operation of power system. Characteristic impedance of a transmission line (surge impedance) is described as the ratio between the voltage and the current of the travelling wave on a line with an infinite length [40]. Surge impedance is a combination of the resistance, inductance and parallel capacitance of transmission lines. A simplified schematic of a SCADA channel is shown in Figure 4.

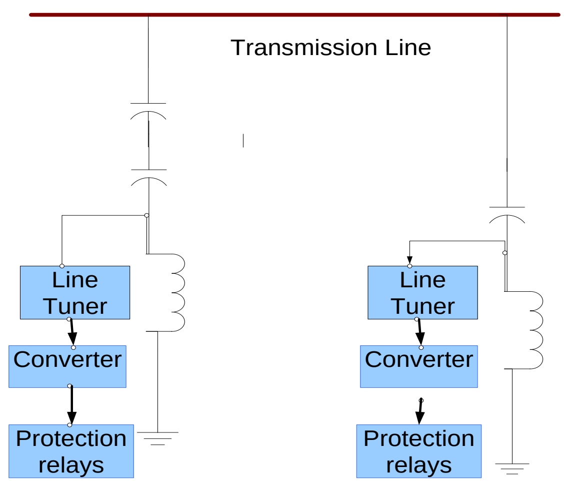


Figure 4 Simplified schematic of the SCADA system

PLC studies provide a good reference to estimate attenuation of SCADA messages over transmission lines. Carrier frequency of PLC channels is much higher than the frequency range of fault signatures. However, the calculation methodology in conjunction with a technical approach with reference to topography of power systems may be utilized to develop the attenuation pattern. Such methodology is expected to provide a rough estimation of originality of fault indicators which appear at a lower frequency ranges (i.e. 20 to 1000Hz).

IEEE recommends a set of guidelines to estimate protection faults in power systems in transmission lines and distribution systems [41]. Again, these formulations are calculated for major system faults and do not provide required estimations for system harmonics and sub- harmonics. On the other hand protection analysis and SCADA approaches may potentially be employed to calculate attenuation of fault signals.

Cross checking fault indicators can be performed by looking at attenuated fault signals from different locations. Thus the signal can be picked up from different locations such as a central point or other parallel consumers nearby.

2.6 Distributed and Central point monitoring

Remote monitoring and central point diagnosis is a low cost and efficient approach to industrial supervision. Central point diagnosis is a well-recognized strategy to identify system failures in power engineering and particularly with transmission faults. Protection systems monitor basic indicators of current and voltage to protect distributed power systems against serious system failures. These faults usually appear as a dramatic increment or a collapse of main system indices such as voltage, current, frequency etc [41]. Subsequently fault detection technologies have been extended to cover tracking fault locations as well. IEEE recommends a guideline to detect location of symmetrical and asymmetrical faults in transmission lines [41]. These developments are sustained by more investigation to recognize various types of faults using supervisory and monitoring systems.

A simplified schematic of a supervisory and protection system using central fault monitoring has been shown in Figure 5.

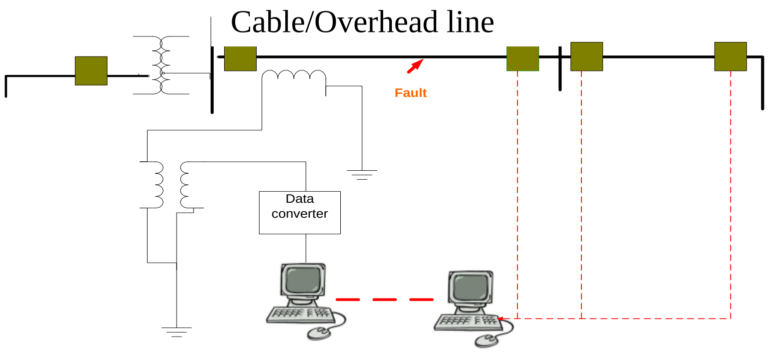


Figure 5 Automated fault detection and diagnosis

An automated fault diagnostic system in transmission lines has been shown in Figure 5. This system continuously collects current and voltage information and processes information using a diagnostic and decision making algorithm. The protection system is responsible for detecting and tracking the fault location and discriminating and isolating the fault in the network.

In general two factors have to be detected to evaluate possibilities of diagnosis. At least one indicator has to be measurable and the indicator or configuration of a set of indicators should be distinguishable from other causes of faults. Using central point monitoring, detection of the presence of faults is debatable as the same signal can be detected in current waveform of the feeding bus. However, it is problematic to discriminate the incident with a high level of confidence. Therefore an accurate topography modelling is required to estimate the possibility of diagnosis.

Central fault diagnosis theoretically may be employed to diagnose MCSA faults providing you have at least one indicator (i.e. fault signals or a given pattern) to discriminate the motor's faults. Therefore, the approach could be useful where the target motor is considerably bigger than other network components in terms of size. Otherwise the evidence provided will not be strong enough to judge the system. Hence further evidence is required to be included for more accurate detection. Improving reliability potentially provides robust solutions without the need for human interference. Gheitasi, A. et al presented a diagnostic approach to evaluate reliability of diagnostic reports and provide immediate and delayed decisions for single electrical motors [43].

Analysis of distributed signatures offers improvements for diagnosis as it is taking advantage of maximum possible accuracy of direct diagnosis whenever available. Also it provides a framework to clarify diagnostic indicators from the noise produced by the propagation of current signals. This research aims at a technical scheme to take maximum advantage of all available measuring points in diagnostic solutions where components of electrical signals are taken as fault indicators. Distributed diagnosis is expected to suggest more reliable results in electrical motors with a direct measuring system and provide early indications of faults for the in-network motors where direct monitoring is not available.

Chapter 3:

RESEARCH TOOLS AND SIMULATION METHODOLOGY

This chapter introduces and acknowledges tools and software that have been used to perform research tasks of the thesis. At first, software packages and technical tools have been described. Data acquisition tools and electric models are described in the next part of the thesis.

3.1 Software selection and configuration

MATLAB/SIMULINK software and its related components have been used as the main tool to generate simulation results, collect information and process simulation and practical data.

This software provides an excellent environment to introduce and manipulate real time and asynchronous data provided by data acquisition equipment. It also provides a set of powerful functions for frequency analysis, numerical and intelligent pattern recognition and other analysing tools that have been employed to analyse raw and pre-processed results of simulation and practical experiments. In addition, MATLAB provides a flexible environment to simulate behaviour of distributed power systems. Providing simulation and processing tools in a software package and perfect compatibility of the software with data acquisition equipment offers an ideal tool to contribute in different research tasks of this thesis. Figure 6 illustrates employment of different components of MATLAB in the thesis.

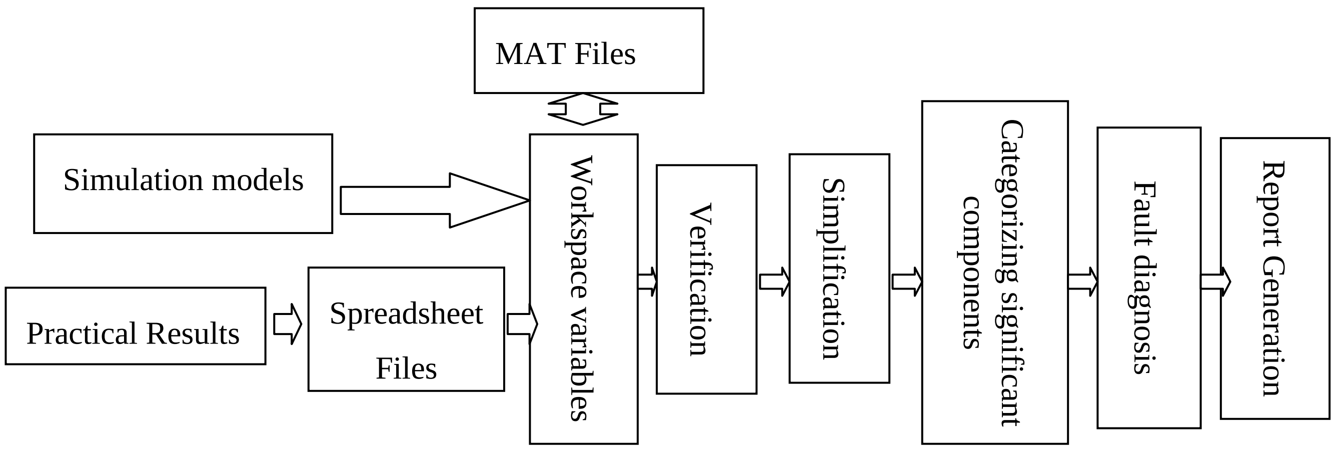


Figure 6 Employment of MATLAB software packages in different parts of the project

Simulation results and results of practical experiments have been employed to produce required information to analyse behaviour of distributed power systems and describe concepts of distributed diagnosis. During processing of simulation, current signals of all electric motors are set to be stored in a dedicated variable for each electric motor. These variables will then be transferred to the workspace environment of MATLAB software. Results of practical experiments have been collected using a data acquisition process in spreadsheet files. These files have been converted to MATLAB variables using the "MATLAB importer wizard". Simulation variables have been set to be similar to results of practical experiments. Then the information has to be validated using a proper function. Subsequently major components of the signal have to be categorized. The next stage is to process significant components of the signal using a proper metrology and finally the diagnostic report has to be generated using a logical process. The process to diagnose faults and produce a report to advise on condition of electrical motors will be described in detail in Chapter 4.

3.1.1 Distributed power system behavioural simulation

SimPowerSystems has been used to model and simulate a typical distributed power system. This model has been utilized to study the propagation of fault indices in distributed power systems and investigate several acting variables. Power-System-Block-set is used to model a scaled down industrial power system and observe network behaviour in a faulty situation. Normal (not accelerated) simulation method has been utilized to produce more accurate simulation results. The simulation model generates 25000 data item per second. Since the simulation time for each model is 3s, 75000 data item will be generated for each measuring point. These measurements will be transferred to the workspace of MATLAB as one dimension variables after completing the simulation.

3.1.2 Verification of simulation results

In order to eliminate weak information and minimise the influence of transient signals a simple mutual verification process has been employed. There are several state variables involved in the operation of electrical motors. Measurement of voltage, rotor speed, torque, and motor current are achievable using the simulation model. All these variables are dependent on each other and hence unacceptable value or transitional behaviour of any of these variables revokes all measurements associated with the current sample taken for data processing. A sample of current waveform has been shown in Figure 7.

Operations of all electric motors are associated with a transient situation in the start-up process. This transient situation appears as a dramatic increment of current and increase of speed from stationary state to the nominal speed of the motor as shown in Figure 7 and Figure 8.

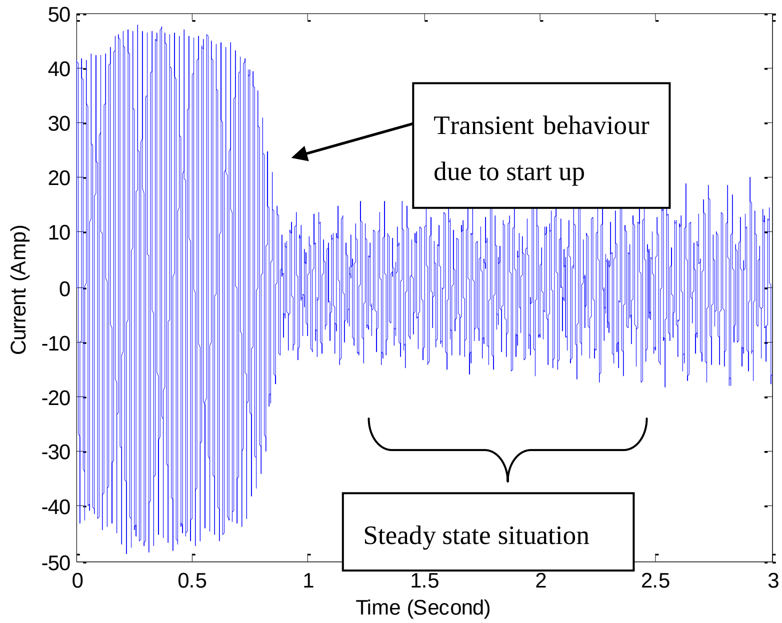


Figure 7 Current waveform of an electric motor which is involved in fault indices (M10, Case study 1[Eh1])

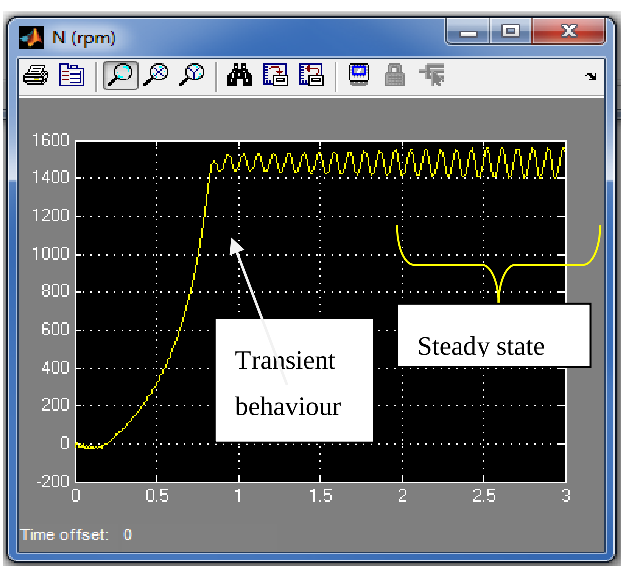


Figure 8 Speed of electric motor during and after the process of start-up

Here, Speed of electric motors has been used to verify simulation results and discriminate transient situations from steady state operation of electric motors. After verifying validity of captured signals, a data processing approach is required to take a good sample of the stored waveform and categorize abnormal frequency points.

3.1.3 Sampling and categorizing abnormal components of motor waveforms

The first step of each diagnostic system is to categorize abnormal components of the waveforms in a proper form than can be employed for further analysis. There are a number of data processing techniques to categorize characteristics of waveforms. Frequency domain, time-frequency domain and wavelet techniques are common methods of signal processing in general [31].

Fast Fourier Transform (FFT) is the most common method of signal processing while dealing with discrete data. This method converts the signal to a number of frequency components where each component is a representative for a sinusoid waveform component of the original signal. In the other work, aggregation of these sinusoid waveforms that are identifiable with a pair of frequency and magnitude forms the original signal. Short Time Fourier Transform (STFT) is the time variant form of FFT where the FFT is calculated for a fixed sample of data and hence it is time variant and changes continuously based on frequency contents of the signal [31]. Wavelet Transform is introduced as an alternative method to analyse abnormal components of signals without allocating a fixed window which limits the resolution of frequency spectrum. Application of Wavelet Transform has been reported in a number of publications [31].

In this thesis STFT has been employed to analyse current signals of electrical motors due to the following reasons:

Dynamic behaviour of distributed power systems and the need to cancel weak results suggest use of a time variant technical solution such as STFT or Wavelet Transform.

Most signatures and fault patterns have been produced using frequency spectrums. Using other signal processing approaches involved in extra work to produce compatible patterns of diagnosis. Therefore FFT and STFT (well matched with FFT) are preferable.

Combination of 1 and 2 suggests that STFT is a better method of signal processing for distributed diagnosis. However, using Wavelet Transform generates higher resolution results which could be useful for discriminating faults with very similar patterns.

Process of data analysis to categorize frequency components of fault indices has been shown in Figure 9.

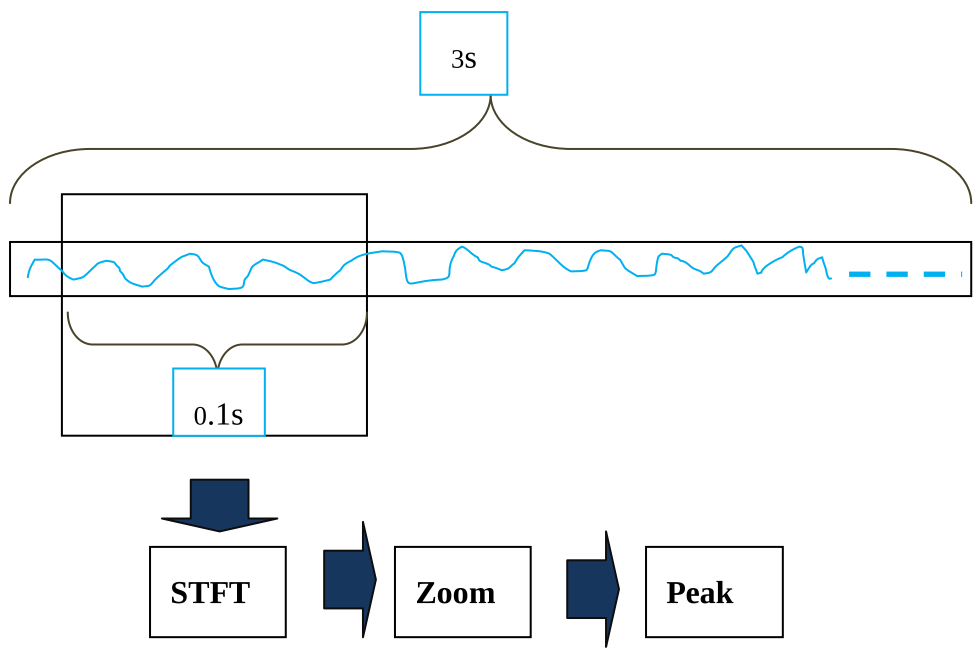


Figure 9 Data processing of stored simulation and practical results

As shown in Figure 9, initially data is partitioned to 0.1s windows. Each window contained 2500 samples of data (see Figure 10). The frequency spectrum of the signal is then calculated. As shown by Figure 10, the spectrum content contains a wide range of frequencies. Since lower frequency bands are significant from MCSA diagnosis, higher frequency components of the frequency spectrum will be eliminated (See Figure 11). Subsequently a threshold is considered to eliminate noise signals.

Threshold value is subjected to topography of the network, level of noise in the site and the requested accuracy. Here 10% of the nominal current is considered as the threshold set point. Finally all local maximums of frequency spectrums of the current waveform, except the main frequency (observable at 50Hz in New Zealand) will be considered as fault frequency components (see Figure 12).

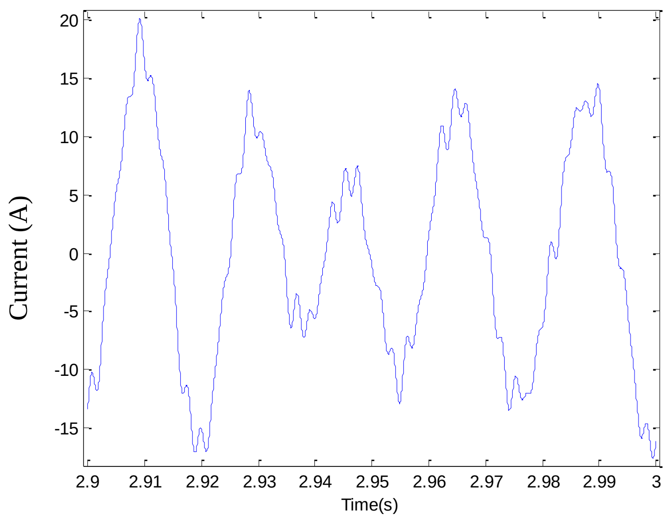


Figure 10 0.1Second of the waveform of Figure 9 in steady state situation

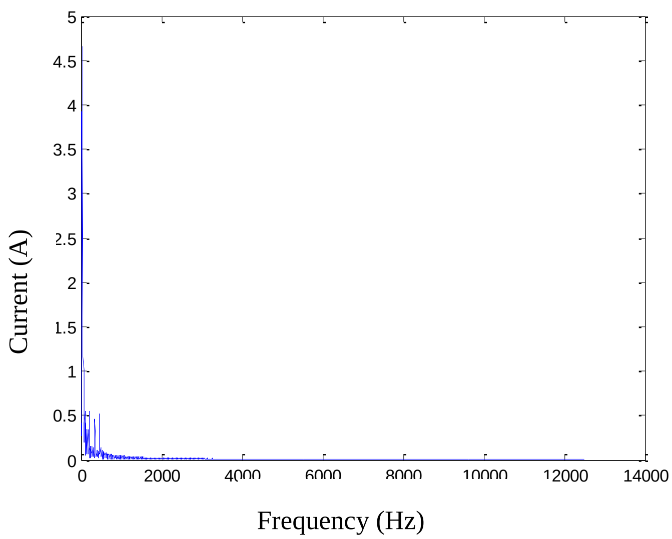


Figure 11 Frequency spectrum of the waveform shown in Figure 12 (Tagged 2.9s - 3s)

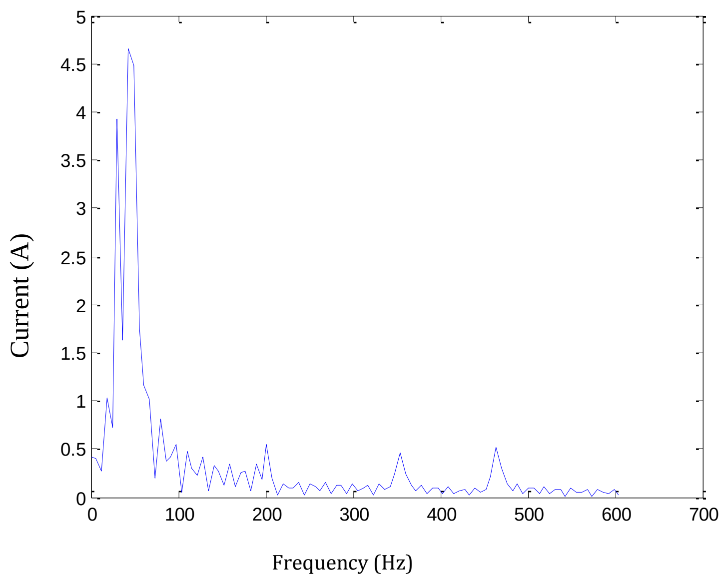


Figure 12 Lower band zoom of the frequency spectrum of the waveform of Figure 13

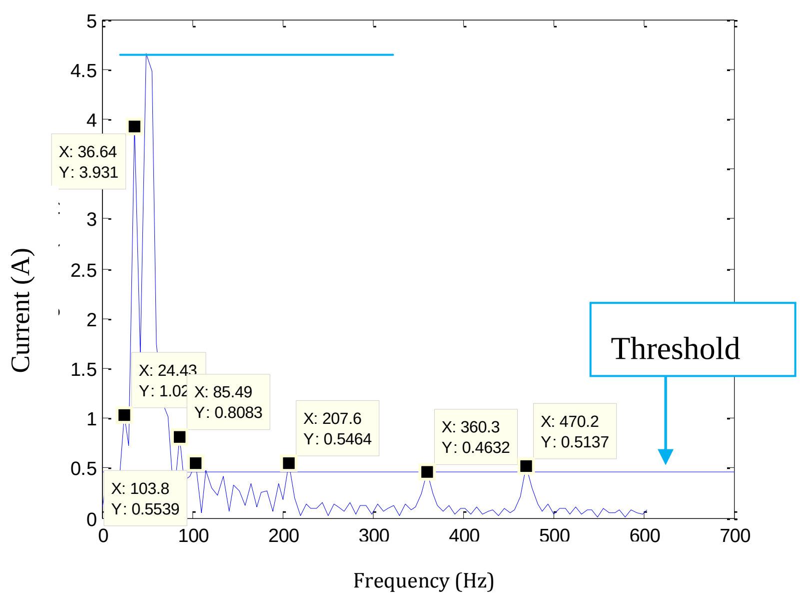


Figure 13 Frequency components of the frequency spectrums in steady state operation of the electric motor

The following significant pairs of frequency-magnitude are identifiable from Figure 13.

(24.43, 1.02), (85.49, 0.8083), (207.6, 0.5464), (360.3, 0.4632) and (470, 0.5137).

Using FFT to analyse current signals of electric motors results in mixing components of transitional and steady state operation of electric motors. Figure 14 illustrates the frequency spectrum of current waveform of the target motor calculated using FFT. As shown here, 15.8Amp is calculated as the magnitude of current in 50Hz frequency which is not a correct assumption.

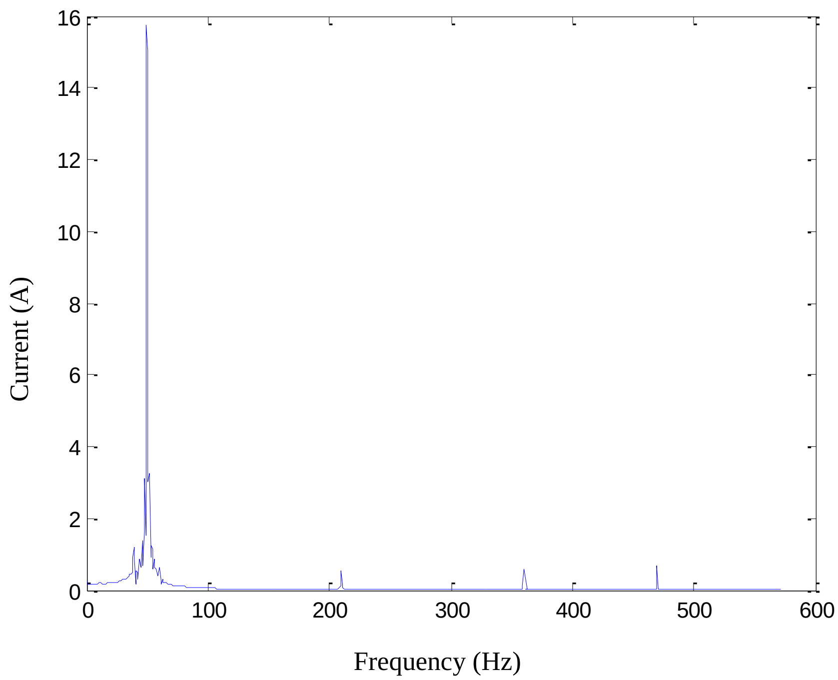


Figure 14 Lower band zoom of the frequency spectrum of the waveform of Figure 3-5

The following functions of MATLAB have been employed to identify fault signals as explained in section 3.1.3. A list of important functions of MATLAB has been summarised in Table 3.

Table 3 Important functions of MATLAB which have been used in the thesis

Function	Comment	Example of use
FFT	Calculate Fast Fourier transform	Y = fft(xx,NFFT)/L;
findpeaks	Return value and location of local maximums of the signal	[pks,locs]=findpeaks(fr0);
newff	Form a feed forward artificial neural network	net2=newff(bb,vx,5); bb is the input matrix, vx is the output matrix and there are 5 hidden layers
Train	To train the neural network	net2.trainParam.goal= 0.01 ; % error target net2 = train(net2,bb,vx);

Details of the implemented programs will be discussed in section 6-2.

3.2 Hardware tools

During the research work, several practical experiments have been carried out with various sizes of induction motors. A number of faults were generated in an artificial way. A Tektronix oscilloscope (TDS2012B) has been employed to store measurement information in a flash memory. Each measurement is stored in an individual spreadsheet file. Measurement information is listed in Table 4.

Table 4 Detailed descriptions of measurements using TDS2012B

Item	Value
Record Length	2.50E+03
Sample Interval	4.00E-05
Trigger Point	1.25E+03
Model Number	TDS2012B
Serial Number	C050177
Firmware Version	FV:v22.11

3.2.1 Experimental environment

In order to validate the simulation results a typical example of an industrial system has been modelled and simulated. A number of induction motors have been connected together via a supply bus (generator or an infinite bus). The test-bed has been implemented in the Power Lab of AUT University and Aucom Electronic Ltd. For each experiment a fault posed to the system in an identical location and current of other parts of the network has been stored thoroughly. The supply bus is fed by a generator in the first test-bed and motors loaded with static mechanical loads. While DC generators have been applied to load induction motors in the second test-bed, the common bus is fed via a stable power bus. One Tektronix oscilloscope has been applied to record measurements in a flash memory. The sampling rate of the measurements was 25,000 samples per second and each measurement takes a second. The model for one component of the network is shown in Figure 15. Network configuration has been shown in Figure 16.

Figure 15 Scaled down test-bed designed in the AUT University to analyse faulty behaviour of electric motors in industrial situations

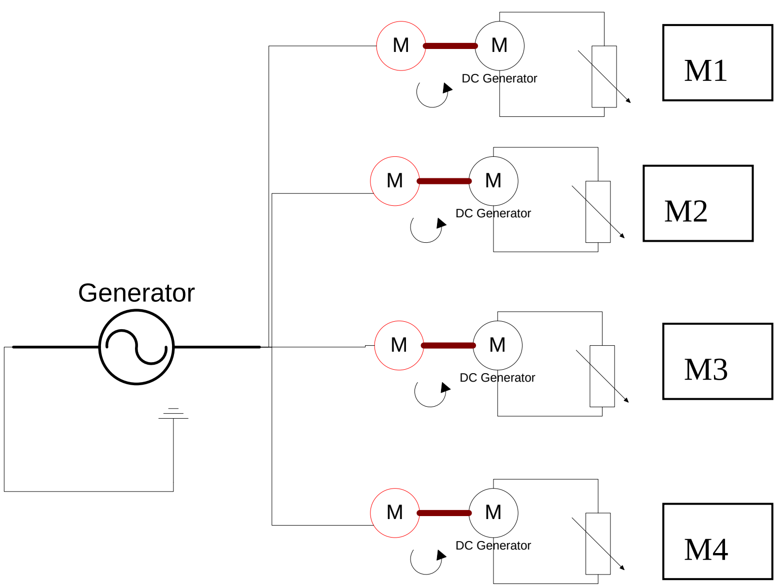
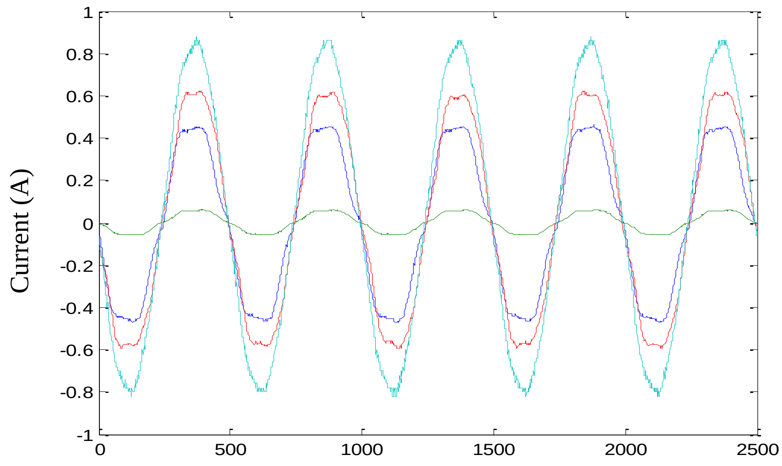


Figure 16 AUT/ AUCOM scaled down industrial system

Electrical signals categorized from individual operation of electric motors are shown by Figure 17.



Time(s)

Figure 17 Individual operations of electric motors - motors are partially loaded (CT ratio is 10:1)

As shown by Figure 17, current signals are not complete sinusoid waves and some other frequency components are detected in the signal of any electric motor. These motors are then connected together via a common bus to compare signal spectrum of motors from different monitoring points.

All motors currents have been captured using single input data acquisition devices and hence this data are not collected at the same time. Measurements taken at different instants of time reduce the quality of association among signals collected from different motors. However the change does not necessarily reduce the quality of measurements because the fluctuating rate is reasonably slow in diagnosis of internal faults.

Characteristic details of electric motors in the AUCOM model have been summarized in Table 5.

Table 5 Characteristics of electric motors that have been employed for the practical experiment

Motor	Power (Hp)	Speed (RPM)	Number of poles	Comment
#1	4 Hp	1440	4	TechoElec& NACN. Co. ltd, Taiwan
#2	4kW	1430	4	IEC60044; IP55 7.62 A; 112 M, Weg,
#3	4kW	1430	4	IEC60044; IP55 7.62 A; 112 M, Weg,
#4	22kW	970	4	Gec machines; Ins class F,D200L 44Amp; NDE 63002; BS5000PT99

Chapter 4:

THEORY OF DISTRIBUTED SIGNATURE ANALYSIS CONCEPT

4.1 Introduction

The diagnosis framework is based on the current signature analysis approach discussed in the previous chapter. This chapter focuses on the specific approach taken to accomplish the objectives of each section in the methodology. Most of the work presented is for the general fault diagnosis of induction motors, but some shows specific applications explained for electrical networks with typical configurations. The particular machines that will be analysed are medium size induction motors loaded with static mechanical torques. These calculations will be generalized to cover a wide range of induction motors in distributed power system networks. The main focus of this study is to apply available diagnostic technologies to improve the reliability and coverage of fault diagnosis technologies.

In this chapter, a typical industrial system has been considered as a configuration of machines connected via few feeding interconnected supply bus. A number of measuring points have been considered to monitor the behaviour of electric motors. See Figure 18.

In order to analyse observation of each measuring point and assess possibility of valid diagnosis, several key factors have to be considered including: influence of fault representatives in electrical signals of neighbourhood motors, signal propagations through power line, estimation of magnitude of attenuated signals, and superposition of signals. Taking into account that each acting variable may affect the reliability of diagnosis, several levels of simulation have to be implemented. A technical approach combined with simulation results has been employed to estimate accuracy of diagnosis in traditional diagnosis. This analysis is followed by a technical discussion on utilization of multiple observations of a single index as a possible metrology of diagnosis and system solution for fault diagnosis versus the traditional individual diagnosis.

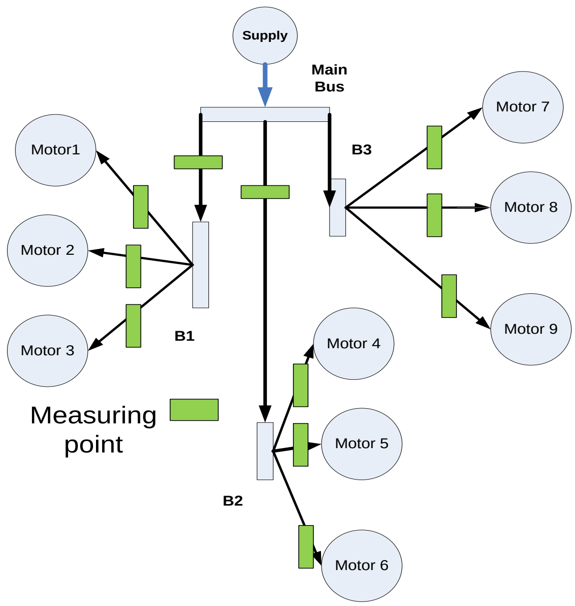


Figure 18 A typical model of an industrial system with three bus and electrical drivesare connectedto power bus

This chapter commences with the theory of motor current signature analysis implemented to monitor and diagnose faults of electric motors. Next, concepts of individual pattern recognition have been investigated in actual power networks. It has been proven that fault signals travel around the power networks and hence propagated signals are misdiagnosed as a fault in other electrical motors. This conclusion demonstrates the needs to monitor the signals of neighbour machines in order to cancel the distributed power system's environmental noise and purify fault signals of the targeted machine.

The pattern recognition method has then been extended to provide a system solution by monitoring all available sensing points using a distributed diagnostic strategy. A matrix of fault indices has been formulated to estimate the association of signals of each measuring point with known fault patterns.

Propagation of fault signals has been formulated to generate a matrix of projected indices for any possible fault in the power network. By comparing this matrix with the matrix of fault indices using a numerical method (Matrix Correlation, Artificial Neural Network, Bayesian etc.) type and origin of faults will be estimated.

4.2 Individual diagnosis

Several methods have been proposed to identify faults using a neural network. In this section, the strategy of motor current signature analysis has been developed to produce a simple numerical model that generates fault indices for any possible fault. These indices will be utilized later on for in-network and distributed diagnosis.

Motor current signature analysis states that mechanical and electrical faults have a unique influence on the frequency spectrum of current signals of electrical motors called signature and therefore, pattern recognition strategy is required to diagnose industrial faults.

4.3 Fault patterns

Here, in order to analyse significant points captured from electric motors, these formulations have been transposed to make the motor slip as the subject. Motor slip has been shown with different names for each type of fault to estimate the associated speed with each individual significant frequency point.

$$s_{ra} = \frac{\frac{Dp}{2} - f_0 K}{-f_0 K p \frac{p}{2}}$$

(4-1) ReconFigured from Equation (I-1)

$$s_{ru} = \frac{\frac{Dp}{2} + f_0 K p \frac{p}{2}}{f_0 K}$$

(4-2) ReconFigured from Equation (I-2)

$$s_{bq} = \frac{D - f_0}{2 f_0^2}$$

(4-3) ReconFigured from Equation (I-7)

f_{ra}, f_{ru} and f_{bq} have been replaced by 'D'. Where D is the frequency of the suspected significant point

s_{ra}: Associated motor slip for rotor asymmetry frequencies

s_{ru}: Associated motor slip for rotor unbalance frequencies

s_{bq}: Associated motor slip for broken bar frequencies

s: Motor slip

p: Number of poles

k: Harmonic order of fault symptom; k=1,2,3,…

f_0: Fundamental frequency

Using the slip index, the suspected speed of the faulty motor can be calculated as shown in equation (4-4).

$$\mathrm{V} = (1 - \mathrm{s})\mathrm{v_s} \tag{4-4}$$

Where:

s: the estimated slip of motor with the suspected speed

V: speed of the target motor

vs: the synchronous speed of the target motor

By substituting any of calculated slips in equations (4-1), (4-2) and (4-3), speed of the motor can be calculated.

According to the above formula, a signature of a fault is a set of frequency components:

$$S_i = \{f_1, f_2, f_3 \ldots f_n\} \tag{4-5}$$

The amplitude of any of these frequency components is a function of the amplitude of frequency component in the signature set, seriousness of the fault and amplitude and nominal current of the motor.

$$M_i = AR\{M_1, M_2, M_3, AR\ M_n\} \tag{4-6}$$

Where

A: Motor's nominal current

R: Index of seriousness of fault: 0<R<1

M_i: Amplitude of the frequency component in a given signature

f_i: Frequency components associated with the fault i

M_i: Indices are usually constant in any type of fault while A and R varies for different size of electrical motors and different seriousness of the fault. These formulations force a maximum possible strength for any frequency components of signature of faults.

Here in order to simulate faults in electrical motors a set of frequencies with tuned magnitude and proportional to the strength of faults has to be utilized in the models.

$$\text{Fault i:} \quad \begin{cases} S_i = \{f_1, f_2, f_3 \ldots f_n\} \\ M_i = AR\{M_1, M_2, M_3, AR.M_n\} \end{cases} \tag{4-7}$$

4.4 Frequency analysis and picking up significant points

Current spectrums of electric motors are usually continuous graphs. These graphs contain a wide range of frequencies with different origin and hence an early frequency filtration is required to cancel unwanted and noise signals.

Placements of significant frequency components are dependent on the speed of the drive and its variation. Therefore, by looking at the rotor speed and the deviation from the nominal speed, frequency spectrum is encapsulated in several significant frequency bands. As an example, significant status bands for an induction motor with speed variation of 1440 to 1450RPM and nominal frequency of 50Hz are shown in 19.

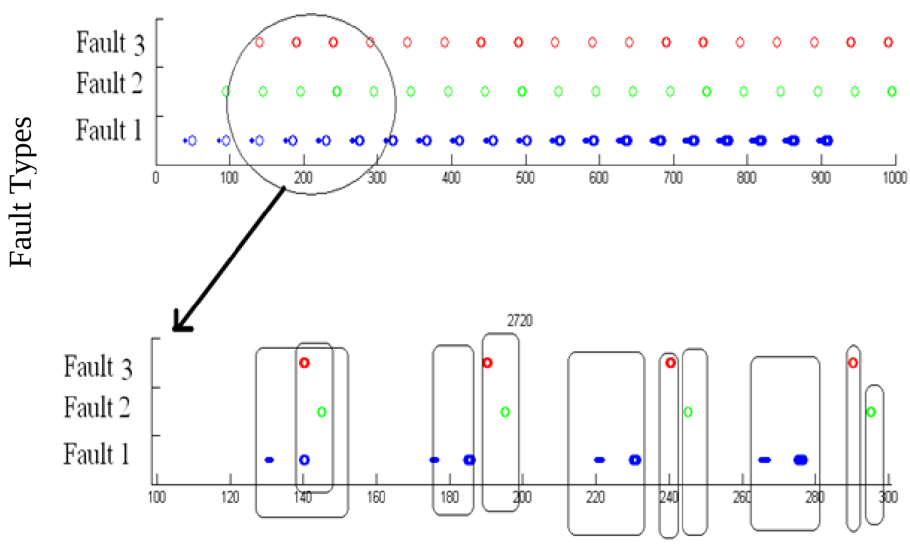


Figure 19 Significant frequency bands for mechanical faults type 1, 2 and 3 as explained a) overview representation over the complete frequency band, and b) detail spectrum within 300Hz

Here in order to categorize significant frequency points, the concept of “local maxima” have been utilized as demonstrated in Figure 20.

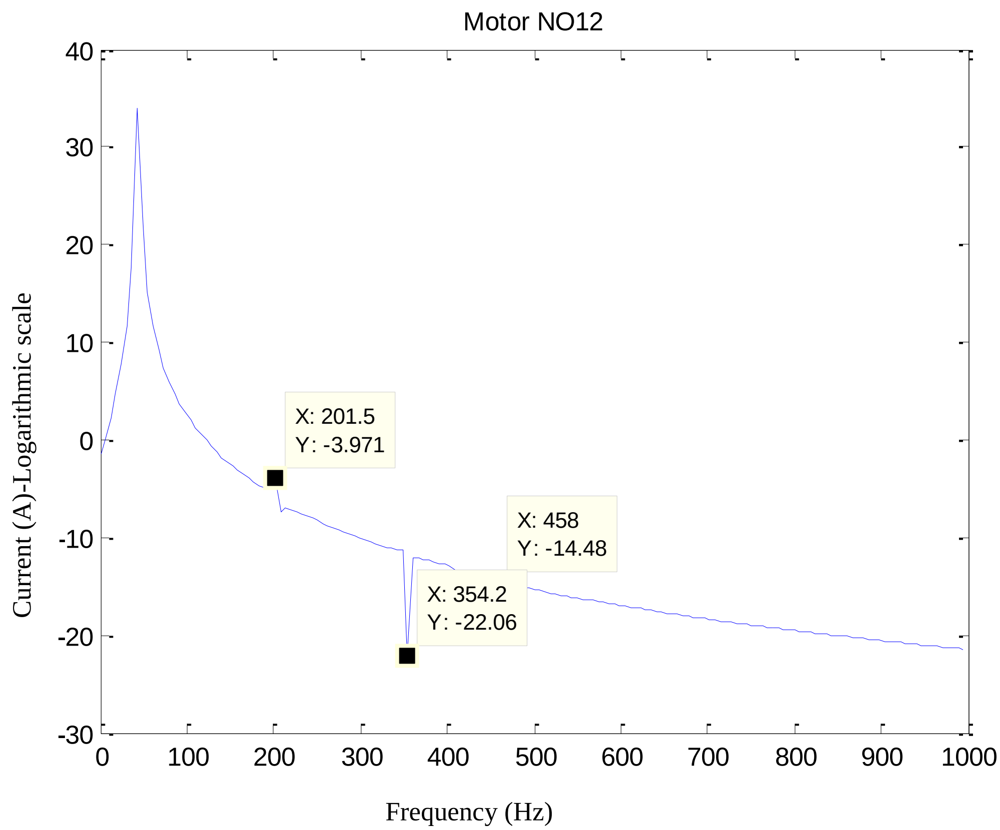


Figure 20 Abnormal frequency points have been picked up from the waveform. Note the nominal frequency is 50Hz and caused by the normal operation of electrical motor and hence is not considered as a component of fault signal

As shown in Figure 20, significant frequency points will be categorized as a set of (f_i, M_i) where f_i is the frequency point and M_i is the magnitude of power spectrum of the current signal.

4.5 Identify origin of significant points

In order to analyse the spectrum of electric motors, initially significant points are considered as potential signals that are caused by a fault. Then, the relevant speed is calculated and checked to see if the speed is in an acceptable range or not.

The next stage is to collect a set of significant frequencies related to faults of the target motor. All local maximums of the current waveform have to be categorized. Then collected local maximums should be matched up to the expected significant frequency bands as demonstrated in section 4.3. All frequency signals that are not matched with significant frequency bands will be removed and the rest of the signals will be classified according to the reference fault. Then, all significant frequency points should be compared against doubted faults to identify their origin.

Here, in order to identify the origin of the fault, pattern recognition method has been proposed to substitute frequency of each frequency-magnitude point in transposed formula of relevant frequencies. Then their suspected speed is calculated based on mechanical properties of the suspected machine. The calculated speed then will be compared with nominated or measured speed of the motor. If the calculated speed is in an acceptable variation range from the nominal/measured speed, the significant point will be classified as an evidence for the suspected fault (look at Figure 21).Using the proposed scheme, one significant frequency point may be a classified form of one suspected fault. However, collection of multiple frequency points generates a unique index for any fault which can be called the fault index.

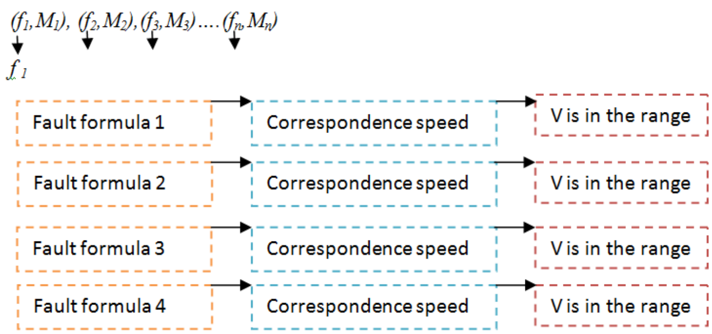


Figure 21 Verification of origin of significant frequency points

An index defined to indicate strength of fault signals for any measuring point. For a given fault type i:

$$F_i = \sum_n \frac{M_{i_n}}{n} \tag{4-8}$$

Where *n* is the harmonic number.

To reduce influence of higher harmonics and consider the higher impact of lower harmonics, the magnitude is divided to the harmonic order for any significant signal and summed to form the fault index of the fault. This formula generates a fault index for any suspected fault. Fault indices are very dependent on the size of electrical motors and level of current in the electrical motors. In order to have the fault indices independent from sizes of electrical motors and hence having a better discrimination, we may use rational fault index as explained in (4-9):

$$F_{ir} = \frac{F_i}{\mathrm{Max}(F_n)} \tag{4-9}$$

Rational fault index is dependent on the motor speed and hence having the actual speed of the target motor or good understanding of variation of speed and its deviation leads to more accurate results.

4.6 Distributed diagnosis

Individual decision making usually results in serious failure in distinguishing type and origin of fault signals in the distributed power system network. Multiple measuring points in the network capture dependent data from their point of view and hence improve accuracy of diagnosis. This helps in discriminating and isolating motor faults with higher accuracy.

4.7 Case study: Signal propagation and fault diagnosis in a semi- isolated environment

A simplified industrial test bed has been simulated to verify propagation of fault indicators and study the concept of distributed diagnosis. The test bed is combined of a few motors connected together via an electric bus and inductive connections fed by a supply bus as shown in Figure 22.

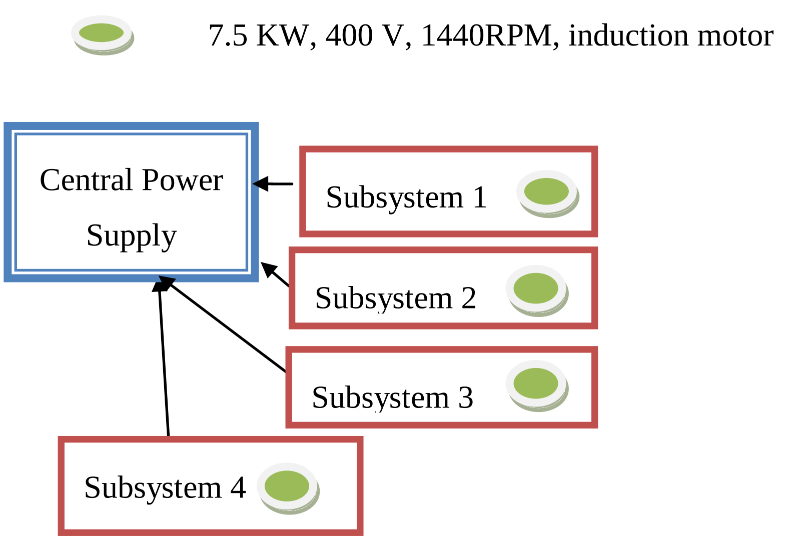


Figure 22 Model of a typical 4-bus system.

As described before, internal motor faults are associated with a set of frequency components; therefore, these faults are modelled by a set of frequency generators with different amplitudes.

Here, a fault signal that represents a MCSA fault is injected in to the current of the motor in substation 4 to observe the reaction of electrical motors to a fault in the neighbourhood. Figure 23 shows the propagation of a 200Hz signal originating from subsystem 4. As shown in Figure 23, the injected signal is observed in current of other induction motors in the neighbourhood.

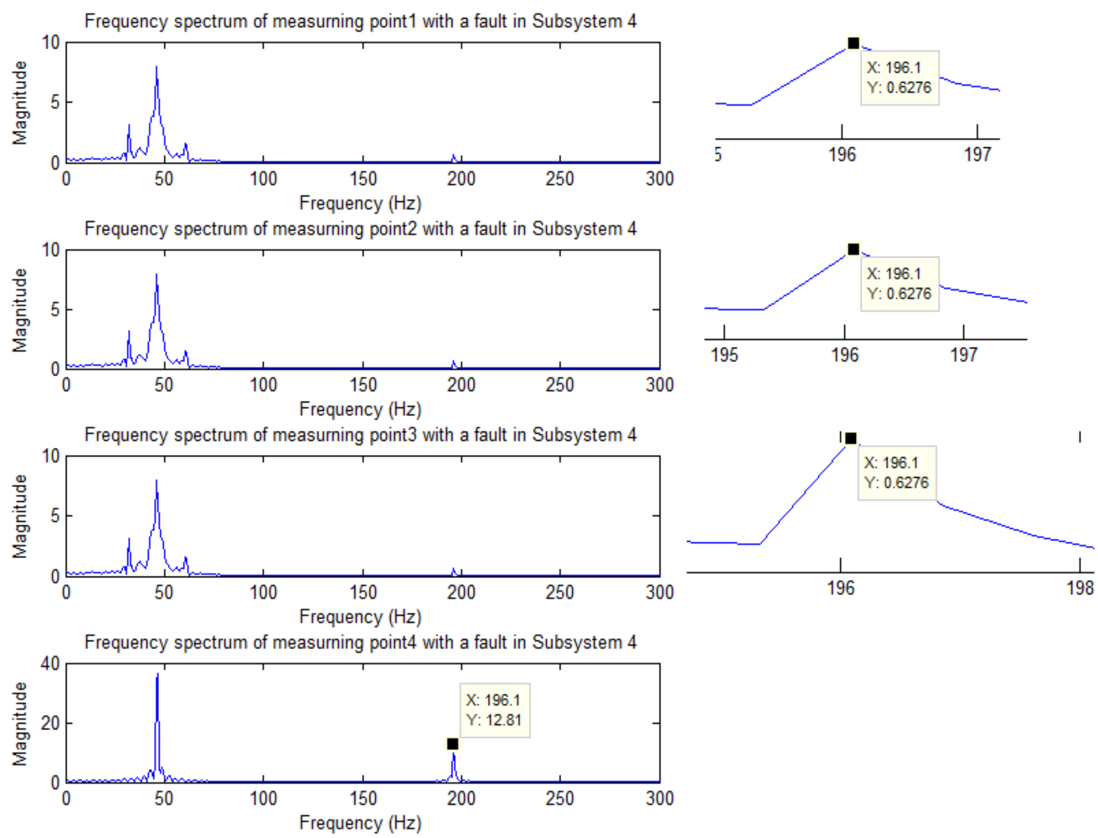


Figure 23 Propagation of a single frequency-magnitude pair inserted in subsystem 4.

Figure 24 demonstrates magnitude of the injected signal and observation in each bus versus the connection impedance between the measuring point and location of the injected signal.

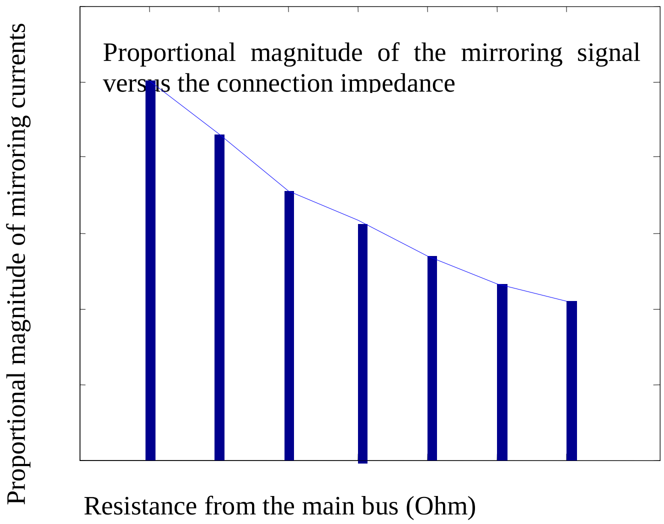


Figure 24 Proportional magnitudes of fault indices versus resistance to the target bus (Simulation results)

As shown in Figure 24, there is an inverse relationship between amplitude of fault indices and resistances of the cable that connects the motor to the bus of the faulty motor. Now, a multi frequency signal is applied to Motor 4 to observe the behaviour of other motors in the power network. As shown in Figure 25, almost for any significant frequency, a number of abnormalities can be observed in spectrums of all measuring points. A closer view at the significant frequencies in subsystems 1 to 4, demonstrates the mutual influence of electrical machines in subsystem 1 to 4. 50Hz, 92Hz, 105Hz and 118Hz are identified as fault frequencies.

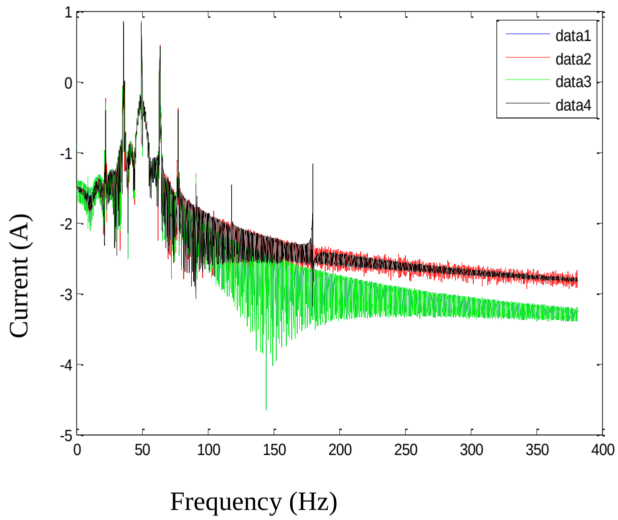


Figure 25 Multi frequency fault caused at Motor 4

This case study demonstrates the inherent propagation of fault signals in a power network. This propagation potentially interferes with the frequency spectrum of other motors. As a conclusion, a multi measurement diagnosis system is required to double check the captured signals and cancel the environmental noise.

4.8 Formulations of fault tracking

Considering data of other measuring points, a set of significant pairs of magnitude-frequencies will be generated. Combination of observed signals while a typical fault is present in one of the network components is a function of properties of electric motors, rotor speed, placement of measuring points and topography of the electrical network as well as indicators of the fault.

In order to develop a concept of fault diagnosis in electrical networks, the concept of fault indices has been extended to cover faults of suspected motors in the same neighbourhood. Here, a matrix of fault indices for any measuring point will be generated. Also, there are several measuring points in any power network and hence there would be a two dimension matrix of fault indices for any suspected fault as shown in 4-10.

$$\begin{pmatrix} F_{i,1,1} & F_{i,1,2} & \ldots & F_{i,1,k} \\ F_{i,2,1} & F_{i,2,2} & \ldots & F_{i,2,l} \\ : & : & : & : \\ : & : & : & : \\ F_{i,j,1} & F_{i,j,2} & \ldots & F_{i,j,l} \end{pmatrix} \quad (4\text{-}10)$$

Where:

$F_{i,j,k}$: Symbol for fault indices:

i: type of the fault(there would be one matrix for each type of fault)

j: Speed band related to a group of electric motors with the same speed.

l: Number of measuring point

Diagnosing the nature and detecting the location of faults in distributed power systems is always associated with reliability issues caused by unwanted signals. This is a common diagnostic problem especially in distributed power systems. There are a number of successful strategies to model the attenuation of fault signals and hence identify the main problem in the network such as [6, 7]. These methodologies lead to a set of reliable recommendations for protection issues in industrial sites [8].

Most fault locating strategies works based on the fact that attenuation of the fault signals in distributed power systems is relevant to the distance of source of faults from the point of measurements. Relations between fault location and attenuation coefficients for short circuit faults have been estimated using the following formula below [42].

$$\begin{bmatrix} V'_a \\ V'_b \\ V'_c \end{bmatrix} = \begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} - d.\begin{bmatrix} Zl_{aa} & Zl_{ab} & Zl_{ac} \\ Zl_{ba} & Zl_{bb} & Zl_{bc} \\ Zl_{ca} & Zl_{cb} & Zl_{cc} \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \tag{4-11}$$

$$d = \frac{V_r I_i - V_r I'_i - V_i I_r + V_i I'_i}{I_i I'_i Zl_i + I_r I'_r Zl_i + I_i I'_r Zl_i - I_r I'_i Zl_r - I_i^2 Zl_i - I_r^2 Zl_i} \tag{4-12}$$

Where

V_a: A-phase voltage;

I_a: A-phase current;

I': The remote-end current infeed on the faulted phase

V'_a: A-phase voltage at fault point;

Zl: Line impedance;

d: Fault distance;

r : Denotes the real part

i: Denotes the imaginary part

This formula has been suggested for single frequency models and power networks have been considered linear and Ohmic. Some modification is required to build up an appropriate index for multi frequency and nonlinear environments of fault signals.

4.9 Multi frequency modelling

Power networks are a collection of several load nodes that are physically connected to each other via electrical connections with a range of attenuation coefficients. Induction machines are the dominant load in most industry sites. Therefore modelling and full understanding of all industrial motors is necessary to estimate the attenuation pattern of a fault signal within electrical networks.

In order to estimate the attenuation of one fault signal in power networks several issues should be considered:

1) The most fault signal related to fault diagnosis is the current signal and theoretically there is no attenuation on current signals while travelling on a power line. These current signals cause voltage drop on electrical bus that result in derivative current.

2) The level of current is not necessarily equal for different electric motors. As a result, high power motors may generate a stronger signal while low power motors cause weaker signals in an equivalent fault signal. Observing magnitude of the acquired signals is not a reliable method to discriminate the origin of fault symptoms in many situations.

3) In order to estimate the voltage attenuation, a major fault and its related signals in Motor 1is assumed to take place. Motor 1 is connected to Motor 2 and 3 in parallel and on the same bus. Current of Motor 3 is supplied by the main bus via Bus B1. Propagation of fault signals to the main bus, influences the entire network by causing some voltage drops in Bus B1 and then the main Bus. The signal is then propagated to other parts of the network. Here, the mirror signal is observable in other parts of the network.

Complete calculation of signal attenuation indices requires full understanding of dynamic of the power network and its components. This information is subject to frequencies of fault signals. They may be altered due to system restructure, serious faults or the normal process of ageing. Here a simple framework has been proposed to estimate the anticipated magnitude of fault signals over the power network. This approach will then be utilized to investigate the originality of fault signals. This method uses different network indices to estimate the impedance of electric machines as the main load of the network and power connection to approximate the anticipated observable signal in current of other electric motors.

4.9.1 Frequency dependent impedance of electric motors

Frequency dependent impedance of electric motors in a given frequency of f can be calculated using the following formula:

$$Z_{M_X} = \frac{dE}{dI} \tag{4-17}$$

Where I is current and E is voltage of an electric motor in the given frequency of X. For example the frequency dependent impedance of electric motors in standard frequency is ratio of the feeding voltage and the motor's current.

Electric motors are inductive loads and hence their impedance varies for different frequencies. On the other hand, frequency of almost all fault signals is bigger than the nominal frequency. As a result, calculated impedance for nominal frequency is usually less than the actual impedance.

4.9.2 Impedance of connections

Power connections including cables, buses and transmission lines are inductive. Similar to the frequency dependent impedance of electric motors, the minimum impedance of connections can be calculated using the following formula:

$$Z_{l_X} = \frac{(V_s - V_e)}{I_l} \tag{4-18}$$

Where V_s is the voltage at the start of the conductor and V_e is the voltage at the end of the conductor

Another way to estimate the line impedance is to multiply the length of the cable by the unit impedance. This calculation returns the minimum impedance because impedance of cables may increase due to ageing and other physical phenomena.

4.9.3 Route impedance

As described in 4.9.1 and 4.9.2 the line and motor impedance may be estimated using equation (4-17) and (4-18). These two impedances are contributing toward the total impedance of the signal path on the way to the Bus. As described before both connections and electric motors are considered to be inductive, however their impedance angles are not necessary the same. This statement results in a boundary for the impedance of Z_{rk_X} as illustrated in Equation (4-19).

$$\sqrt{\left(Z_{Mk_X}^2 + Z_{lk_X}^2\right)} \le Z_{rk_X} \le Z_{Mk_X} + Z_{lk_X} \tag{4-19}$$

4.9.4 Attenuation of propagated signals

The generated signal propagates in all power networks until effectively dissipated. The current signal causes some voltage drop as it propagates in the network and influences all bus with the resultant voltage. The generated current signal then causes a voltage in the direct bus.

$$V_{Bus\ 1} = i \times Z_{B1_X} \tag{4-20}$$

Where Z_{B1} is the total impedance observed in Bus 1.

Z_{B1} is a combination of many impedances and hence detailed calculation of Z_{B1} requires a difficult process of estimating all impedances. The bus impedance in the nominal frequency can be calculated using the following formula.

$$Z_{Bi-nominal} = \frac{V_{Bk}}{I_{Bk}} \tag{4-21}$$

Where

V_{Bk}: is the nominal voltage measured in Bus k

I_{Bk}: is total current passing the Bus k in radial power networks

If total impedance of Bus 1 is considered as a known value, then the resultant voltage caused by fault signal of I can be calculated using the following formula:

$$V_{B1} = i_1 \times Z_{B1_X} \tag{4-22}$$

The resultant voltage then causes consequential current in all branches connected to the Bus. For example V_{B1} causes a current signal with a similar frequency in route 2. This current can be calculated using the following formula.

$$i_{1\to2} = \frac{V_{B1}}{Z_{r2_X}} \tag{4-23}$$

$$i_{1\to2} = i_1 \times \frac{Z_{B1_X}}{Z_{r2_X}} \tag{4-24}$$

Resultant voltage can be calculated in other bus. For example for Bus0:

$$V_{Bus0} = V_{B1-i} \times Z_{B1\to B0_X} \tag{4-25}$$

Where $Z_{B1\to B0}$ is the total impedance between Bus 1 and Bus 0.

For the nominal frequency, $Z_{B1\to B0}$ can be calculated using the following equation:

$$Z_{N(B1-B0)} = \frac{V_{N(B1)} - V_{N(B0)}}{I_{N(B1\to B2)}} \tag{4-26}$$

Estimating the magnitude of the appearing signals in B0, ease out calculating the resultant voltage in other bus and electric motors. For example the resultant current flows from Bus 1 to Bus 2 can be calculated using the following formula:

$$i_{1\to B0,B1} = \frac{V_{B0}}{Z_{B1-B2_X} + Z_{r4_X} \| Z_{r5_X} \| Z_{r6_X}} \tag{4-27}$$

Subsequently voltage in B2 can be calculated using the following formula:

$$V_{B2} = V_{B0} - Z_{B1-B2} \times i_{1\rightarrow B0,B1} \tag{4-28}$$

Then resultant current in all routes that are directly connected to Bus 2 can be calculated by dividing the resultant voltage by the route impedance in frequency of the given signal. For example the resultant current in Bus 4 is:

$$i_{1\rightarrow 4} = \frac{V_{B2}}{Z_{r4}} \tag{4-29}$$

Making use of equations Equation 4-17 to Equation 4-29, the relationship between current signals appearing in different places can be generated for well-defined power networks. However for most power networks these impedance indices in all frequencies are not available. Following simplifications ease out formulating real networks.

Considering theory of Motor current signature analysis, frequency of most fault signals are higher than the nominal frequency (50Hz in New Zealand).In addition all major impedances in distributed power systems are inductive. Consequently:

$$Z_{rN} < Z_{rX} \tag{4-30}$$

$$Z_{lN} < Z_{lX} \tag{4-31}$$

$$Z_{M_N} < Z_{M_X} \tag{4-32}$$

These equations bound the minimum value of connections, motors and route impedances. Another statement to limit the impedance value can be categorized from equation (4-19).

$$\sqrt{\left(Z_{Mk_X}^2 + Z_{lk_X}^2\right)} \leq Z_{rk_X} \tag{4-33}$$

Using the Ohm law, resultant mirroring current can be estimated as following:

$$i_{1\rightarrow 2} = i_1 \times \frac{Z_{B1_X}}{Z_{r2_X}} \tag{4-34}$$

Also resultant current observed in current of parallel electric motors that are connected directly to a bus is:

$$i_{m\rightarrow n} = i_m \times \frac{Z_{Bm_N}}{Z_{rk_N}} \qquad (4\text{-}35)$$

Then magnitude of the mirror current caused by the Motor 1 in current of Motor 2 will be:

$$i_{1\rightarrow 2} = i_1 \times \frac{Z_{B1_N}}{Z_{r1_N}} \qquad (4\text{-}36)$$

This chain process is continued to cover any other electric in the distributed power system. However, mirror signals resulted from a motor more than two bus away from the original fault would be attenuated significantly by the impedance of the power connections and hence can be neglected.

In equation (4-36), $\frac{Z_{B1_N}}{Z_{r1_N}}$ is the attenuation of the fault signal. Here the attenuation index δ has been defined as the estimated proportion of propagated signal to the original one. Therefore:

$$i_{m\rightarrow n} = i_m \times \delta_{m\rightarrow k} \qquad (4\text{-}37)$$

Where

$\delta_{m\rightarrow k}$ is the estimated propagated signal in electric motor k which is originally caused by motor m. it is usually smaller than 1 but if in-network motors are significantly different it may be even bigger than 1.

4.10 Propagation of fault signatures

Assume a set of fault signals caused by a fault in an electric motor. The measured signal is anticipated to be comparable to the fault signature as described in equation (4-7). The fault signal then will be propagated in the power network thoroughly. For the signal X, related to fault in electric motor m observed in the measuring point k.

$$A_{i,m,k_X} = M_{i,m_X} \times \delta_{m\rightarrow k} \qquad (4\text{-}38)$$

Where A_{i,m,k_X} is the anticipated magnitude of the fault signal X, caused by electric motor m and observed in current of electric motor k as a result of fault i in electric motor m.

The above formulations demonstrate an estimation technique to discover the magnitude of mirror signals in distributed power systems. This information will be utilized to clarify the original signal from neighbouring faults and identify the origin of signals caused by in- network fault.

4.10.1 Propagation analysis and fault diagnosis

A numerical method can generate a diagnostic report using fault indices. The anticipated range of signals due to a presumed fault (Projected Matrix) can be compared with the matrix of fault indices (F). Correlation of the projected matrix with the matrix of fault indices provides a good index to examine the validity of the presumed fault.

Also A_{i,m,k_X} indices can be compared with the measured signals to generate a unique indicator to point to the fault and identify the type of the fault.

In this thesis as a case study two methods have been applied to describe fault indices and find the origin of type of the fault. The first method tracks propagation of fault indices using correlation between the projected matrices and the fault indices. The second method utilizes artificial neural networks to interpret fault indices in each situation. The numerical case studies will be demonstrated in chapter 7.

4.11 Pattern of propagation of fault indices

In order to provide a visual observation of propagation of fault indices in industrial situations, concept of propagation charts are developed using equations (4-19) to (4-31). As described in propagation equations, transmission of fault signals from one point to another point can be verified. In order to produce the propagation graphs two levels of comparison have to be taken. Initially signal propagation will be discussed among transmission bus and then the judgment process will judge all electric motors in each bus compared to each other.

4.11.1 Signal propagation among buses

At the first level propagation of fault indices from one bus to another bus will be judged. Looking at Equation (4-38) and considering Equation (4-33) and Equation (4-19), a range can be determined to estimate maximum and minimum magnitude anticipated fault indices from one bus to another bus. This process compares each pair of bus with each other and verifies whether a fault index of one bus can be considered as originated from another one. An arrow can point to the faulty bus and demonstrate potential transmission patterns of the signal. In a case where an arrow connects two buses together and demonstrates potential transmission of signals between two bus and another arrow points to another bus in the same level as a potential origin of signal, the first arrow logically can be ignored. For example: Bus 1→Bus 2 and Bus 2→ Bus 3 and Bus 1→ Bus 3 where Bus 1, Bus 2 and Bus 3 are in the same level, suggested that the signal has been originated from Bus 3 and manifested in other bus. For a more complex configuration, these arrows should be referred and interpreted based on network topography. For example a power network with configuration of Figure 26 in a perfect propagation pattern for a fault that is originated from Bus 2.

Bus 3→Bus 2, Bus 4→Bus 2: in the highest level (relationship between Bus 3 and Bus 4 is not important) And

Bus 2→Bus 21, Bus 22→Bus 2: in the lower level

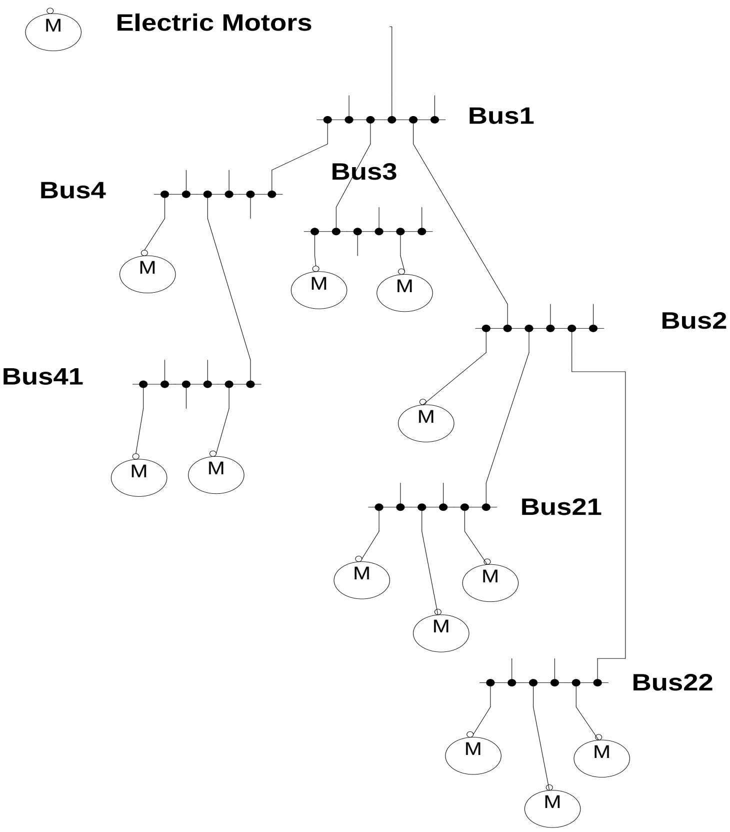


Figure 26 An example of power network with multilevel bus

4.11.2 Signal propagation among components of each bus

After identifying the faulty bus, the next stage is to discriminate the faulty motor. In order to accomplish the discrimination, a comparison process similar to section 4.11.1 compares all motors in pairs and assesses possibility of transmission of fault indices between each two measurement points. A perfect distribution pattern appears as all arrows point to the faulty motor and comparison arrows point to none of measuring points if faulty motor is not included in the assessment.

4.11.3 Graph of propagation pattern

Here, in order to illustrate results of estimations in section 4.11.1 and 4.11.2 a graph of propagation pattern is introduced. This graph employs comparison results to estimate the origin of faults in the network. Placement of electric motors and bus in the graph is a function of configuration of power that illustrates network connections and demonstrates propagation of fault indices in the network. For example for an electrical network with 3 bus in the highest level and 4 electric motors in each bus (Figure 26), graph of Figure 27 has been conFigured for further studies.

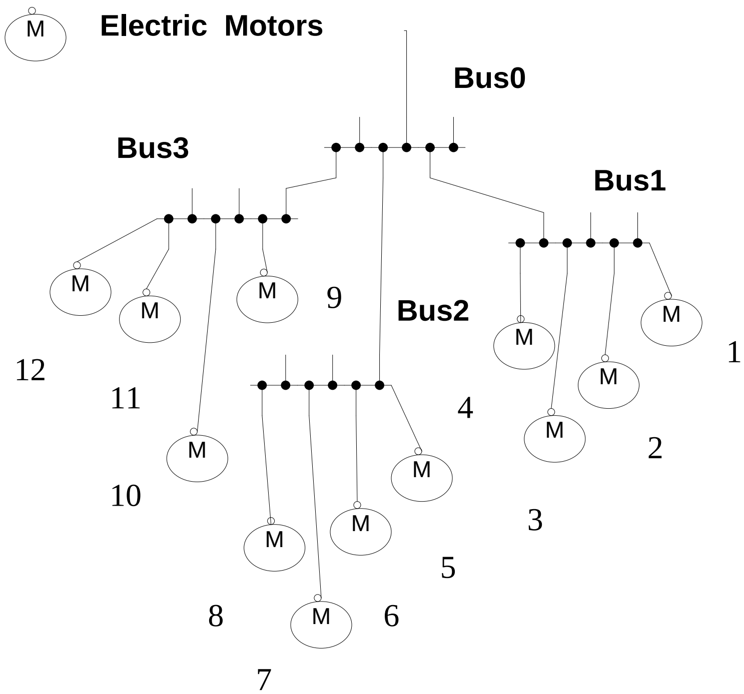


Figure 27 Example of distributed power system with three buses

Figure 27 has been taken as a working example for a typical scaled down distributed power system to simulate behaviour of distributed power systems. In order to demonstrate propagation of fault signals, graphs of propagation patterns have been employed as shown in Figure 27. Here the graph has been divided in three areas to represent three buses. Electric motors have been shown in each area and comparison arrows connect these motors and electric bus to point to the original cause of the fault indices.

Thick green arrows represent transmission of fault signals between bus and point toward estimated source of signals in each pair comparison. Yellow lines illustrate an equal value between two points, or describe a situation where direction of fault signals is not verifiable using propagation equations. Blue (pointing up) and red (pointing down) lines show direction of fault representatives from one motor to another in each bus. Red circles point at the estimated origin of transmitted fault indices in each comparison. And star signs point to the origin of fault signals.

Figure 27 is an example of propagation pattern for a power network with 12 electric motors. In this example all electric motors are similar and the power network is symmetrical and even handed. Details of this network have been discussed in chapter 5. This case study (Case study 1) has been analysed in details in chapter 6 and chapter 7.

For this particular example level of proportional fault indices of fault type 2 are as following:

- In Motor 1, Motor 2, Motor 3 and Motor 4: 1.9
- In Motor 5, Motor 6 and Motor 7: 1.2
- In Motor 9, Motor 10, Motor 11 and Motor 12: 1.8
- In Motor 8: 5.3

Since levels of all motors in Bus 1 are almost the same, according to equations (4-19), (4-33) and (4-38) it is impossible that one generates the signal for other measuring points and hence the signal may be caused by an external source. Similar situations can be observed in Bus 3. Also among motors in Bus 2, Motors 5, 6 and 7 have a similar situation and therefore another motor could cause the signal in these motors. The only candidate is Motor 8. Extra verifications using equations (4-19), (4-33) and (4-38) suggest that Motor 6 is big enough to cause the signal in all electric motors. The simplicity of this case study is due to symmetrical propagation of fault indices which causes symmetrical attenuation of the signals in all electric motors. The verification process can be illustrated using few arrows:

1. Comparing level of signals in Bus 1 and Bus 3:level of signals in Bus 1 is slightly bigger than the level of signal in Bus 3 so Bus 3> Bus 1
2. Comparing level of signals in Bus 1 and Bus 2: level of signals in Bus 1 is smaller than the level of signal in Bus 2 so Bus 1< Bus 2
3. Comparing level of signals in Bus 2 and Bus 3: level of signals in Bus 2 is bigger than the level of signal in Bus 3 so Bus 2> Bus 3
4. All motors of Bus 1 have similar proportional fault indices so they can be connected with yellow lines and without using any arrow
5. All motors of Bus 3 have similar proportional fault indices so they can be connected with yellow lines and without using any arrows
6. Motors 5, 6 and 7 have a similar situation and therefore another motor could cause the signal in these motors. The only candidate is Motor 8. Extra verifications using equations 4-19, 4-33 and 4-38 suggest that Motor 6 is big enough to cause the signal in all electric motors.

Figure 28 illustrates an ideal situation where all arrows point toward one electric motor and there is no preference in ownership of fault indicators in other neighbour bus. Hence Motor 8 can be nominated as the origin of fault 1 with a very high accuracy. In more general situations, a more difficult situation will be expected and numerical calculations may ease out interpreting the propagation results. As shown in Figure 28, the origin of fault signals is discoverable by looking at the direction of arrows. For this particular example association of fault indices with all electric motors are discoverable. However fault indices of Motor 8 and Bus 2 are considerably bigger than the rest of the indices.

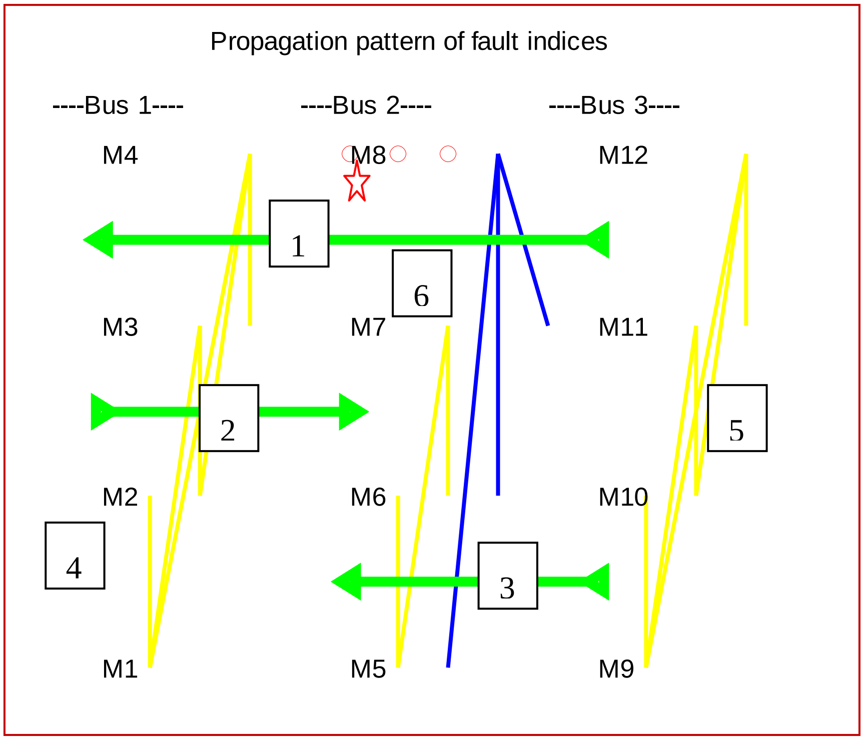


Figure 28 Fault propagation pattern for a uniform industrial network with a fault in Motor 8

As described before, the ideal pattern of diagnosis is where:

a) All arrows point toward one bus as the origin of the signal

b) All electrical motors in the bus point to one motor as the origin of the signal in their motors

c) Propagation formulations suggest no transmission between neighbouring motors in the bus.

These situations advise a reliable diagnosis toward origin of fault indices. However in many situations, propagation graphs may point to more than one motor. Or other directional arrows may suggest fault signal transmission between healthy electrical motors due to presence of noise signals. Numerical solutions may provide an interpretation of the given charts and provide answers with a limited reliability. Also intelligent solutions such as artificial neural networks can improve the reliability of diagnosis by training the network behaviour and elimination of environmental interruptions.

4.12 Summary

This research has formulated a few effective methods of diagnostics for electric motors based on the theory of Motors Current Signature Analysis. Individual diagnosis whenever a single motor is a target is an effective method and may automatically identify the type and strength of faults in electrical motors. Individual diagnosis has some shortcomings for real industry situations where several motors contribute to the existing signals of the target motor. Signal propagation is formulated for typical electrical networks to estimate the attenuated fault signals caused by a fault and validate the originality of fault signals. A method has been proposed to discriminate faults based on signal propagation and identify major faults in electrical networks. Then two numerical methods are demonstrated to deal with a more complicated situation using a numerical calculation.

These diagnostic approaches can be applied together or may be utilized individually. This thesis recommends using an individual diagnosis to identify definite faults in electric motors, use the attenuation factor to double check the originality of signals, and discriminate the fault using the propagation pattern and finally use a numerical method to detect the origin and type of the fault in the discriminated zone. This approach reduces the amount of processing and has a higher accuracy due to applying multiple diagnostic methods at different levels. Model formulations and approaches will be suggested and tested in following chapters.

Chapter 5:

DISTRIBUTED POWER SYSTEM BEHAVIOURAL SIMULATION MODEL

Development of the simulation model and methodology of data collection will be described in this chapter. The typical model of an electric motor, the surrounding industrial environment and motor faults are three major parts of the simulation. These facilitate a method to estimate the behaviour of power networks against in-network fault events. The simulation data then will be verified using a scaled down industrial system with few practical experiments.

5.1 Simulation concept overview

A scaled down distributed power system with multi bus has been taken as a case study. Each motor is provided with a measuring point to monitor its voltage and current signals continuously. The designated sensor for each motor records the trend signal. Duration of samples, frequency of diagnosis and frequency of sampling are subjected to the type and accuracy of diagnosis. Here a case study has been taken as an example. Required settings have been adjusted for the selected case. The current signal will be analysed using frequency spectrums and passed to the diagnostic system. Analysis of this spectrum will identify the possibility of observing fault evidences. Sensors related to a given sub-bus report their observations to their cluster head and the main processing unit collects the information and provides the final decision. Here all components of the model are described thoroughly. The model has been simulated in several stages to verify its functioning and validity of the recorded information. The simulated prototype will then be generalized. The next stage is to pose a fault in the network and capture diagnostic information. This information will then be analysed to identify the pattern of propagation of fault signals, estimate the mirroring signals in each point and provide possible solutions of diagnosis.

5.2 Model of the distributed power system

Several models have been proposed to demonstrate behaviour of induction motors. [44] and [45]. The most common model for induction motors is proposed by IEEE. This model uses fourth order electrical and second ordering mechanical equations to estimate the behaviour of electrical motors. The model describes basic electric and mechanical characteristics of the motor using quadratic equations [45]. IEEE recommends using the following circuit (Figure 29) to estimate behaviour of electric motors.

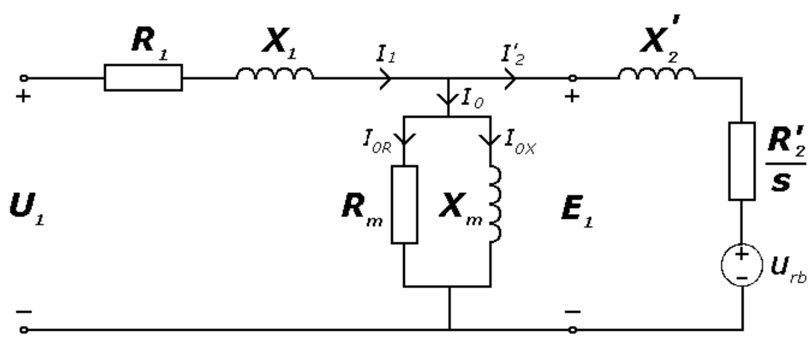


Figure 29 Equivalent circuit of polyphase Induction Machine

Where:

U_1: stator terminal voltage

E_1: stator e.m.f generated by resultant air-gap flux

R_1: stator effective resistance

X_1: stator leakage reactance

R_m: iron core-loss resistance

X_m: magnetizing reactance

R'_2: rotor effective resistance referred to stator

X'_2: rotor leakage reactance referred to stator

u_{rb}: e.m.f due to the saturable iron bridges in the rotor slots

I_0: sum of magnetizing I_{0X} and core- loss I_{0R} current components

I_1: stator current

I'_2: rotor current referred to stator

S: Motor slip (stator speed-rotor speed)/(stator speed)

Figure 29 is resulted from the following quadratic formulations. (5-1)

$$\frac{dF_{qs}}{dt} = \omega b\left[v_{qs} - \frac{\omega}{\omega b} F_{qs} + \frac{r_s}{x_{ls}}\left(\frac{x_M}{x_{lr}} F_{qr} + \left(\frac{x_M}{x_{ls}} - 1 \right) F_{qs} \right) \right]$$
$$\frac{dF_{ds}}{dt} = \omega b\left[v_{ds} + \frac{\omega}{\omega b} F_{qs} + \frac{r_s}{x_{ls}}\left(\frac{x_M}{x_{lr}} F_{dr} + \left(\frac{x_M}{x_{ls}} - 1 \right) F_{ds} \right) \right]$$
$$\frac{dF_{qr}}{dt} = \omega b\left[-\frac{\omega - \omega r}{\omega b} F_{dr} + \frac{r_r}{x_{lr}}\left(\frac{x_M}{x_{ls}} F_{qs} + \left(\frac{x_M}{x_{lr}} - 1 \right) F_{qr} \right) \right]$$
$$\frac{dF_{dr}}{dt} = \omega b\left[\frac{\omega - \omega r}{\omega b} F_{qr} + \frac{r_r}{x_{lr}}\left(\frac{x_M}{x_{ls}} F_{ds} + \left(\frac{x_M}{x_{lr}} - 1 \right) F_{dr} \right) \right]$$
$$\frac{d\omega r}{dt} = \frac{P}{2J}\left(T_{em} - T_{mech} \right)$$
$$T_{em} = \frac{3}{2}\frac{P}{2\omega b}\left(F_{ds} i_{qs} - F_{qs} i_{ds} \right)$$

Where

d: direct axis,

q: quadrature axis,

s: stator variable

r: rotor variable,

F_{ij}: the flux linkage (i=d or q ;j=s or r),

r_r: rotor resistance,

r_s: stator resistance,

x_{ls}: stator leakage reactance,

x_{lr}: rotor leakage reactance,

P: numbers of poles,

T_{em}: electrical output torque,

T_{mech}: load torque,

ω_e: stator angular electrical frequency,

ω_b: motor angular electrical base frequency,

ω_r: rotor angular electrical speed.

The specified model illustrates normal operation of electric motors with a good approximation. IEEE model has been employed using MATLAB to simulate behaviour of induction motors. In order to consider impact of mechanical faults in the proposed model, a block of fault has been integrated in model of electric motors.

As described in Chapter 4, section 4.3, a set of magnitude- frequencies that is proportional to the strength of faults can be utilized to model internal faults of electric motors. Equation (4-7) in chapter 4 describes the MCSA formulations to locate fault frequencies in the spectra of current waveforms. Frequency configurations of current spectrums of fault indicator signals have been estimated in equations (4-1) to (4-18) of the literature review chapter. By utilizing these formulations a set of parallel voltage sources in conjunction to appropriate impedances can cause a situation similar to incident of fault conditions. Figure 30 shows a model of an induction motor that is integrated with model of an internal fault.

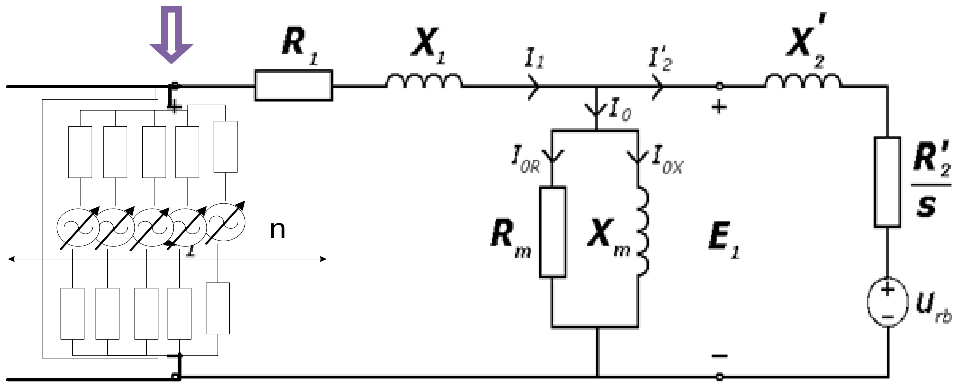


Figure 30 Model of induction motor in conjunction with fault model to describe MCSA faults

One of the limitations of the IEEE model is its shortcomings in event of voltage drops. This problem has been resolved by monitoring electrical torque and the motor speed for each experiment. Steady speed and constant torque during a period of time; verify the correctness of the measurement.

Here MATLAB simulation toolbox has been employed to simulate behaviour of induction motors in event of MCSA faults. As discussed before, three phase low voltage squirrel induction motors are the main load in most industrial sites. Therfore, 7.5kW/400V induction motors have been taken as the default value for electric motors in each case study.These motors have been loaded via different mechanical torques.

This model initially has been employed to observe behaviour of electric motors in faulty conditions. Then the model has been altered to generalize the results over a group of induction motors.

Equations (4-1) to (4-18) of chapter 4 have been employed to model motors faults. MCSA faults have been modelled as a set of frequency- magnitude pairs with a series impedance to limit and control fault signals. Fault models (2.A) will be included in model of the target motor to observe the behaviour of the network in abnormal situations (See Figure 31).

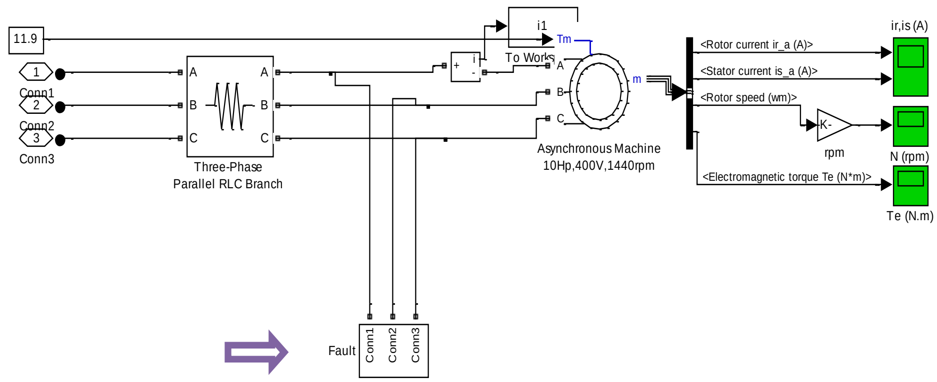


Figure 31 Fault model as a combination of several voltage sources with series impedance

Currents of electrical motors have been recorded using a set of variables for a period of three seconds with resolution of 25000 readings per second. Then the first two seconds of the recorded data will be eliminated from the waveform to cancel the influence of start-up transients. The remaining data is compatible with resolution and accuracy of Tektronix signal analyser which has been used to store current waveforms in practical experiments. This resolution is excessive compared to frequency of fault signals. The data acquisition tool does not provide the option to reduce the signal resolution therefore, all measurements have been provided with the same sampling rate. During each experiment, current, torque, speed and supply voltage of each electric motor is recorded to verify validity of experiments. The current signals are only signal utilized for process of fault detection and diagnosis.

Current, torque, speed and the supply voltage of one of electric motors are shown in Figure 32 and Figure 33.All measurements have been recorded with baud rate of 25000 samples per second.

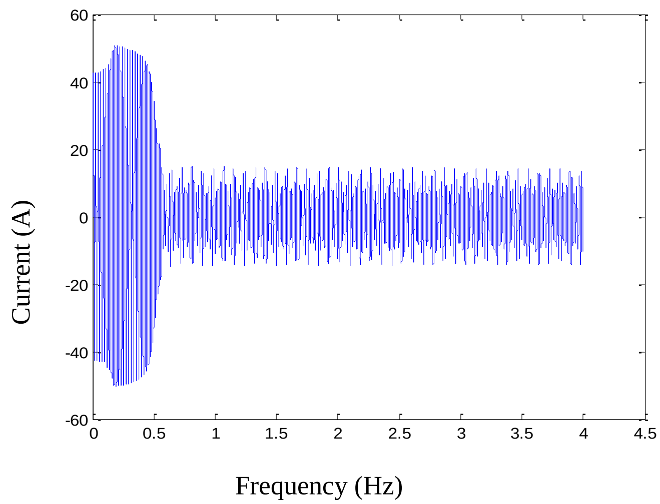


Figure 32 Current waveform of a single motor running individually

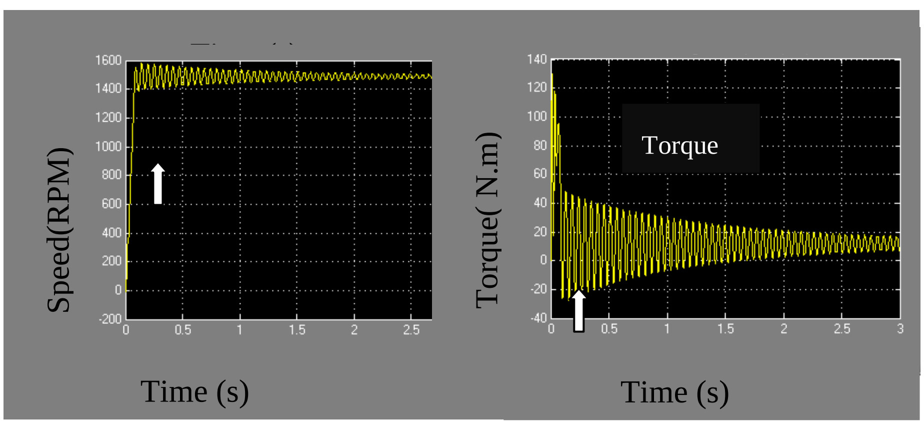


Figure 33 Measurer of speed and torque for the simulated electrical motor

As shown in Figure 32 and Figure 33 the first few seconds are involved in startup transients. These transients may manipulate fault signals therefore; first two seconds of all current waveforms will be eliminated. Analysing components of electrical waveform in absence of transient behaviour eases out the signal processing and pattern recognition. Frequency spectrum of healthy functioning of the sample motor has been shown in Figure 34. Then a fault is inserted in a model of the electric motor. A frequency spectrum of a motor while running with a fault is shown in Figure 35.

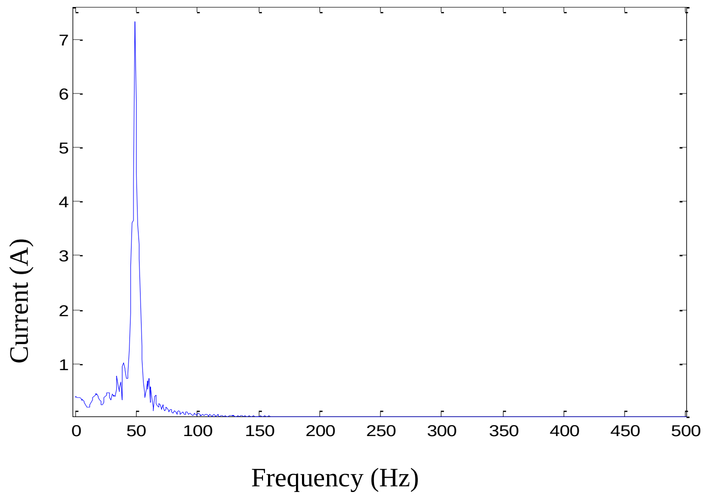


Figure 34 Frequency spectrum of the sample electric motor in healthy operation

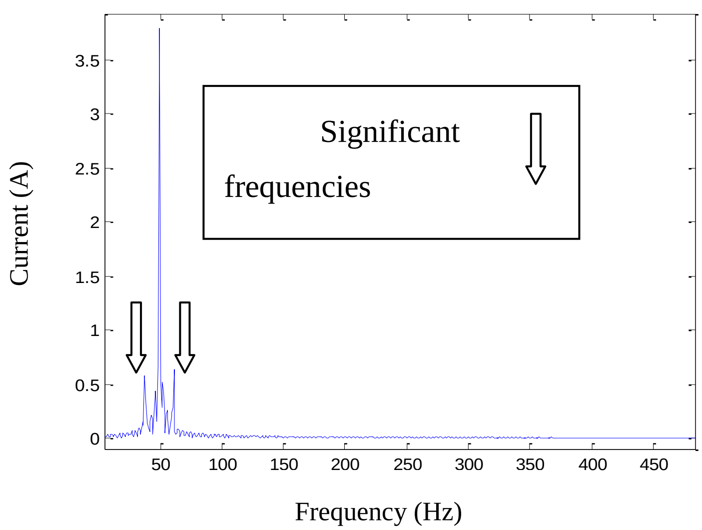


Figure 35 Frequency spectrum of the sample electric motor while a fault model inserted in model of the electric motor

As shown in Figure 34 and Figure 35, the simulation model successfully produced the fault pattern for the sample motor. This model then will be extended to a group of electric motors working in different locations of a typical industrial network.

5.3 Multiple motors in a bus

In order to simulate propagation of fault signals in industrial power networks a combination of multiple electric motors has been taken as a working model. A set of electric motors is connected to each bus. Then a number of consumption buses are connected to the main bus which is supplied by a supply bus. Figure 36 shows the simulation model for a consumption bus with four motor subsystems.

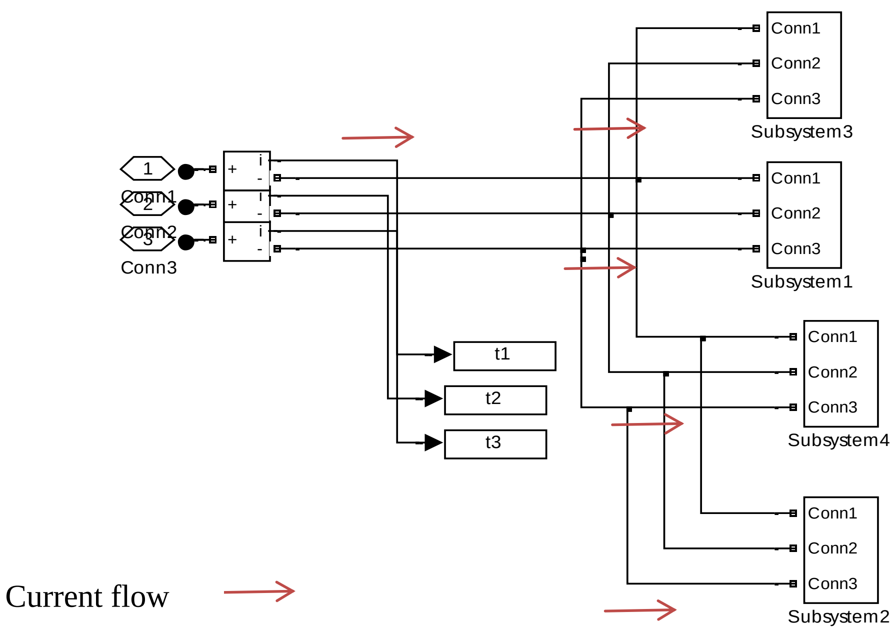


Figure 36 Model of multiple electric motors in a bus

Electric buses are electric conductors which carry current of a group of electrical appliances and make a common connection between several components. They always have a very low resistance compared to network connections. Therefore attenuation influence of bus can be neglected. Bus aggregate and supply current of electric motors via (a) supplying cable(s) connected to the bus. Current passing from the bus is the sum of currents of all electric motors supplied by the bus. For example for Bus 1:

Magnitude of each frequency band in current spectrum of the supplied current is sum of magnitude of all currents for particular frequencies.

$$M_{\text{Bus }1} = M_1 + M_2 + M_3 + M_4 + .. + M_n \tag{5-2}$$

Where:

M_n: is Magnitude of a particular frequency point of the current waveform

On the highest level, three subsystems have been connected to the generation bus via different media. There is a static load of 1MW parallel with other subsystems to simulate the normal industrial situations (Figure 37).

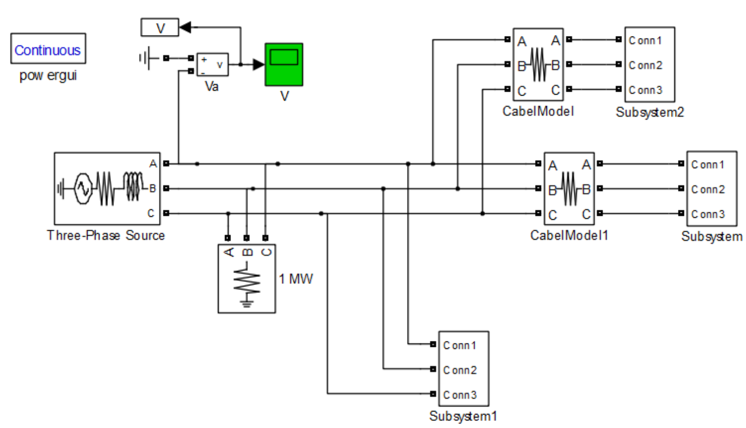


Figure 37 Overview of the simulation model (the Network Model)

As described earlier, the system may be extended by duplicating segments systematically, therefore the model can be assumed as a typical system for nearly all linear industrial networks. Details of the simulation model are given by APPENDIX II. Standard framework of load flow analysis has been used to calculate, voltage and current around the network. Details of Matlab simulation methodology are achievable from [44].

5.4 Frequency analysis and power spectrum

As explained in the theory chapter, in order to find fault indicators, frequency spectrums of current signals have to be calculated. Here Fast Fourier Transform with a limited number of samples per time, is employed to estimate frequency spectrums of current signals. 100ms of data with sampling rate of 25000 samples per second has been taken as a sample for frequency transforms. This selection allows identifying minimum frequency of 10Hz (One whole wave) and up to 2500Hz with a minimum approximation of 10 samples per each cycle. 25000 samples per second have been selected to keep the compatibility between simulation results and the data acquisition system in practical experiments.25000 samples per second is higher than the needed frequency resolution. This selection is to keep up a correspondence with accuracy of the dedicated data acquisition system for practical experiments.

Since fast Fourier transform (FFT) generates complex numbers, the absolute value of the each frequency point has been utilized to identify fault signals in frequency spectra. As an example, frequency spectrum of the model explained in Figure 37 has been shown in Figure 38.

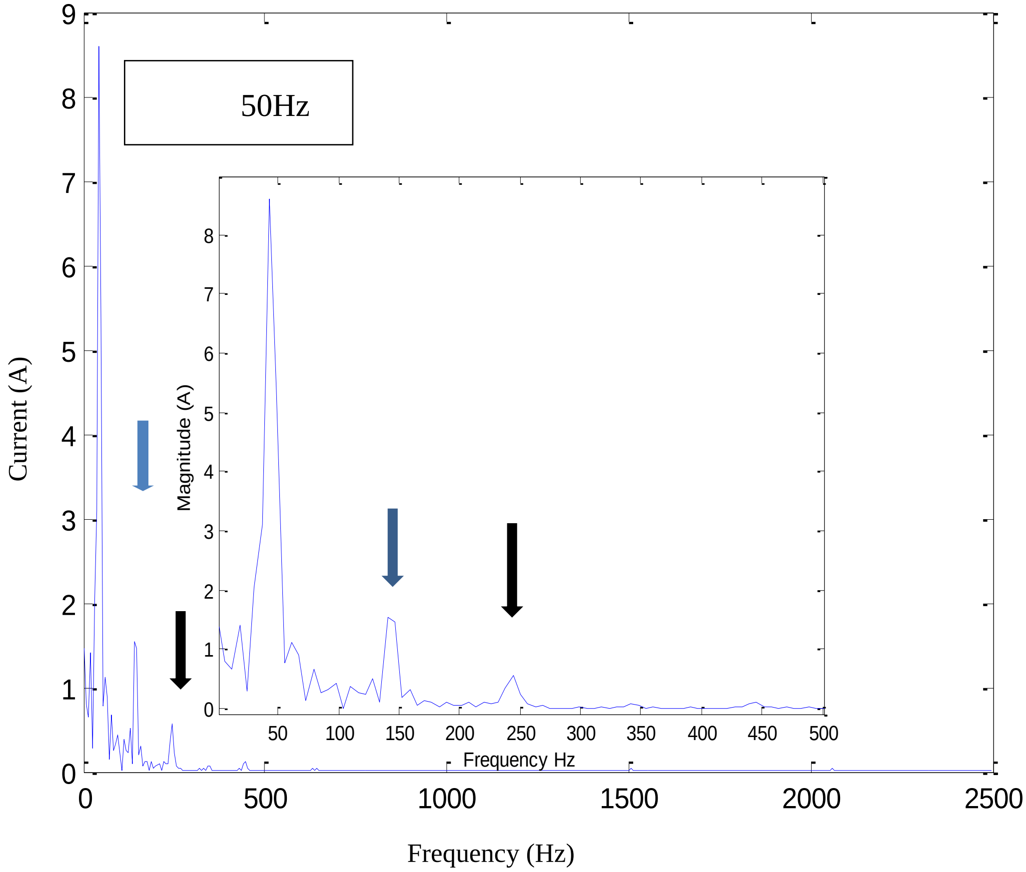


Figure 38 power spectrum of the current signal

As shown in Figure 38, all fault signals are observed around 50Hz, which is caused by normal operation of the electric motor. However two fault frequency points are located 25Hz lower and 25Hz higher from the nominal frequency. This is a potential indicator of a mechanical fault.

As shown in Figure 38, no fault signal is observable in the extended view. Therefore a limited band of frequencies (the interior graph) is satisfactory of the group of selected motor faults. Extended view of frequency is appreciated in event of high frequency faults e.g. cavitations incidents.

Another faulty waveform has been shown in Figure 39. As shown here three fault frequency points are observable in waveform of electric motor No 1.

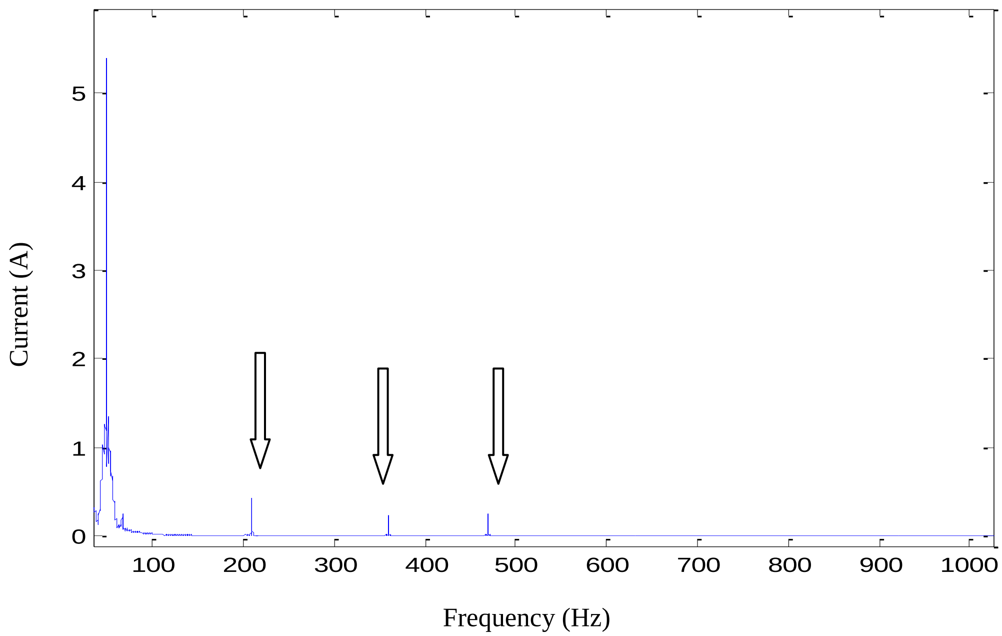


Figure 39 Frequency spectrum of current waveform of the faulty motor

Here a fault model has been inserted in model of an electric motor. This variation is the direct influence of a mechanical fault (See Figure 40), that causes unhealthy operation of the motor. Here fault has been modeled as a set of frequency components. Inserting external frequency components manipulates the incoming voltage and alters characteristics of the supplied voltage. As shown in Figure 40, manipulating current and voltage of bus using fault models influences mechanical characteristics of electric motors. This phenomenon produces a similar alteration in practical situations.

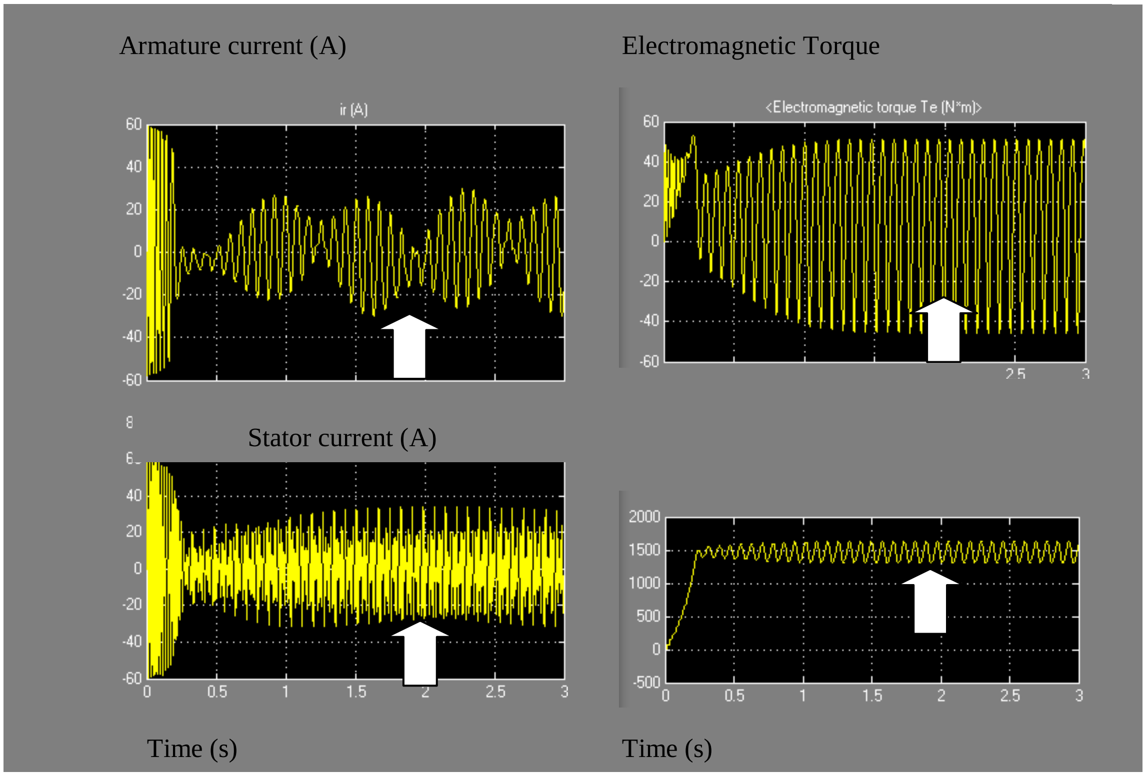


Figure 40 Waveforms of a) rotor current, b) stator current, c) electromagnetic torque and d) the motor speed for a typical electric motor in the faulty mode.

As shown in Figure 40, rotation speed and electromagnetic torque are in an acceptable level despite the oscillation caused by the fault model. On the other side, current interruptions due to presence of fault signals are observable in both starter and rotor currents. This observation satisfies the verification process as explained in the previous section. Negative speed or pulsing electromagnetic torques are example of occurrence of fault in the simulation model and hence are failure in verification of the simulation system.

Current spectra of all electrical motors supplied via Bus 1 have been shown in Figure 41. A fault is integrated in Motor 1 and frequency spectrums of electric motors have been estimated using simulation.

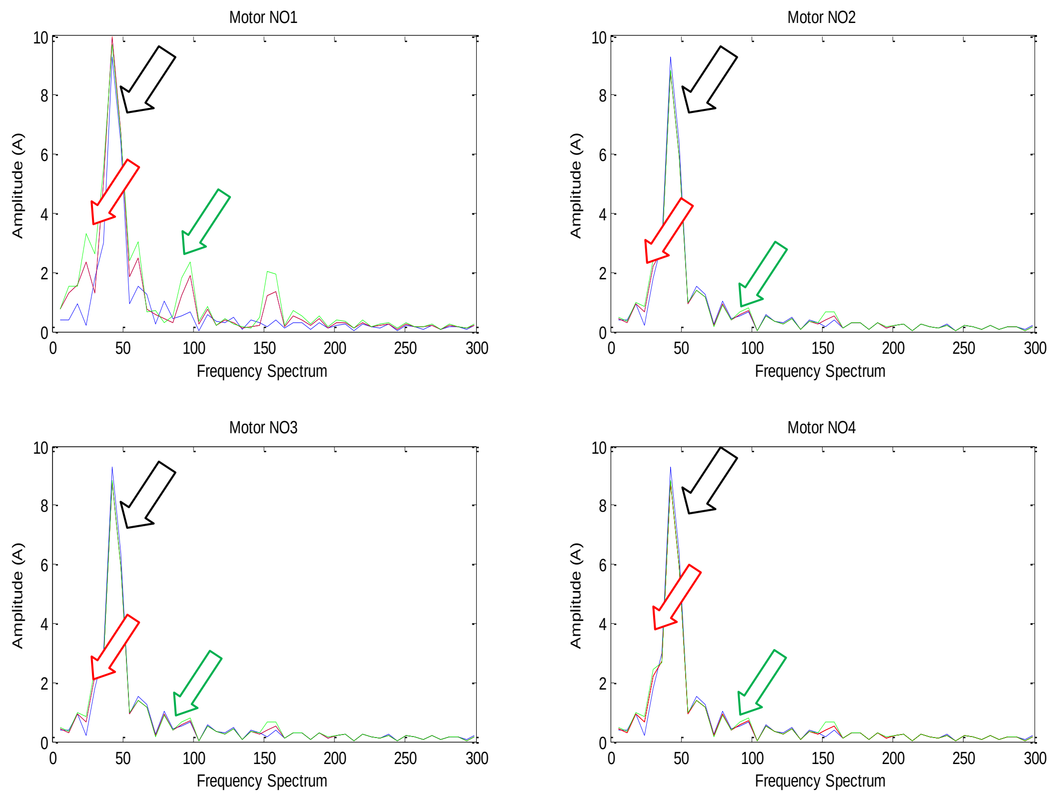


Figure 41 Current spectrum of a simple industrial model with 4 similar electrical motors is shown, Blue: all healthy, Black with a minor fault in Motor 1, green a more serious fault in Motor 1.

As shown in Figure 41, there are several abnormalities that are observable in waveform in the target electric motors. Also Current manipulations in other electric motors are observable as an indirect influence of incidence of fault.

Referring to Figure 41, the fault in Motor 1 is observable in other electric motors. However the fault signal has a greater observation in the target motor. Propagation of fault signals may result in false warnings in in-network equipment. Any process of fault diagnosis will be more reliable using the network approach. Also as explained in the previous section, altering network topography may change mechanical and electrical waveforms of each electric motor in the network. Figure 42 demonstrates variation of the rotor current, stator current and speed of the target motor in the network.

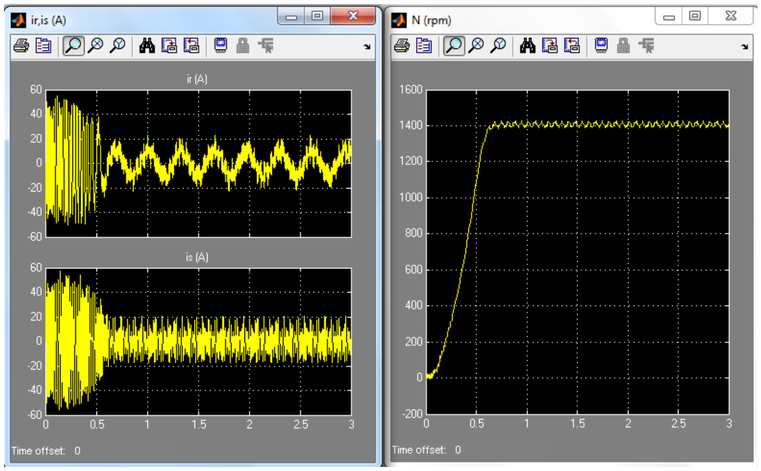


Figure 42 Waveforms of rotor current, stator current and the motor speed for a group of electrical motors (fault incident in Motor 1.)

Any linear industrial scenario can be simulated by duplicating segments of the described model. Here a scaled down industrial model is taken as an example to evaluate signal propagation and also to formulate fault diagnosis via distributed processing.Considering behaviour of motors and bus in response to a fault model and assuming that one motor is the source of a fault with different strength, various conditions can be expected. Matlab Simulink has been employed to validate the concept of distributed diagnosis in industrial networks.

In this simulation, two types of major faults are investigated in a typical industrial network: rotor asymmetry and rotor unbalanced faults. Therefore, two fault indices are defined to evaluate strength of fault events throughout the power networks:

F1: index of association of the suspected electric motor with fault type 1 (Rotor Asymmetry)

F2: index of association of the suspected electric motor with fault type 2 (Rotor Unbalanced)

These indices provide evaluation factors to identify involvement of faults with a set of electric motors with suspected faults. The methodology to calculate fault indices has been demonstrated in chapter 4.

Chapter 6:

RESULTS ON MODELLING FAULT PROPAGATION OVER THE NETWORK

6.1 Introduction

This chapter targets at evaluation of the concept of distributed diagnosis using simulation results. Atypical scaled down distributed power system has been shown in Figure 43. The system will be employed to simulate behaviour of distributed power systems while a system component is associated with a faulty behaviour. The model consists of a scaled down industrial power cluster and a sensor network to collect the acquired information, analyse the primary results and pass pre-processed information to the main processing unit. Modelling and simulation approaches for each component of the system have been explained in the previous chapter.

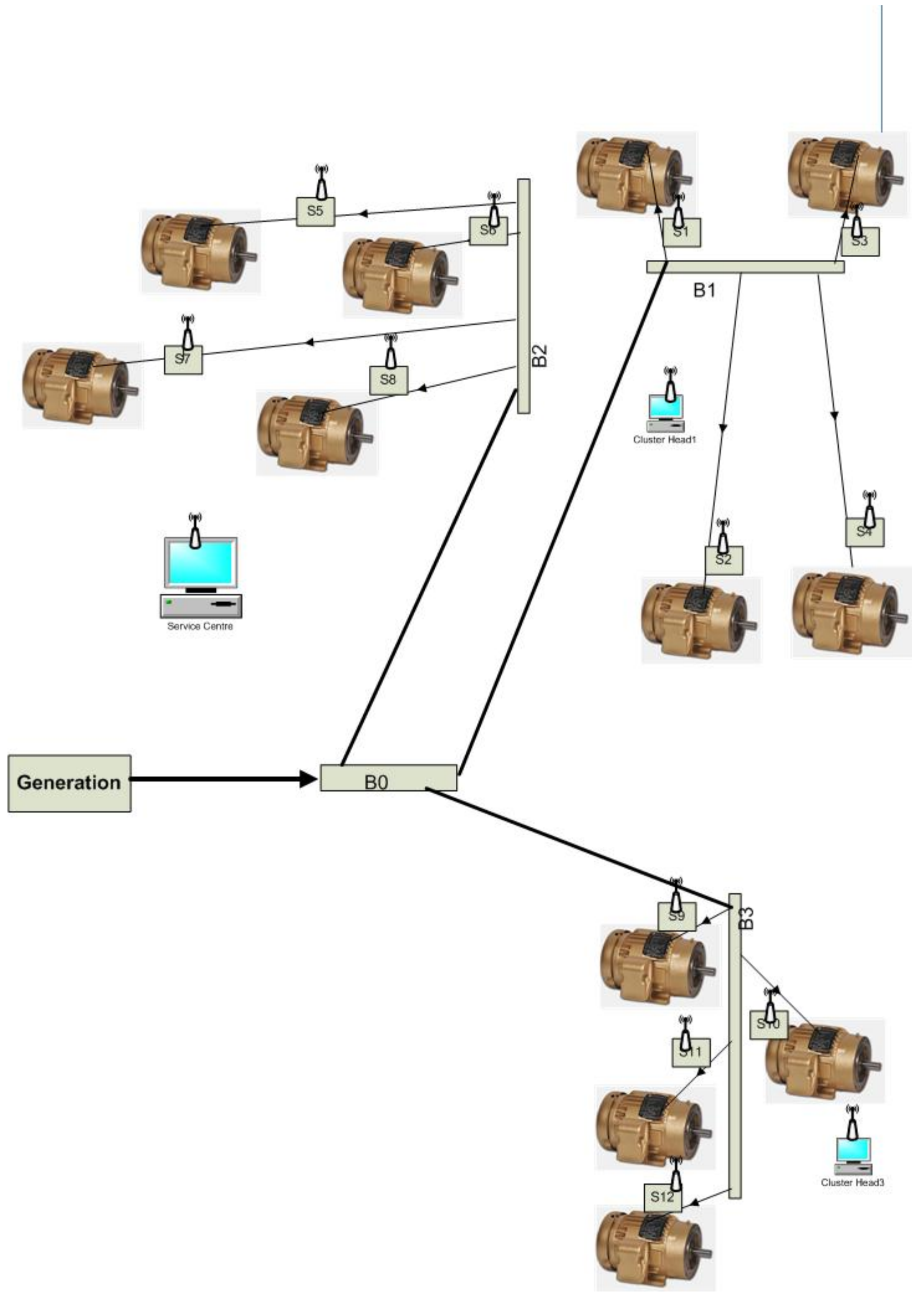


Figure 43 General structure of the simulation model as described in chapter 3

As discussed in chapter 3, each fault is defined by a predetermined signature spectrum. Each signature is a combination of multiple frequency points with a given magnitude. Prefect observation of a fault is appearance of all components of the fault signature as dominant frequencies of electrical motors. However in reality, fault signals may be attenuated in different ratio also extra significant points may influence the signals due to presence of noise. Therefore a methodology is required to discriminate noise signals with original components of the signature and detect the type and cause of the fault in each situation.

This simulation covers a wide range of industrial configurations. The study has taken into consideration that there are various industrial topographies. This also considers the fact that there is a range of industrial faults that may be associated with any electric motor and a number of case studies have been selected to cover a wide range of faults in small scaled industrial sites. These simulation target linear situations where no more than two faults appear simultaneously in the network.

Size of electric motor, types of faults, speed of the faulty motor, and configuration of the simulation model are acting variables in this simulation. Altering these indices and changing the location of the faulty motor produces multiple observation of fault incidence. Here different types of fault signatures have been tested in a uniform network with similar motors, uniform network with different motors, dissimilar motors and configurations, two similar faults in different locations and two different faults in different locations have been employed to analyse propagation of fault signals and possibility of fault diagnosis within the given network.

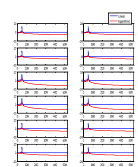
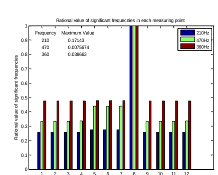
This chapter describes and debates propagation of fault signals throughout the network and behaviour of induction motors in response to occurrence of a fault in a different location. The next chapter utilises results of this chapter to diagnose the cause and type of the fault using theory of distributed fault diagnosis.

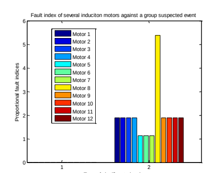
In this chapter, impact of a faulty motor in frequency spectrums on other electric motors will be simulated. All other electric motors are considered healthy at time of measurement. As described earlier, a model of 12 electric motors in three main subsystems has been employed for simulations. This experiment has been repeated to cover several situations as detailed in the following sections

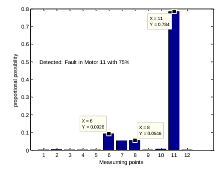
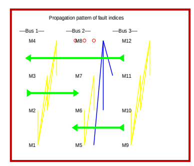
6.2 Software implementation

Following MATLAB programs have been implemented to implement the concept of distributed signature analysis and perform thesis tasks.

Table 6 List of MATLAB programs to implement thesis tasks

Filename	Function	Example of use
Showoneof	To show linear and logarithmic frequency spectrums of all motors of the site	Figure 45 
showspect.m	To evaluate and illustrate value of specific signals with known frequency points in different measuring points	Figure 47 

sppy.m	To estimate involvement of a fault frequency point in three known faults using the process of pattern recognition. To calculate fault indices for a given waveform by categorizing fault frequency-magnitude pairs and passing them to SPPY	
Patarz.m	Identify significant points and pass them to SPPY to calculate fault indices	
Challenge1.m	To load simulation variables, organize them and calculate fault indices using **Patarz.** This program is employed to calculate fault indices manually	Figure 62 
Challengecon2.m	To run simulation files automatically, produce fault indices using patarz and saving organized fault indices in a file. This program is used to generate training information for the neural network	

nnexSome4.m	To form and train a neural network to estimate the fault location in the network. This program uses Challengecon2.m to collect information. The network then can be reused by other applications to estimate different case studies.	
Testnn.m	To use the neural network formed and trained by nnexSome4.m to find the fault in different case studies.	Figure 72 
chart1.m	To illustrate propagation of fault indices from one location to another location and estimate the fault location based on the propagation pattern. This program requires challenge1.m to run before execution	Figure 63 

As shown in Table 6, a number of MATLAB programs have been implemented to perform the thesis tasks. These programs are attached in Appendix III.

6.3 Single incident

Single incidences of faults are the most common situation in most small scaled industries. While in large scaled distributed power systems the network is usually involved in sets of different types of faults with different levels of severity. In this section different faults with different topographical configurations have been discussed to verify the usability of the approach of distributed diagnosis.

6.3.1 Uniform network

Initially a uniform industrial network has been simulated with following specifications:

Impedance of each electrical motor to the main bus is set to1 Ω resistance and impedance of each bus to the main bus is set to $0.6\ \Omega$(resistive)and 0.6Ω(inductive).

The network model has been shown in Figure 44.

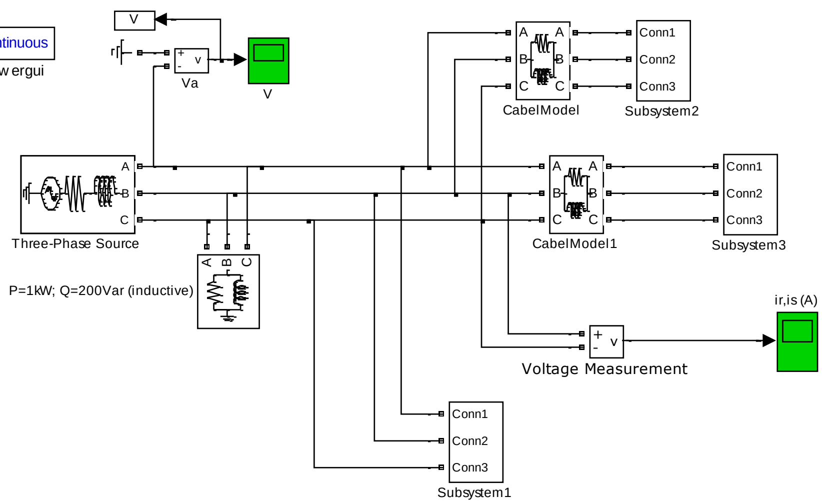


Figure 44 Primary model of unique simulation model (EH1.mdl)

Current spectrums of all electric motors before occurrence of any faults have been shown in Figure 45.

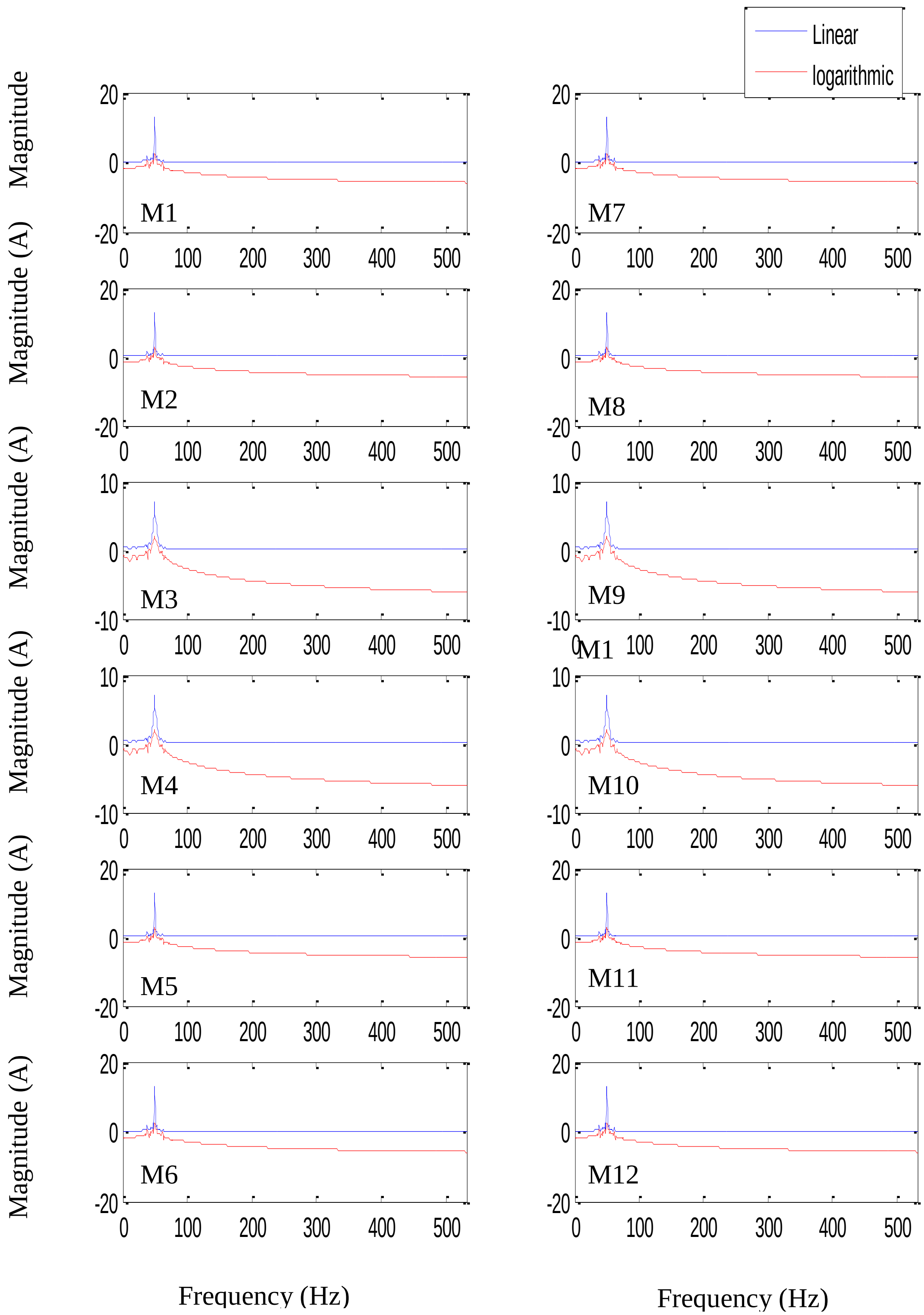


Figure 45 Current spectra of electric motors in a healthy and uniform network(Different loading)-Case study 1

As shown in Figure 45, all waveforms are similar and there is no abnormality observable in frequency spectrums of electric motors. The only significant point appears at 50Hz which is the nominal frequency of the network.

Now an imperfect representative signal for fault type 2 has been formed and inserted into Motor 8 with following specifications:

Voltage	Phase	Frequency
170	0	210
190	0	470
167	0	360

(Current indicators of Fault 1)

As shown in Figure 46, this fault has an observable impact on current spectrums of all electric motors. This is due to propagation of fault signals through the network.

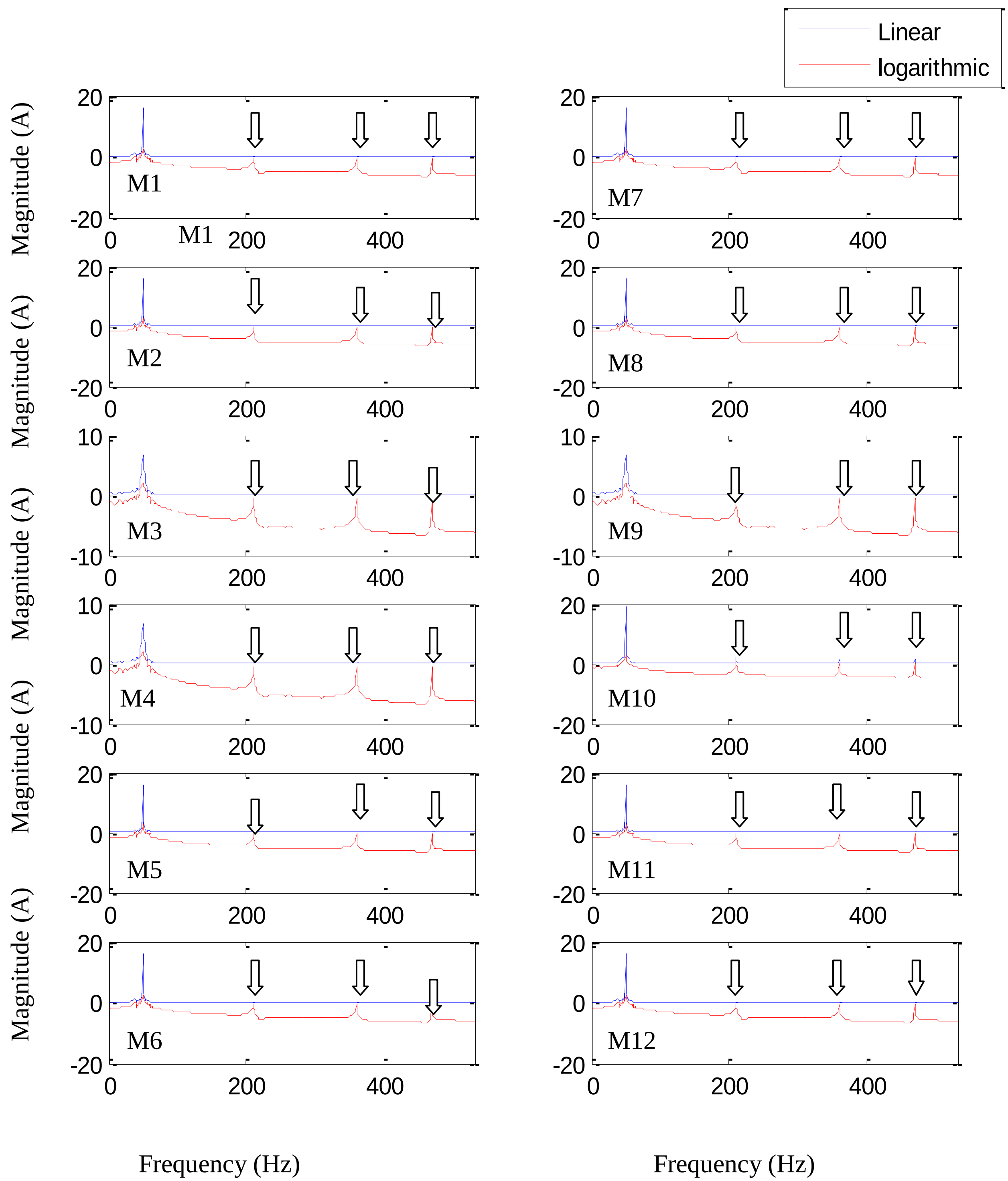


Figure 46 Current spectra of electric motors in a symmetrical industrial system with a fault in Motor 8

Magnitude of fault signals at each measuring point is shown in Figure 46.Figure 47 provides competitive information about the fault while Figure 46 addresses overall waveform components of each measuring point. Combination of these two Figures provides a bigger picture to judge degree of association of each measuring point with the inserted fault.

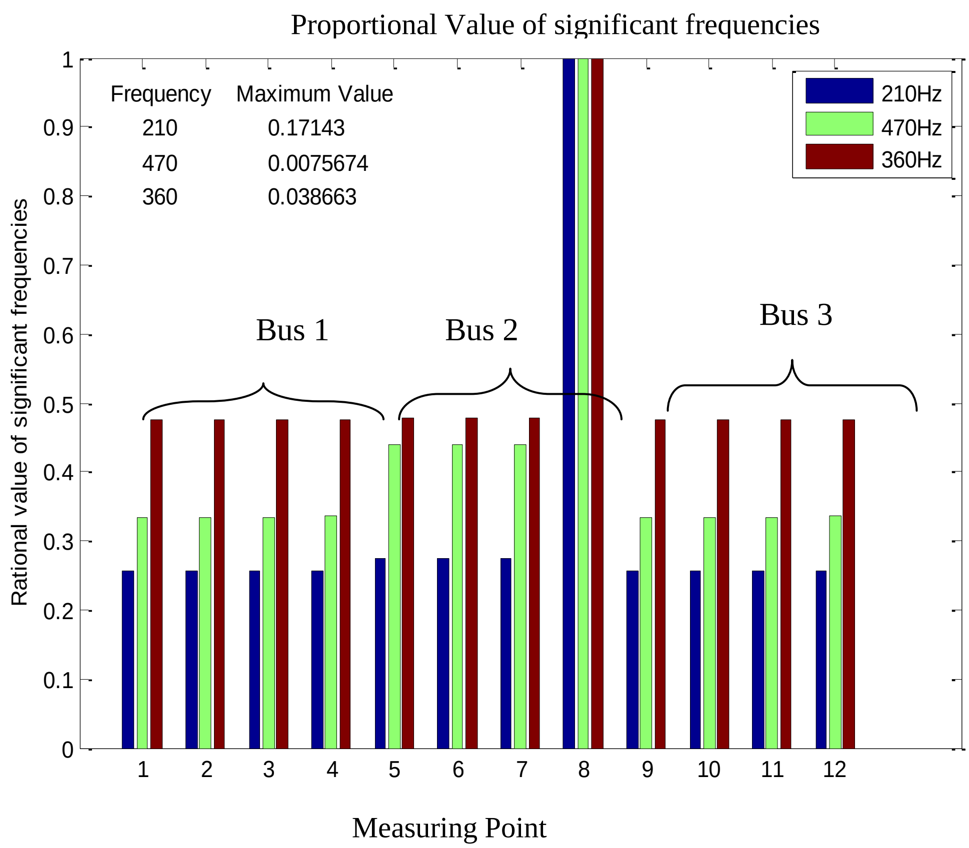


Figure 47 Proportional value of fault frequencies at each measuring point in a uniform network (Motor 8 is faulty) - Case study 1

Referring to Figure 47, the magnitude of fault signals in the Motor No. 8 is dramatically higher than levels of signals in other motors. Also the level of propagated signals remains the same in motors of healthy bus. This behaviour is the perfect match for propagation of fault signals as described in chapter 3. Therefore using a simple comparative analysis, Motor 8 can be detected as a perfect candidate for the origin of the fault demonstrated in Figure 46 and Figure 47. These signals can be eliminated from waveform of all other motors for further behavioural analysis. Evenhanded behaviour of the network is due to similarity of the network which eases out estimating attenuation of fault signals throughout the network.

6.3.2 Unsymmetrical industrial power system- Case study 2

Here a more general industrial power network is simulated. In this network similar to Case study 1, all electric motors are similar. But they have been connected to supply bus via dissimilar connections with unsymmetrical impedances [File: eh2.mdl].

Frequency spectrums of all electric motors in healthy mode have been shown in Figure 48. As illustrated here, change of connections may make a considerable alteration in frequency spectrums of current signals. These frequency points may be confused with fault indicators and cause misdiagnosis. This will be investigated in the next chapter, that current waveform assumed as a random observation of an industry site.

Now a similar fault representative with half of the strength of fault 1 has been integrated in model of Motor 3. The inserted fault representatives are smaller than the previous case study and hence smaller alteration in frequency spectrum of electric motors is anticipated.

Figure 49 demonstrates magnitude of fault signals throughout the network. Here, unlike the previous case study, fault signals are not visually observable in current spectrums of most electric motors. There is no noticeable interference among other electric motors.

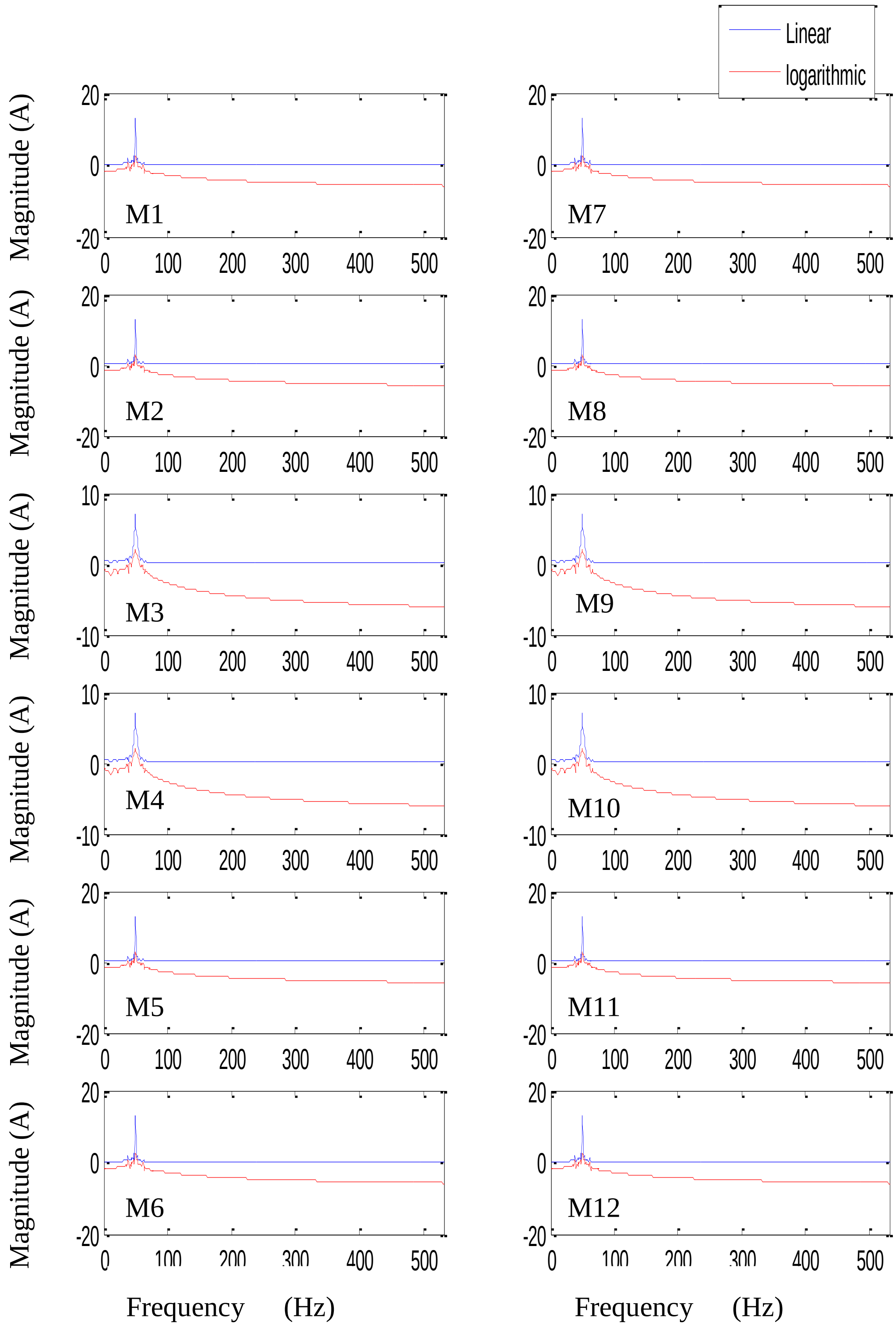


Figure 48 Frequency spectra of a model of similar motors in an unsymmetrical network

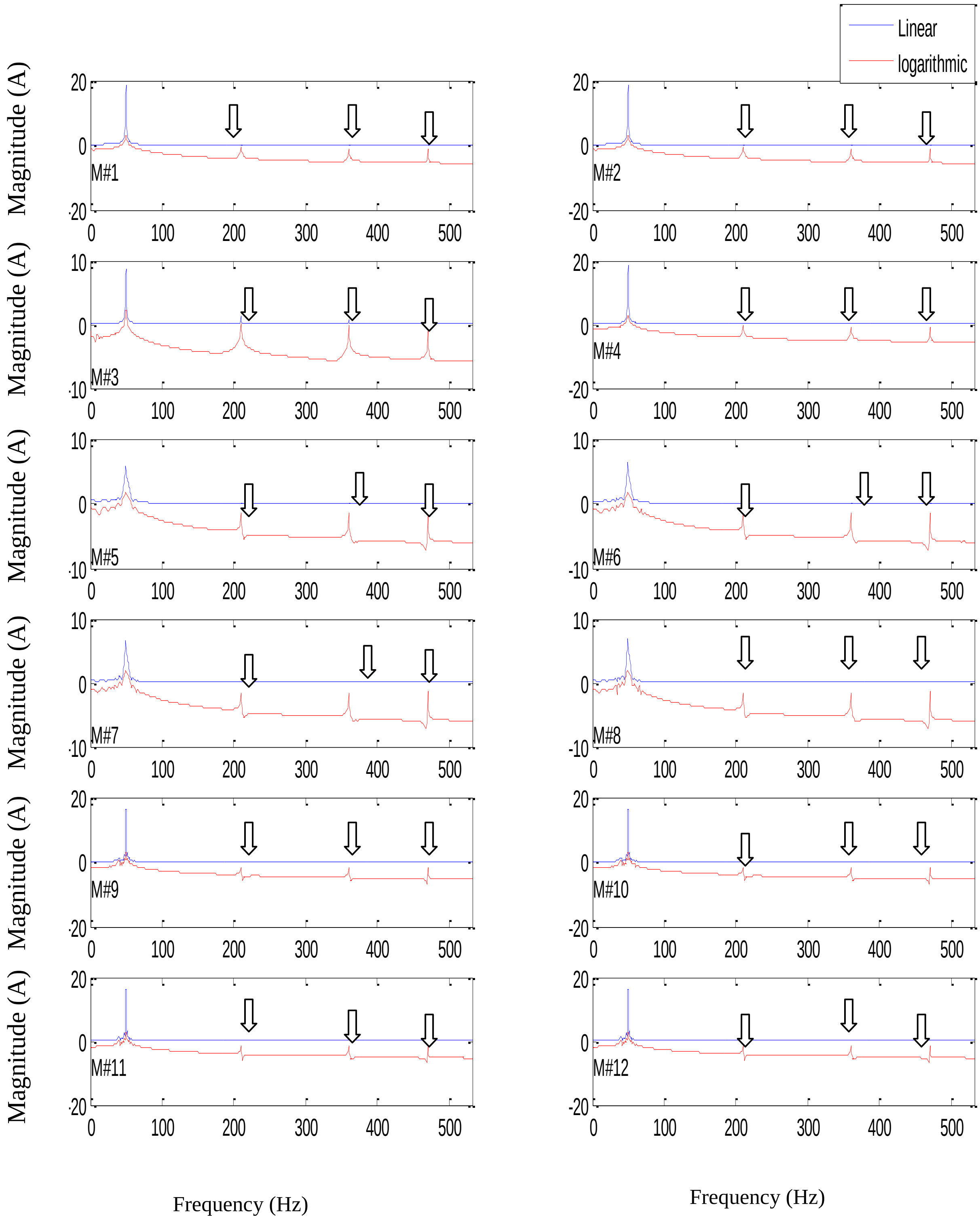


Figure 49 Current spectra of electric motors in an unsymmetrical industrial system with a fault in Motor 3

In order to compare magnitude of fault signals and evaluate the level of signals with the anticipated pattern of propagation, magnitude of signal components of the inserted fault has been shown and drawn in Figure 50.

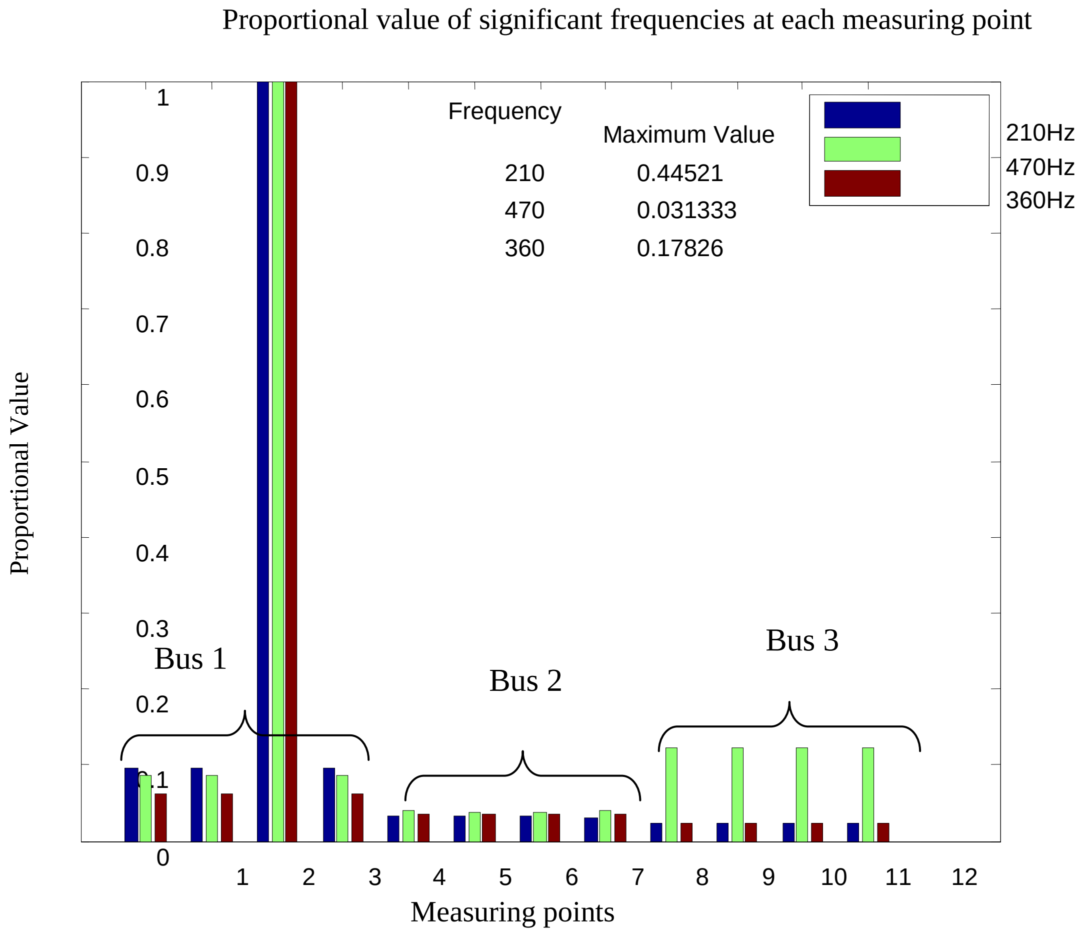


Figure 50 Proportional value of fault frequencies at each measuring point- Case study 2

Similar to the previous case study, all frequency components of the fault have similar behaviour and their level stays the same in healthy bus. Magnitudes of frequency components of the fault are noticeably higher than magnitudes of signals in other electric motors. All evidences clearly indicate that all fault signals are originated from Motor 3.

From observation of Case study 1 and 2 it can be concluded that networks with similar components usually have a linear behaviour and the only acting variables in attenuation of fault signals are impedance of the signal path and placement of the measuring point in the network. As shown in Case study 1, major faults result in interference in captured signals and hence misdiagnosis while small and less severe faults may have no visual observation in current signals of other motors.

6.3.3 Dissimilar machines- Case study 3[eh3.mdl]

In order to extend coverage of simulation, more general conditions with different electrical motors will be investigated. As shown in Figure 51, current of electrical motors varies from 6A to 50A.

Referring to Figure 51, many abnormal frequency points are observable in current spectrums of healthy motors. Magnitudes of significant points are considerably bigger than fault frequency points in Case study 2. As discussed in section 2, these frequency signals make the process of diagnosis more difficult.

Here two types of faults are tested to analyse attenuation of fault signals and verify detestability of the fault in each situation.

Firstly, fault 1 is integrated in Motor 11 to observe the response of electric motors in event of fault incidents.

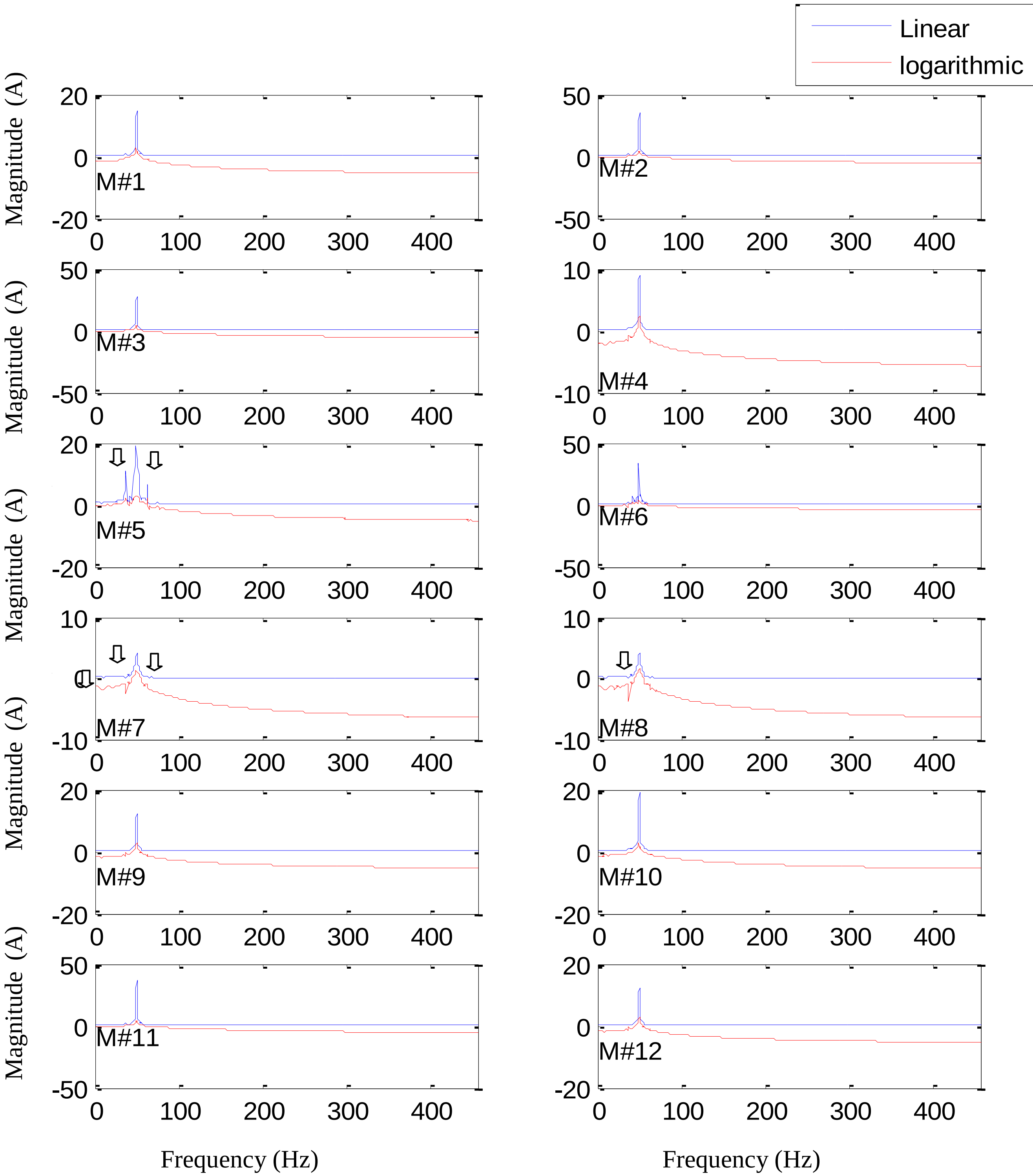


Figure 51 Current spectra of healthy electric motors of Case study 3. All motors are induction and squirrel cage but with different power rating and different loading condition

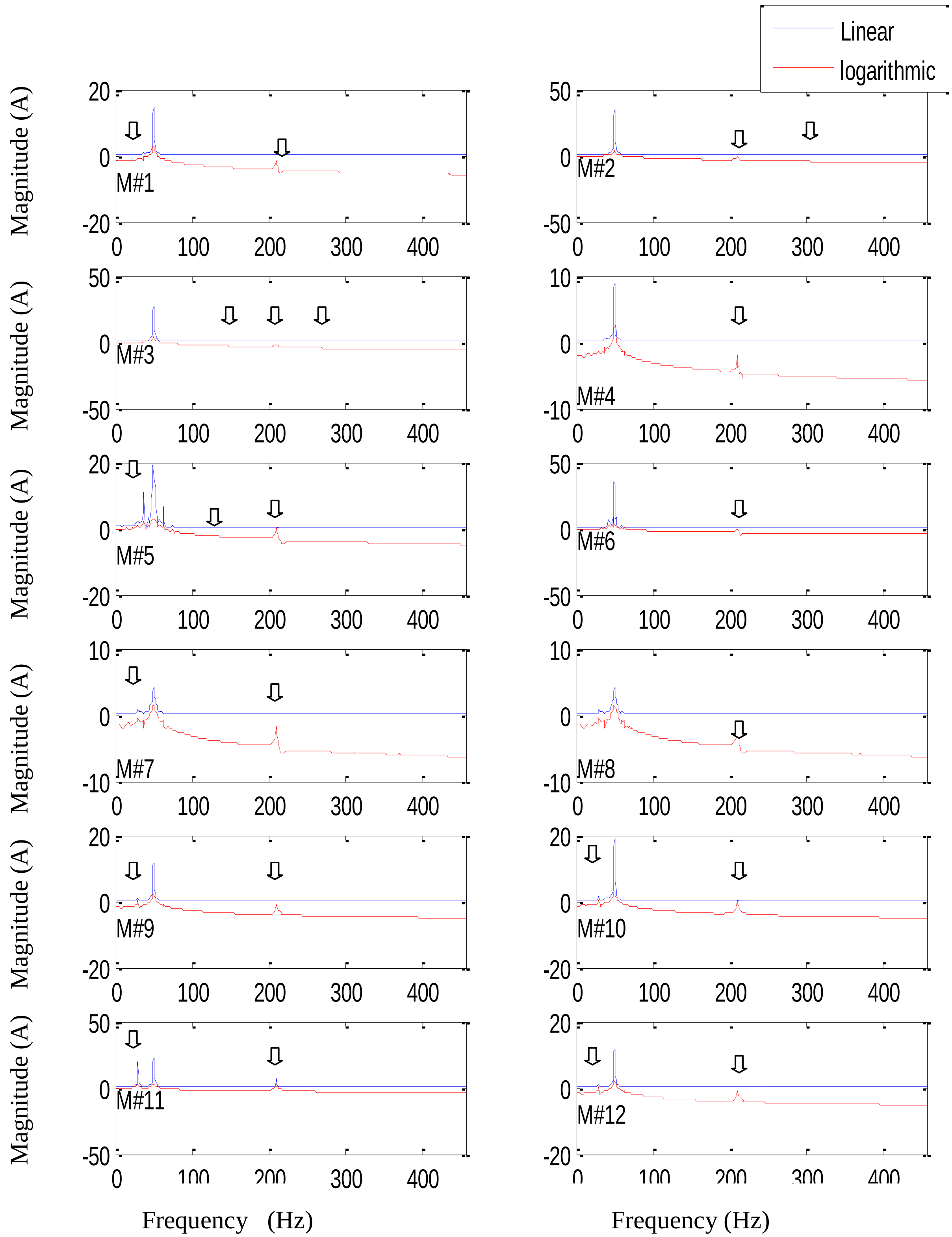


Figure 52 Current spectra of electric motors after fault in Motor 11(Fault 1)- Case study 3

As shown in Figure 52 the integrated signals propagate in the network. However the main appearances of the inserted signals are observable in Motor 5 and Motor 11. Also there are several major fault signals observable in the network. These waveforms cause a serious doubt in identifying the origin of the fault. A graph of the magnitude of fault signals has been shown in Figure 53 to acquire more information about the incident.

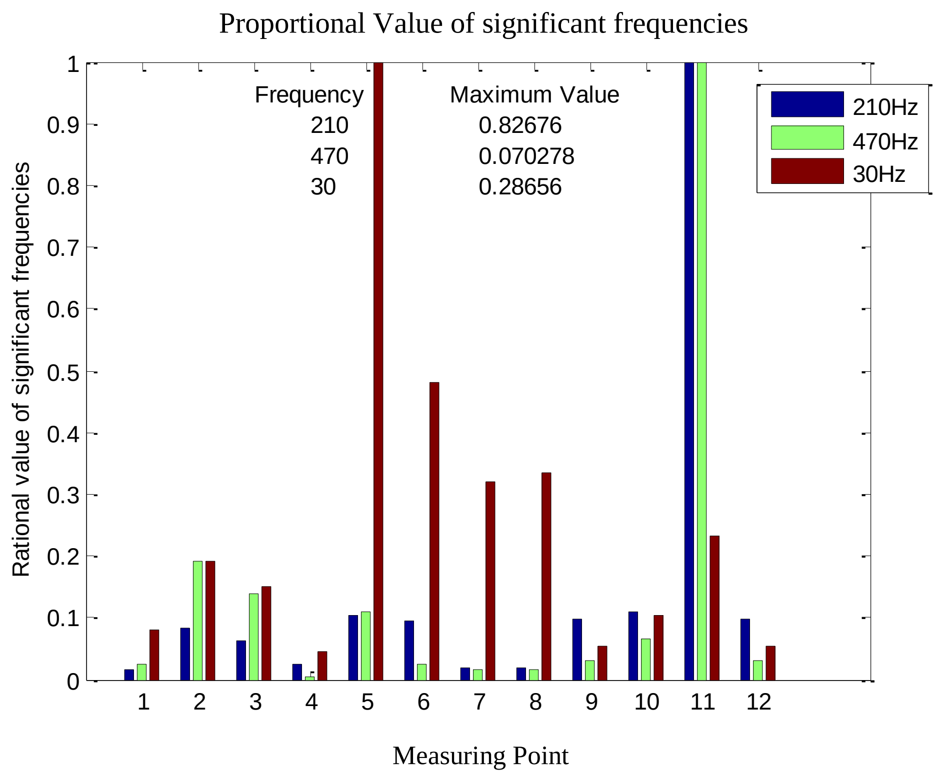


Figure 53 Proportional value of fault frequencies (fault 1) at each measuring point- Case study 3

As shown in Figure 53, the magnitude of fault signals does not follow the pattern explained for Case study 1 and 2. Maximum amplitude appears in different locations and fault signals have different attenuation patterns. The only judgment can be taken based on amplitude of signals that recommends that Motor 11 is the origin of 210 and 470 Hz while Motor 5 is responsible for 30 Hz frequency. This is a false diagnosis as all components of the signal originated by Motor 11.This situation will be discussed and analysed in chapter 6.

6.3.4 Dissimilar motors-Case study 4

Now another fault with a different magnitude- frequency configuration has been integrated in Motor 11 to simulate the network behaviour for fault type 2. (EH31)

Voltage	Phase	Frequency	
170	0	74	Fault 2
190	0	106	
167	0	084	

Unlike fault 1, all fault frequencies are around the nominal frequency. The frequency spectrums of electric motors have been shown in Figure 54.

As shown in Figure 54, fault signals propagate all over the network. However magnitude of fault signals varies from point to point. Fault signals are clearly observable in current signals of all motors that are connected to Bus 3. But fault signals dissipate significantly before they become observable in waveform of electric motors. In order to view propagation of fault signals, magnitude of fault signals in all measuring points has been shown in Figure 55.

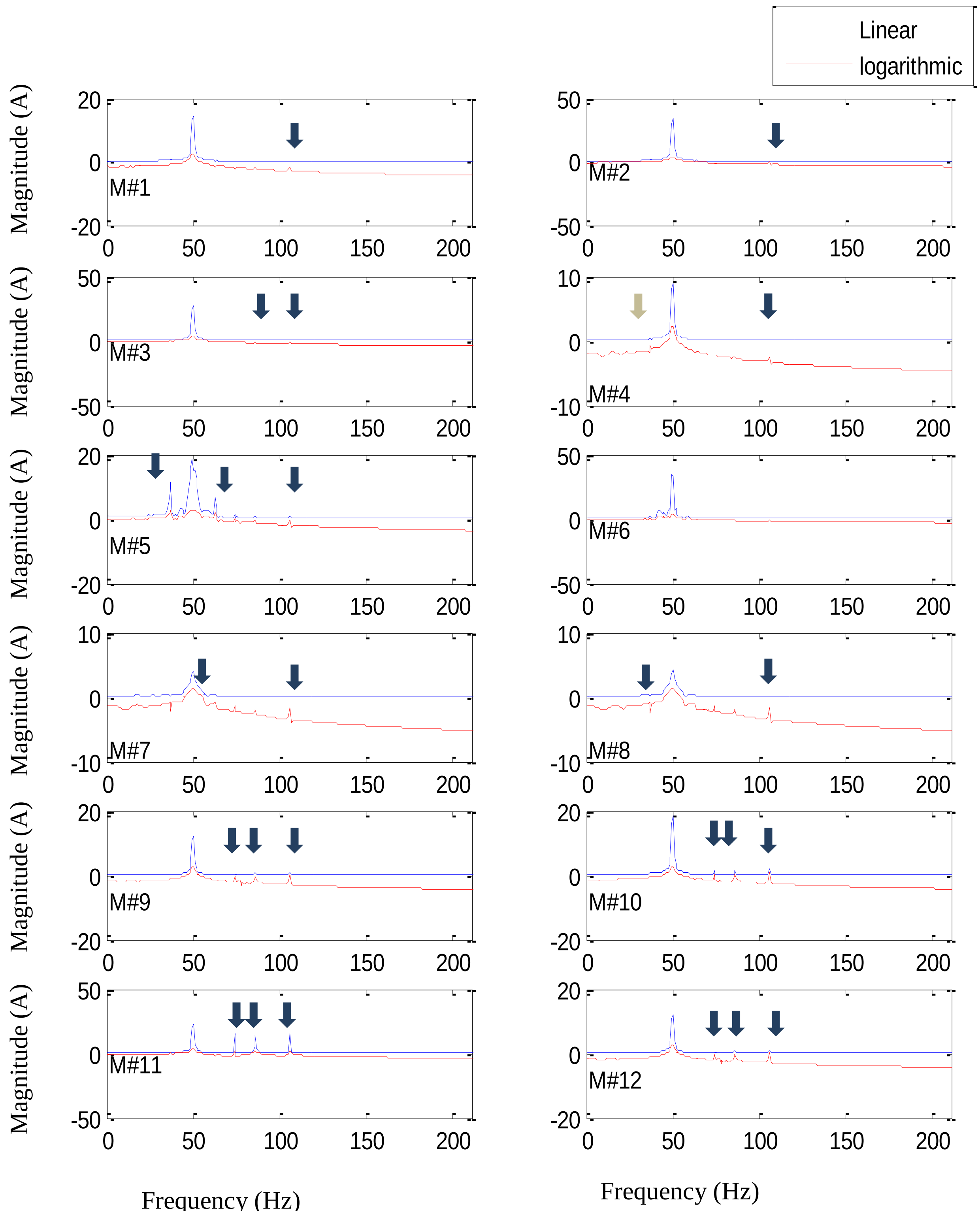


Figure 54 Frequency spectra of electric motors in an unsymmetrical, disimilar power network with a fault in Motor 11-Case study 4.

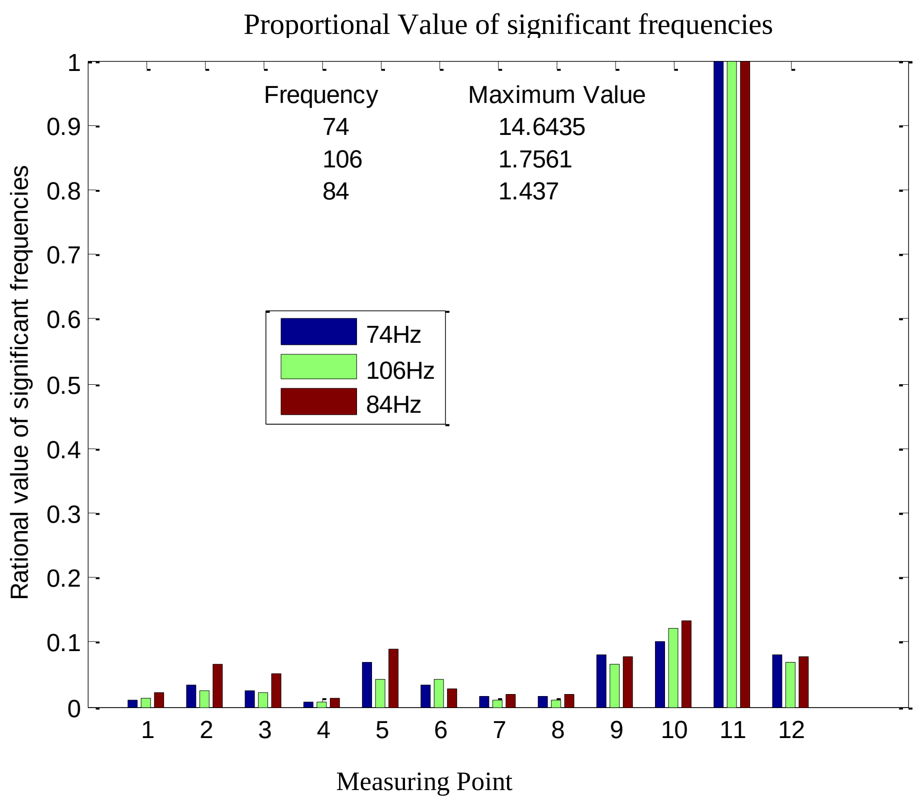


Figure 55 Proportional values of fault frequencies (related to fault 2) at each measuring point. (Fault in 11)- Case study 4

Referring to Figure 55, maximum magnitude of fault signals appear at measuring point 11. However, the network has different attenuation for each fault signal.

6.3.5 Dissimilar motors- Case study 5(eh4.mdl)

Here, another fault with a different magnitude-frequency configuration has been integrated in Motor 6 to simulate the network behaviour for fault type 1.

Voltage	Phase	Frequency	
170	0	65	Fault3
190	0	48	
167	0	78	
167	0	28	

Where: $V_{max} = 1490RPM$ and $V_{min} = 1460$ RPM

Again to analyse behaviour of the network and compare magnitude of significant points in current waveform of electric motors, magnitude of fault signals in all measuring points has been shown in Figure 56.

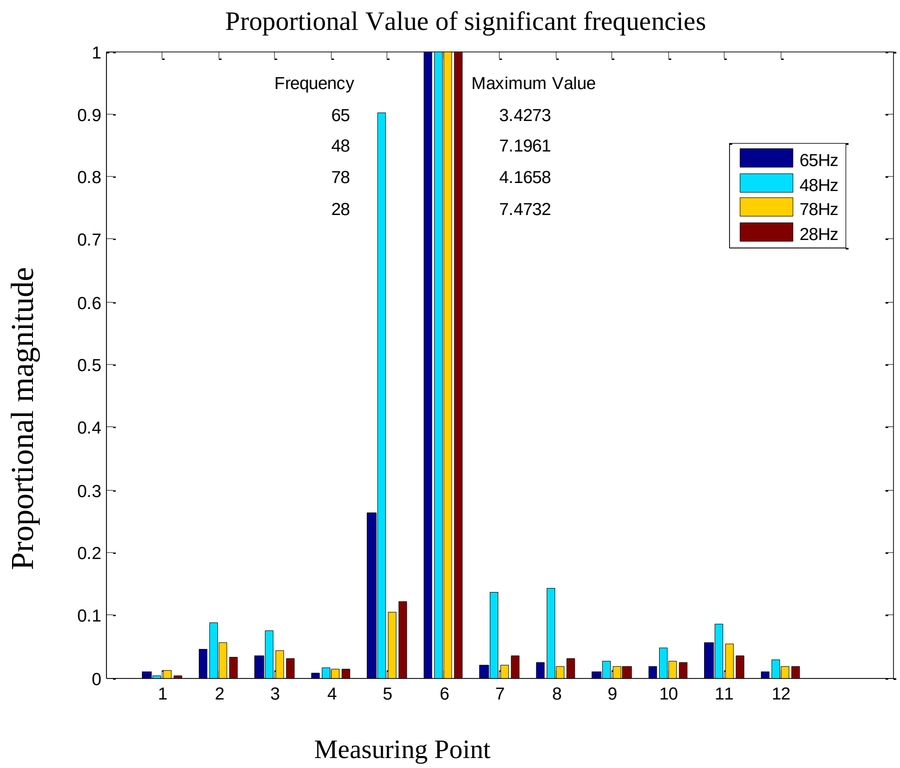


Figure 56 Rational values of fault frequencies (related to fault 3) at each measuring point (fault in Motor 6)- Case study 5

As shown in Figure 56, at least 4 may be detected as associated with a kind of fault. However, maximum of fault signals appear in Motor 5 and Motor 6. Therefore, visual observation would recommend considering both Motor 5 and 6 as the origin for the incident. Chapter 7 resolves the accuracy issues using the technical method explained in chapter 3.

6.4 Multiple faults in the network

6.4.1 Two similar faults in the network (Case study 6) [eh6]

Here an incident of two similar faults in two parts of the network will be investigated. As a case study the fault model 3 has been integrated in Motor 6 and Motor 11. The network described in Case study 5, has been selected for the experiment. Frequency spectrums of all electric motors have been shown in Figure 57.

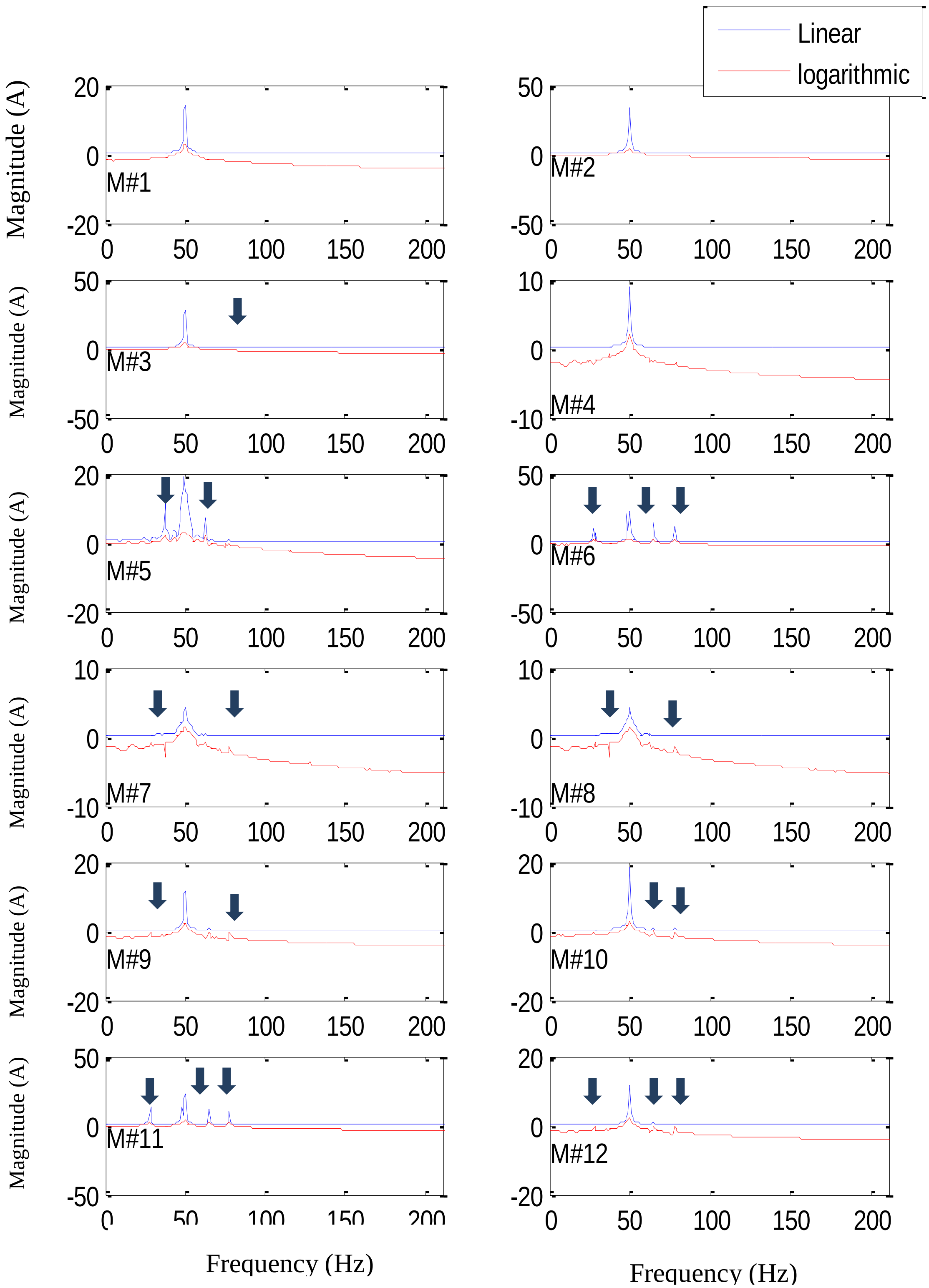


Figure 57 Frequency spectra of electric machines. There are two similar faults integrated in the network- Case study 6

Visual observation indicates Motor 5 and Motor 12 as possible faulty motors. However, none of them originally associated with any fault. This false interpretation can be corrected partially by looking at a graph of the magnitude of fault signals as shown in Figure 58.

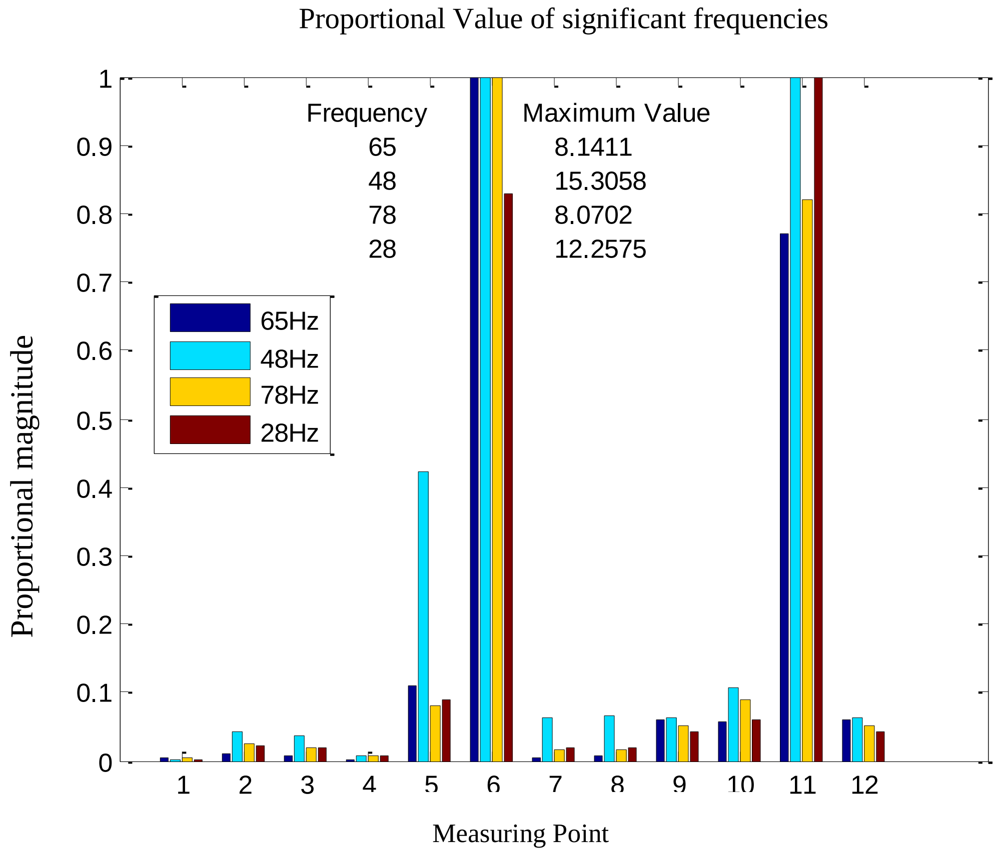


Figure 58 Rational values of fault frequencies (related to fault 3) at each measuring point. (Similar fault in Motor 6 and Motor 11)- Case study 5.

Looking at Figure 58, Motor 2, 5, 6 and 11 can be taken as possible causes of the fault. Therefore neither traditional current signature analysis nor comparative approaches can result in having an acceptable diagnosis. Further investigations in chapter 6, will provide more accurate results for the case study using the distributed approach and propagation analysis.

6.5 Two different faults in a network- Case study 7[eh5.mdl]

In this section behaviour of the power network in event of two different faults will be investigated. To simulate an incident with 2 different faults, the fault in Motor 6 stays the same and another fault that is described by equation 6-4 has been integrated in Motor 12.

$$
\begin{array}{lll}
\text{Voltage} & \text{Phase} & \text{Frequency}
\end{array}
$$

$$
\left\{\begin{array}{lll}
170 & 0 & 35 \\
190 & 0 & 44 \\
167 & 0 & 70 \\
167 & 0 & 30
\end{array}\right\} \qquad \text{Fault 4}
$$

Where: $\mathrm{V_{max}} = 1420\mathrm{RPM}$ and $\mathrm{V_{min}} = 1440\mathrm{RPM}$

Frequency spectra of electric motors have been shown in Figure 59.

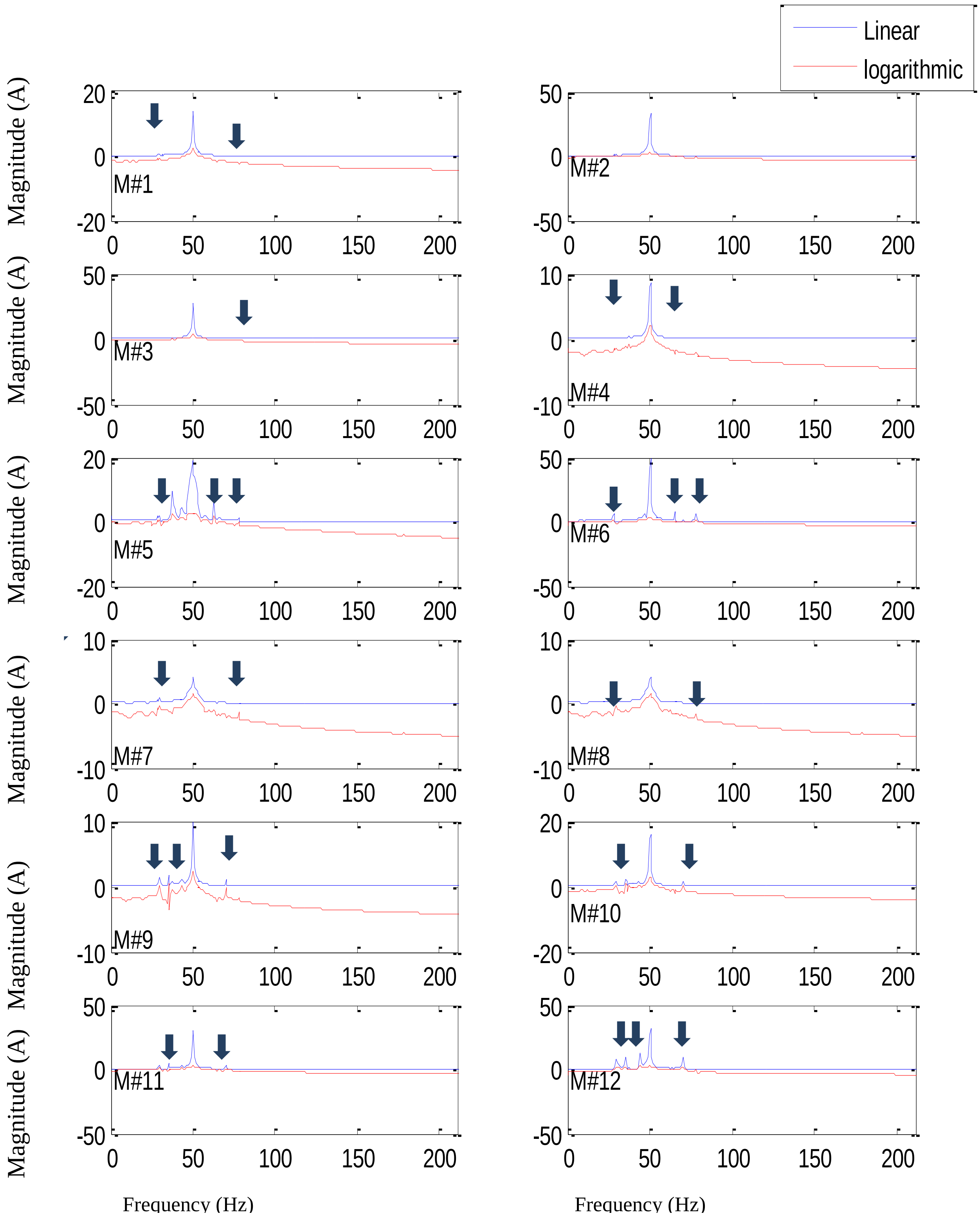


Figure 59 Frequency spectra of electric motors in event of two disimilar faults in different places of the network-Case study 7

Similar to the previous situation, by no means faults of Motor 6 and 12 can be discriminated using visual analysis. However if the fault signals are known and filtered from each waveform and clustered for each fault individually, a better description of the network is achievable.

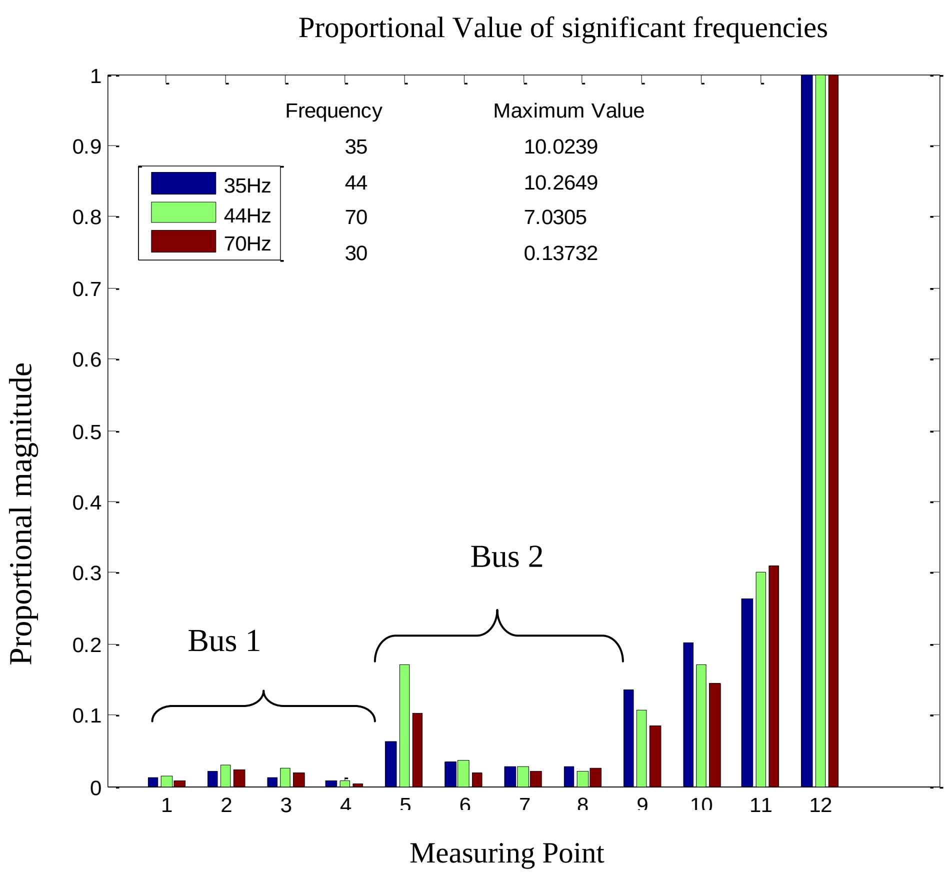


Figure 60 Proportional values of fault frequencies (related to fault 4) at each measuring point-Case study 7.

Figure 60, discriminates the frequency components that are related to fault 4 and indicates Motor 12 at the origin of fault frequencies. Motors of Bus 1 and Bus 2 with neglecting the value of

35Hz line in measuring point 5 are completely correlated with the propagation pattern described in chapter 4.

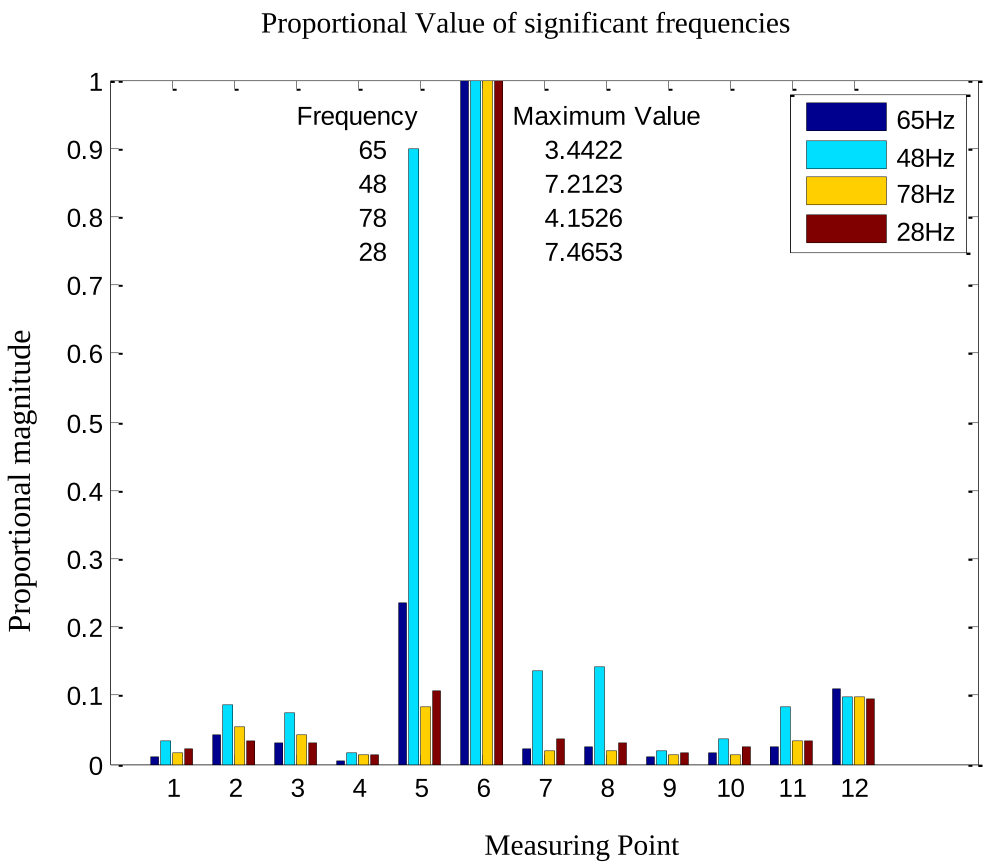


Figure 61 Proportional values of fault frequencies (related to fault 3) at each measuring point- Case study 7.

Figure 61, discriminates the frequency components that are related to fault 3 and indicates motors 5 and Motor 6 as the origin of the fault. This assumption is very close to the correct diagnosis. But to clarify the uncertainty, further analysis is necessary.

6.6 Conclusions

A number of industrial case studies have been analysed by evaluating the concepts of individual and distributed diagnosis. As shown in this chapter, components of current spectra in each electric motor are closely influenced by other in-network electric motors. Propagation of fault signals during minor faults is negligible, but in major fault incidents, signal propagation may cause unnecessary warnings in healthy motors. In many cases, tracking fault signals and comparing them with the propagation patterns as described in chapter 3, clearly discriminate and describe the original source of the fault. In other situations, further technical approach is necessary. In general, for any diagnostic process, fault frequencies have to clearly discriminated, to differentiate between faults.

Chapter 7 employs observations of this chapter to implement and evaluate concept of distributed signature analysis.

Chapter 7:

TECHNICAL SOLUTION AND EVALUATION

7.1 Introduction

This chapter aims at implementing and evaluating the concept of distributed diagnosis using simulation results and practical experiments. Here, current spectrums will be analysed without any bias to estimate delectability of the inserted fault and approximate reliability of diagnosis. As discussed in chapter 6, individual diagnosis may result in serious failure in distinguishing type and origin of fault signals in the network. Multiple measuring points in the network capture dependent data from their point of view and hence considering data of other measuring points improve accuracy of diagnosis and help in discriminating and isolating motor faults.

In order to implement concept of distributed diagnosis, fault indices and propagation charts, have been employed. Fault indices are measured to evaluate involvement of each data with the given fault. These indices are estimated using a pattern recognition strategy, as described in chapter 4. Propagation charts advise direction of propagation of estimated fault indices using attenuation patterns as explained in section 4-11, within the network and hence identify origin of signal.

Taking into account that fault type, speed of the faulty motor, strength of the fault and location of the faulty motor are acting variables of diagnosis, several situations have been considered to evaluate concept of distributed diagnosis. The first part of this chapter concentrates on simulation results demonstrated in chapter 5. Then a number of case studies have been investigated using fault indices, propagation graphs to diagnose motor faults in chapter 5 case studies. And finally, an artificial neural network is taken as an example of employing smart decision making strategies in interpreting fault indices.

7.2 Analysis of simulation data

A number of experiments have been analysed referring to simulation case studies explained in chapter 6. In each Case study fault indices and propagation charts will be demonstrated and described to evaluate ability of distributed diagnosis in estimating more accurate results.

7.2.1 Similar electrical motors Case study 1

As shown in chapter 5, propagation of fault signals is easily interpretable if fault signals are detected using process of pattern recognition. Related fault indices for fault type 1 and 2 as described in chapter 3 are shown in Figure 62.

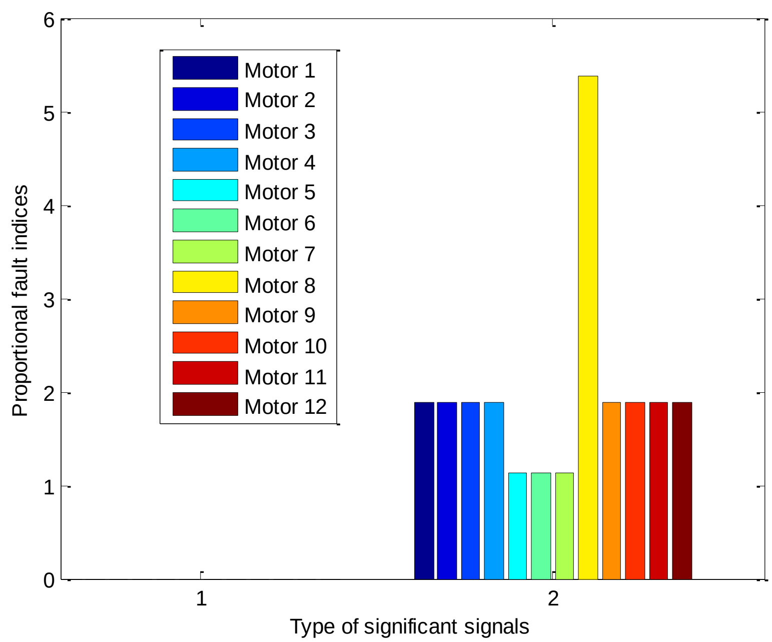


Figure 62 Fault indices of electric motors in a uniform industrial network while a fault inserted in electric Motor 8 (Case study 1) [File: eh1]

As shown in Figure 62, association with fault type 2 has been observed for all electric motors. However fault indices of Motor 8 and Bus 2 are considerably bigger than the rest of indices. Similarity of electrical motors causes an almost uniform attenuation of fault indicators. Propagation patterns provide a clearer view of transmission of fault signals to locate origin of faults in the network.

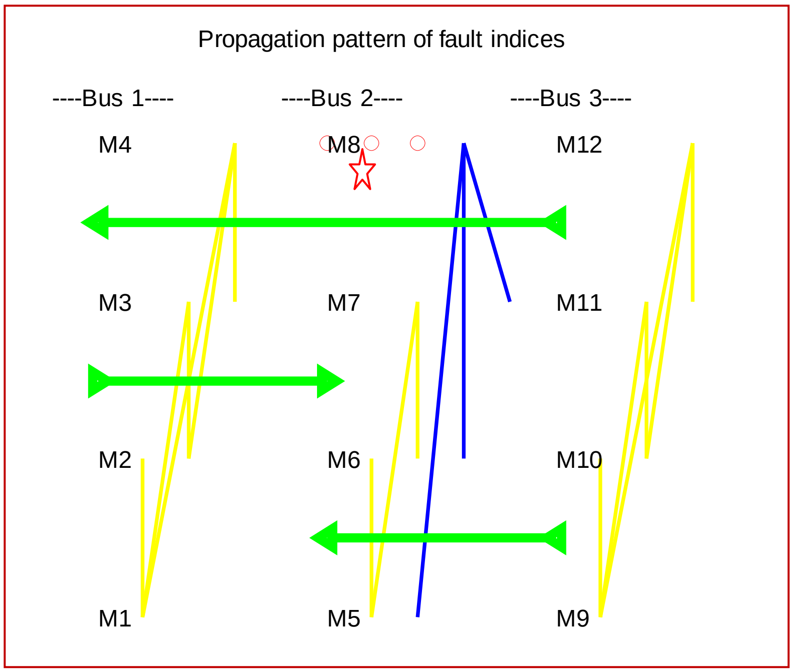


Figure 63Fault propagation pattern for a uniform industrial network with a fault in Motor 8. The attenuation pattern and propagation indices clearly indicate Motor 8 as the cause of Fault #1 (speed range 1450 to 1480RPM)

Figure 63 illustrated an ideal situation where all arrows point toward one electric motor and there is no preference in ownership of fault indicators in other neighbour bus. And hence Motor 8 can be nominated as the origin of fault 1 with a very high accuracy. In general situations a more difficult situation will be expected and numerical calculation may ease out interpreting the propagation results.

7.2.2 Dissimilar machines [eh3 and eh4] Case study 3

As described in chapter 5, here more general situations will be discussed. Electric motors are selected from different types; they are running in different speed ranges and are working in an unsymmetrical network. Here, unlike section 7.2.1 some abnormal frequencies are observable in frequency spectrums of healthy motors and propagation patterns of fault signals as shown in Figure 64

are not following a uniform scenario. Therefore fault diagnosis is more difficult compared to previous case studies. Here to cover all electric motors a wider range of speeds have been selected.

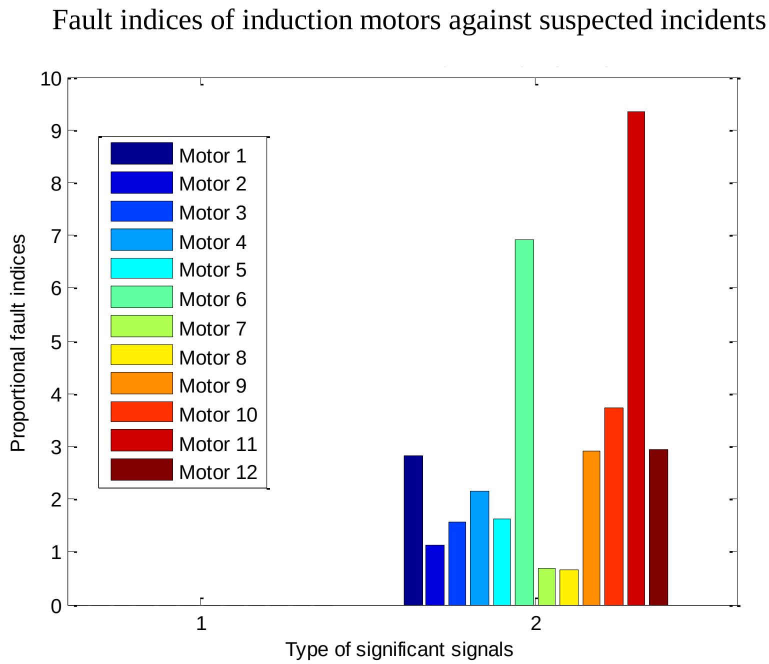


Figure 64 Fault indices for electrical motors in a dissimilar and unsymmetrical network with a fault integrated in Motor 11. Case study 3: speed range is 1410 to 1470RPM

As shown in Figure 64, Motor 11 has the maximum value while Motor 6 and Motor 10 appear to be highly associated with the incident.

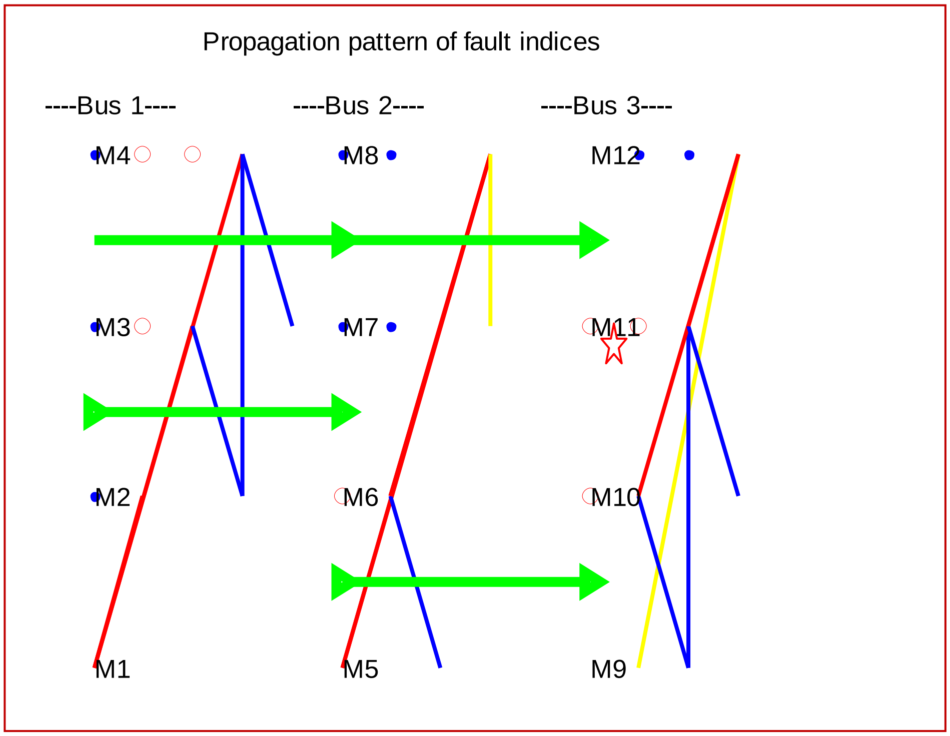


Figure 65 Fault propagation pattern for an unsymmetrical, dissimilar network with a fault #1 in Motor 11. Case study 3

As shown in Figure 65, propagation pattern points out Motor 11 as the source of fault, however Motor 6 and Motor 10 also are considered as suspected motors. This confusion is caused by signals which were originally generated by normal operation of electric motors. An adaptive numerical solution may cancel the background noise and provide the correct answer.

Prior analysis has been done in the dedicated range of speed for the faulty motor which is 1410 to 1480RPM. Any alteration in estimating speed of electric motors may result in estimation error. For example, altering speed range to 1400 to 1420RPM, while electric motors are not running is this speed range produces different faulty indices.

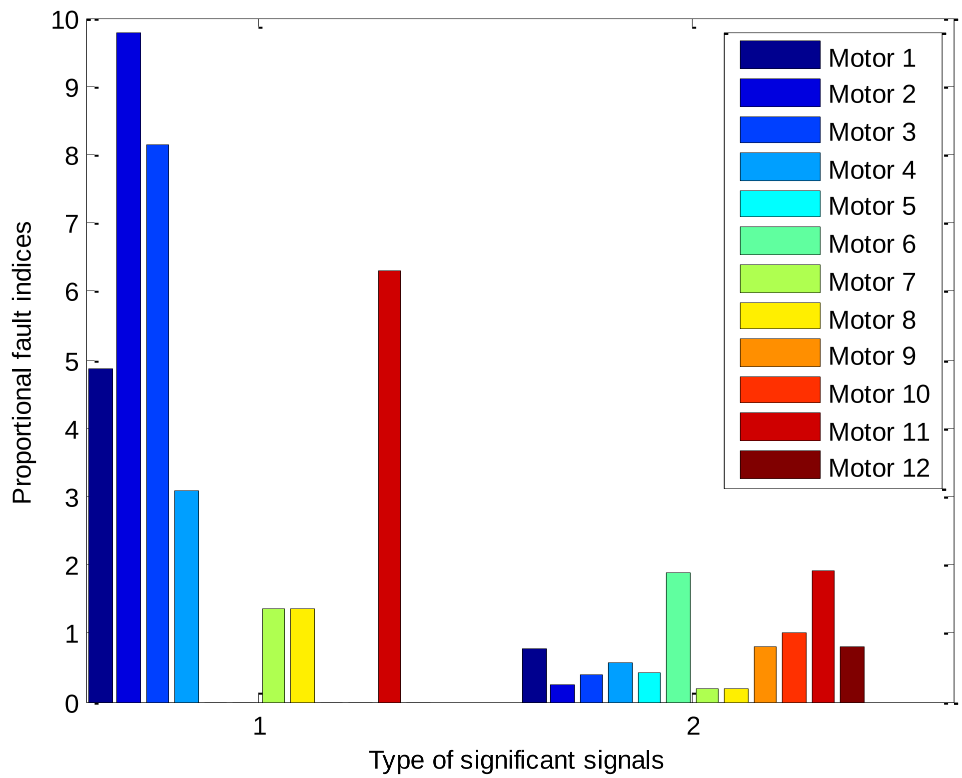


Figure 66 Fault indices for an unsymmetrical electrical network (speed range is 1400 to 1420RPM)

Incorrect fault indicators result in getting inaccurate answers in further processes. As shown in Figure 66, this selection results in diagnosing Motor 2 as associated with fault type 1.

7.2.3 Multiple faults in the network (eh5) [Case study 6]

In this section methodology of distributed analysis will be evaluated for the situations where more than one fault is associated with the network. Case studies 5 and 6 of chapter 5 have been employed to produce required data. Initially situation of two similar faults in the network (Case study 5) is analysed to illustrate fault indices and propagation patterns in the network.

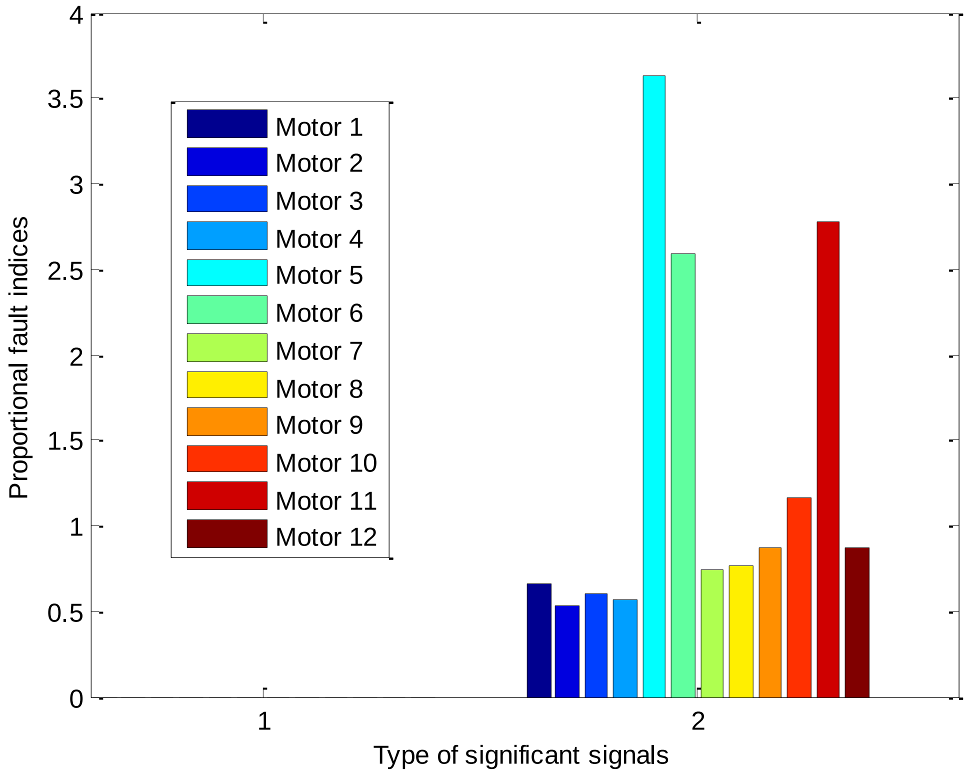


Figure 67 Fault indices of electrical machines in an unsymmetrical dissimilar network with two similar faults in Motor 6 and Motor 11- Case study 5

As shown in Figure 67, related fault indices for Motor 5 are higher than other electric motors. Motors 6 and 7 also appear to have significant level of fault signals. Propagation pattern of fault signals has been shown in Figure 68 (wrong diagnosis).

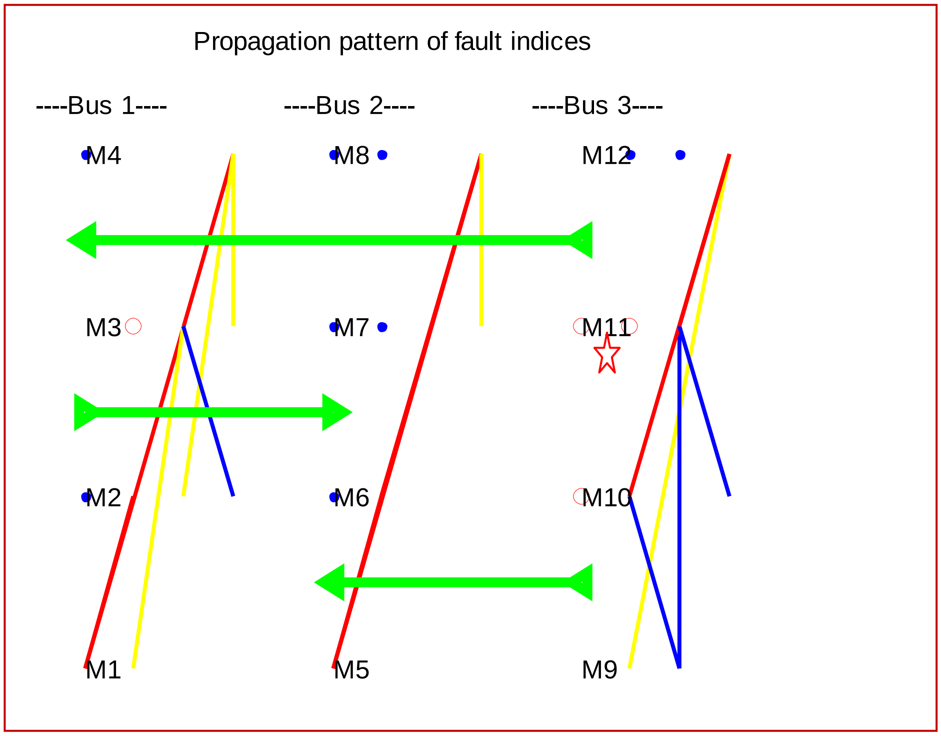


Figure 68 Attenuation chart for faults for Case study 6. The chart refers to Motor 11 in Bus 3.

Propagation pattern points to Motor 11 as the origin of fault signals (wrong answer). Therefore, as shown here, monitoring fault indices and attenuation of fault signals are not sufficient to diagnose similar faults in the network and each diagnostic process may point at only one electric motor.

The next case study is to evaluate the network in event of two different types of faults in the network. (As shown in Case study 6 in chapter 5). Similar to previous situations, frequency spectrums do not provide enough information to estimate the fault and origin of fault signals, however, differentiation of fault representatives discriminate network faults. Here operation speed of Motor 6 and Motor 11 are different, therefore two different sets of fault indices and two different propagation patterns may be calculated.

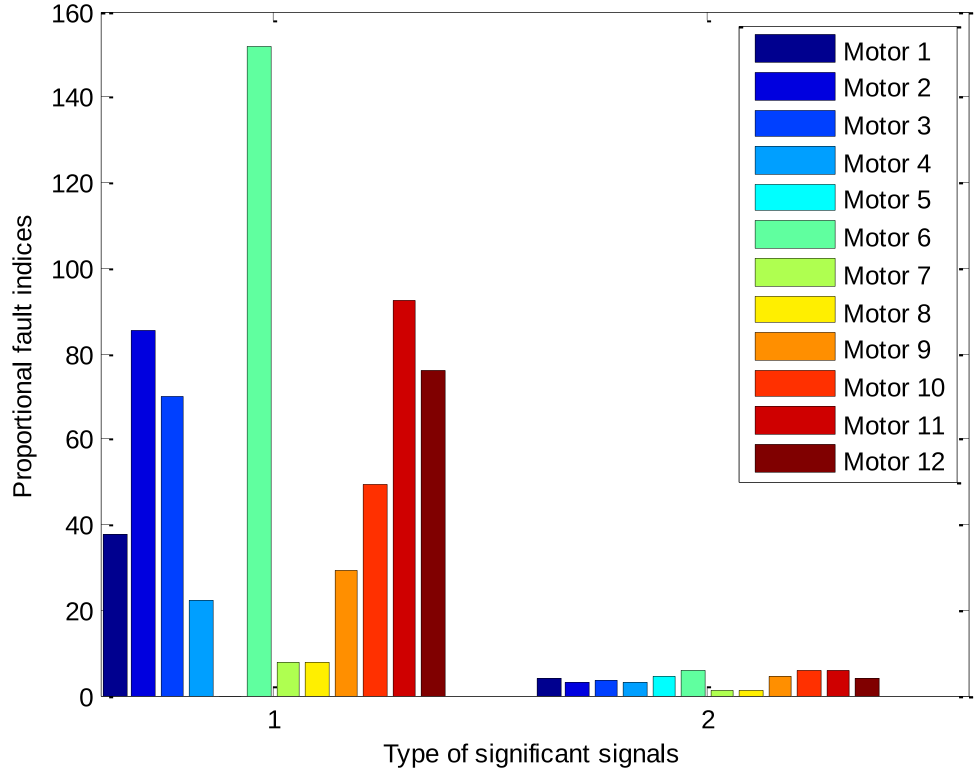


Figure 69 Fault indices of electric machines with two different faults in Motor 6 and Motor 11- Case study 6.(speed range is 1410 to 1490RPM)

As shown in Figure 69, two sets of fault indices are detectable. Fault indices point at different points. Fault type 1 in Motor 11, and fault type 2 in Motor 6 are considerably bigger than their neighbours. Since Motor 6 and Motor 11 are running at different speeds, customized fault indices can be calculated.

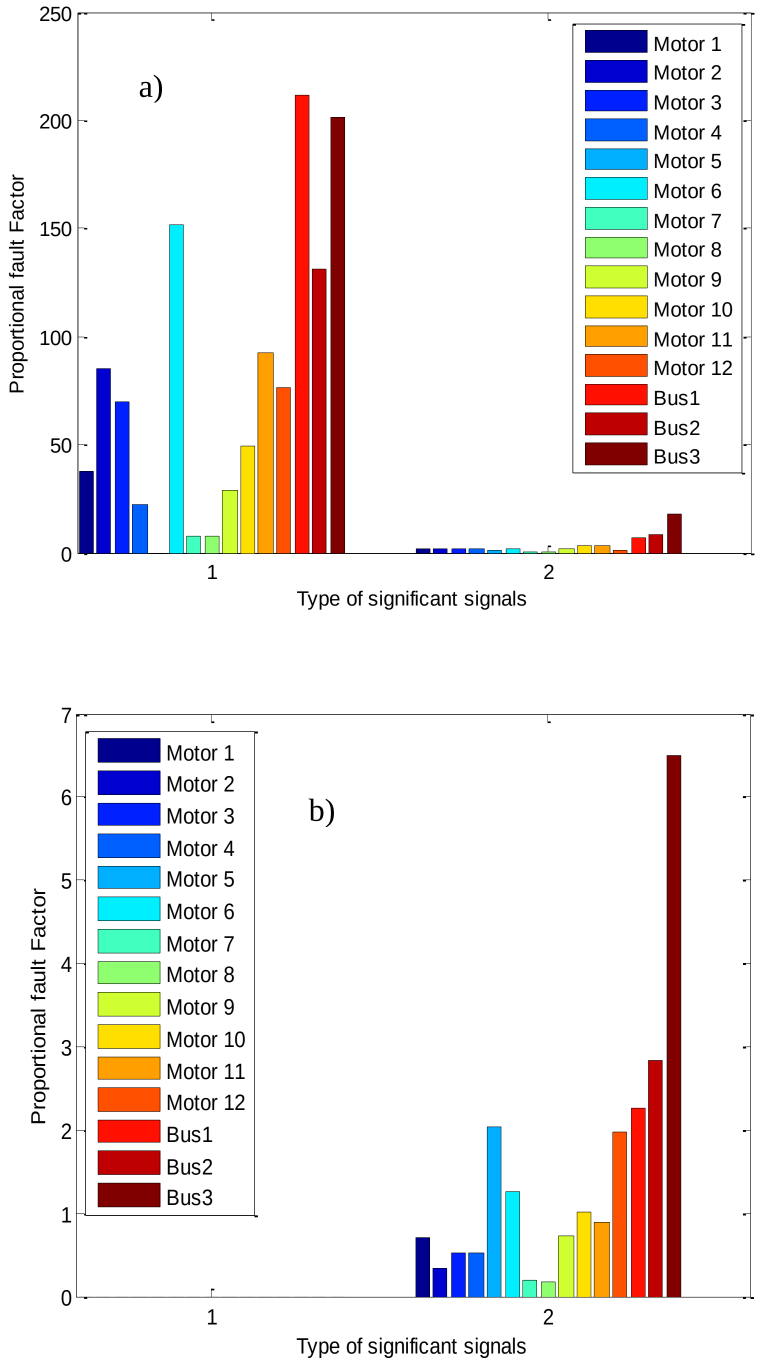


Figure 70 fault indices of motors in Case study 6. Two faults have been integrated in model of two electric motors. a) Speed range 1420RPM to 1440RPM; b) speed range 1460 to 1490RPM

Figure 70.a strongly illustrates presence of fault type 1 in Motor 6 while Figure 70.b refers to presence of fault 2 in both Motor 6 and 12. Taking into account that Motor 6 a has been detected as associated with fault type 1 and considering cross section of fault indicators, Motor 12 can be estimated as the source of fault signals related to fault type 2.

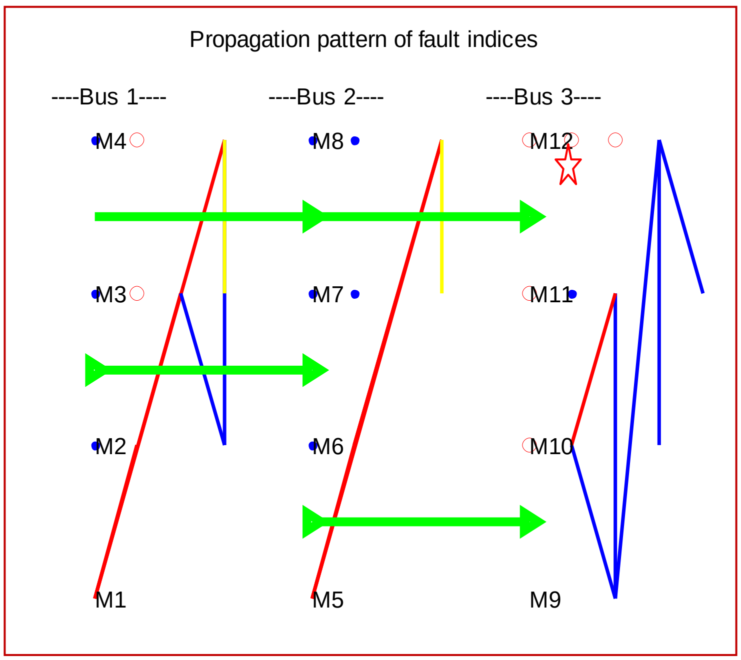


Figure 71 Attenuation chart for fault for Case study 6. Two different faults in the network with customized indices related to fault type 2

As shown in Figure 71, attenuation pattern of customized fault indices refers to Motor 12 as the origin of fault 2.

7.3 Discussion

In order to evaluate different acting variables in fault diagnosis, simulation results have been summarized in Table 7.

Table 7 Evaluation of simulation results

Case Study	1	2	3	4	5	6	7
Faulty motor	Motor 8	Motor 3	Motor 11	Motor 11	Motor 6	Motor 6 and Motor 11, similar faults	Motor 5 and Motor 12, different faults
File name	eh1	eh2	eh3	eh31	eh4	Eh6	eh5
Type of fault	Major/ High frequency -T2	Minor/High frequency	Major/ High frequency-T2	Major/ around 50Hz frequency	Major, different type, close to 50Hz	Major, different type, close to 50Hz	Similar to CS6 in Motor 6, and another type of fault with frequency components around 200Hz
Motors	All the same	All the same	Different motors	Different motors	Different motors	Different motors	Different motors
Topography	Uniform	Unsymmetrical	Unsymmetrical	Unsymmetrical	Unsymmetrical	Unsymmetrical	Unsymmetrical
Fault is observable in the faulty motor	Y	Y	Y	Y	Y	Y	Y
Fault is observable in healthy motors	Y	N	Y	Y	Y	Y	Y
Fault detection and diagnosis using fault Indices and propagation patterns	Y	Y	N	Y	N	N	Y

As shown in Table 7, whenever a major fault appears in the network, fault indices are observable in all healthy motors. Most of these confusions have been resolved using propagation patterns. However in few situations extra verifications are required. On the other side since all measuring points provide individual observations of the same fault event, the system potentially is capable of providing solutions for motors without direct measuring points. In this situation, faults can be observed indirectly by monitoring and comparing fault impacts in current signals of neighbouring motors. Here as an example, a neural network has been implemented to assess feasibility of providing better results using numerical solutions. This attempts to initiate a new pathway for future works in area of fault diagnosis to provide a robust and reliable solution for fault diagnosis in induction motors.

7.4 An attempt to interpret fault signals using neural networks

Several numerical and intelligent methods may be utilized to interpret fault indices. Here as an example, an artificial neural network has been employed to interpret fault indices and provide a numerical solution.

Artificial neural networks are being applied to many industrial problems including pattern recognition, data classification and data interpretation [46]. Artificial neural network produces a functional solution to reproduce output files with the given input files. Therefore, reliability of results is very dependent to the quality of the training data. There are different types of ANN networks. The most common ANN is feed-forward networks with back propagation learning method [46].

In this case study, a feed-forward network has been used to estimate the origin of the fault. The network is trained with simulation experiments using back-propagation technique. MATLAB neural network toolbox has been employed to process signals, for the neural network and provide the result for the given task. A matrix of fault indices (12 inputs) has been used to indicate faulty motors as the output of the ANN model using the Boolean logic (1 for faulty and 0 for healthy). Here as an example results of Case study 3 [eh3] has been employed to verify the operation of the ANN network. Details of the neural network have been summarised in Table 8.

Table 8 Brief specification of the implemented artificial neural network

Item	Specification of the implemented artificial neural network
Selected experiments	Major occurrence of fault type 1 in four motor (out of 12 motors) in the site. 1 experiment per each bus
Network type	Feed forward
Number of hidden layers	5 layers
Input data for each experiment	Fault indices of all measuring points during the incident. The input for the ANN network is a one dimension matrix of 12 inputs where each data is the fault index in a measuring point.
Output of the network	Digital matrices refer to the fault as 1 and others as 0. For example: [0 0 0 1 0 0 0 0 0 0 0 0] for fault in Motor 4
Method of learning	Back propagation
Train goal	0.01

$$N(F) \rightarrow O \tag{7-1}$$

Where:

F: matrix of fault indices

N: Artificial neural network model- to locate the origin of one pattern of fault in each time.

O: Matrix of outputs

Where O is [0 0⋯.1⋯.0 0] for the fault caused by motor *n* and 1 is located in *n* th place in matrix of outputs.

A number of experiments are required to train the network. These experiments have to cover all ranges of different situations in the power network. Here electrical motors will be classified based on their location in the bus and distance to the main bus. In this case study experiments of healthy situation for all electric motors, major fault in Motor 3, major fault in Motor 6, major fault in Motor 9 and major fault in Motor 12 have been selected as inputs of training iteration of the network. These experiments cover minimum of one sample fault for each bus. Training data has been summarised in Table 9.

Table 9 Training Data for the neural network model

Fault location **Major Fault-Type**	**Fault in Motor 3**	**Fault in Motor 6**	**Fault in Motor 9**	**Fault in Motor 12**
Fault Indices in motors 1 to 12	1.5368 1.8044 1.6228 1.1164 1.4894 2.7884 0.3435 0.3397 2.0109 2.4842 1.5235 2.0165	1.5672 2.0635 4.0797 1.1404 3.3089 0.5413 0.3827 0.3744 1.9531 2.3798 0.5841 1.9650	1.4475 1.6958 1.5428 1.0454 1.2775 4.3698 0.3821 0.3709 1.7390 2.2960 1.4250 1.7510	1.4305 1.6544 1.4703 1.0468 3.5381 4.3741 0.4304 0.4222 4.1090 1.8672 1.9416 1.3707
Fault location	Bus 1	Bus 2	Bus 3	Bus 3

Then in order to observe the system behaviour results of Case study 3 (fault in Motor 11) has been utilized to verify the event of occurrence of the same fault in Motor 11.

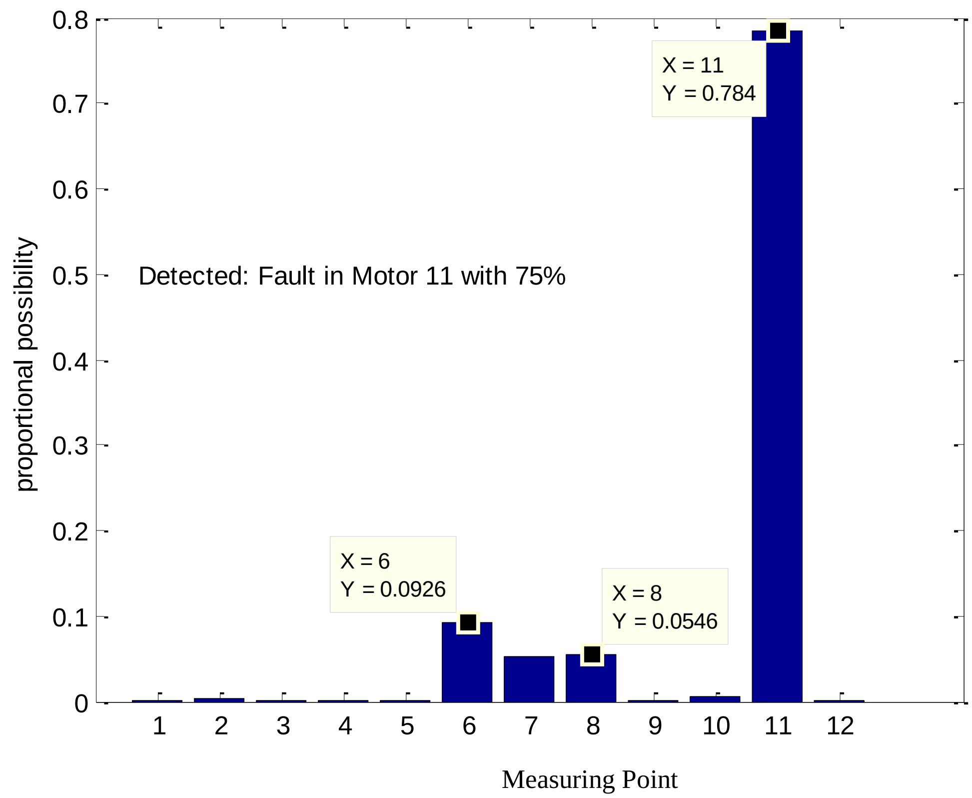


Figure 72 Fault indicators calculated by the neural network show a high number related to possibility of presence of fault type 1 in Motor 11.

As shown in Figure 72, Motor 11 is detected as a faulty one, which is the correct answer and hence the network is supposed to be prepared for further experiments.

Here in order to test robustness of diagnostic system, we assume all measuring points in subsystems 2, 4, 6,8,10 and 12 have been turned off and the diagnostic system is receiving data from measuring points 1, 3,5,7,9 and 11. This situation can be considered for two types of events where the direct measuring point is available for the faulty motor or the faulty motor lost the direct monitoring system. To analyse first type of incidents, results of Case study 3 have been employed again for the new situation (with working measuring point). Simulation outcomes have been shown in Figure 73.

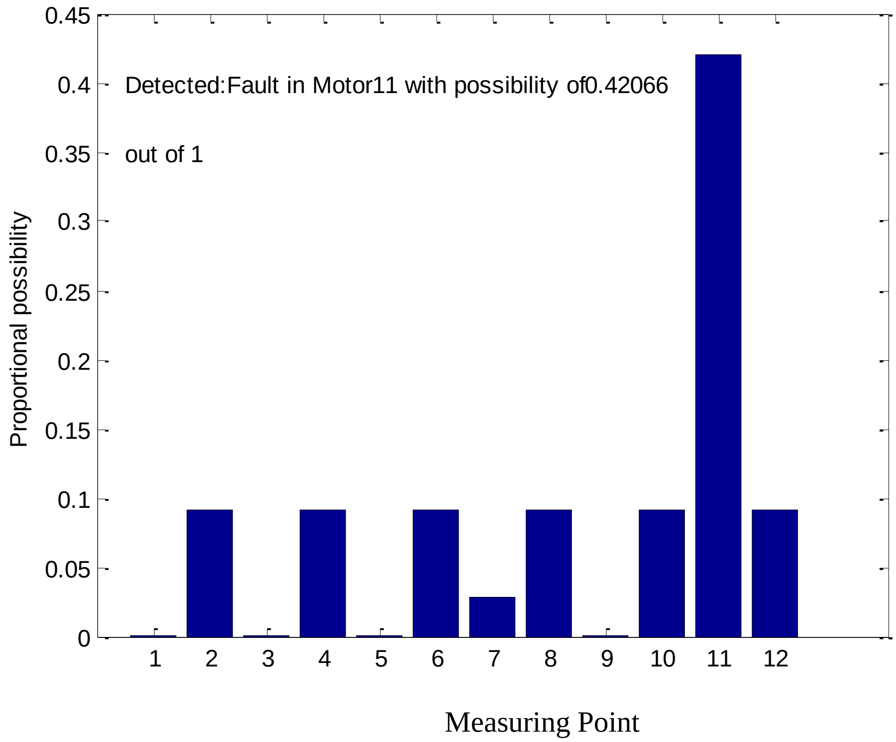


Figure 73 Neural network output for a typical power network for Case study 11 (Some measuring points are missing but not the direct one)

As shown in Figure 73 where fault still is diagnosable but with a less degree of confidence. Figure 74 shows the output of neural network when all measuring points are available except the direct measuring point for Motor 11.

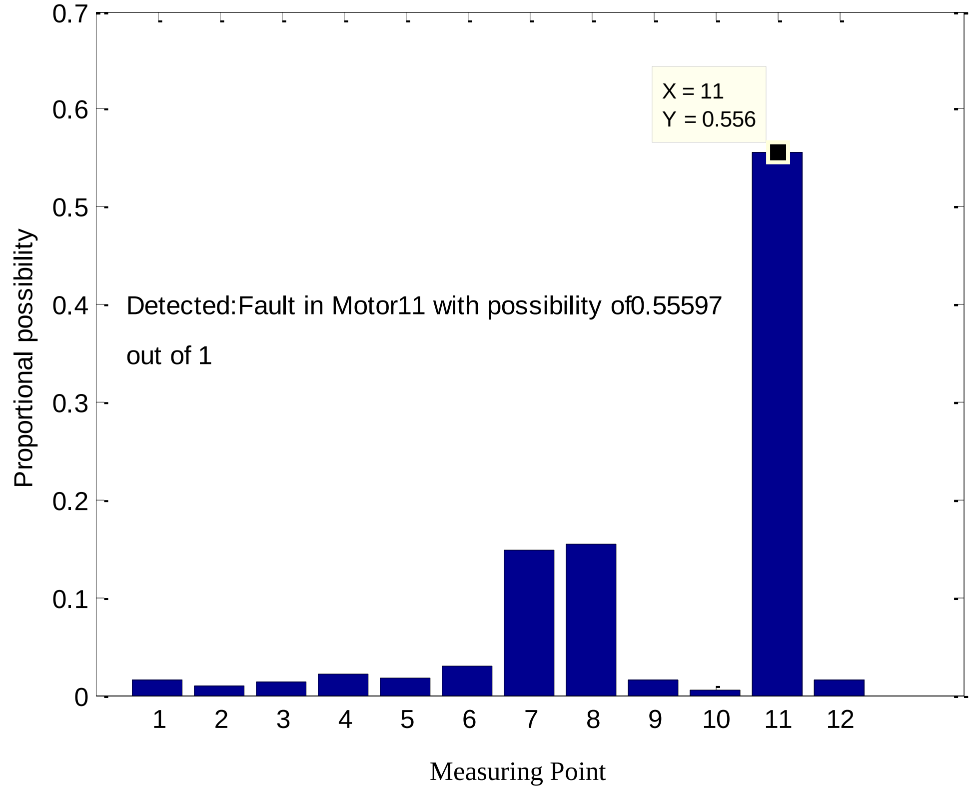


Figure 74 Neural network output for the network Case study 3 when direct measuring point is missing

As shown in Figure 74, neural networks point to the fault location with a lower level of confidence compared to the situation when all measuring points are available; but with more confidence compared to the previous situation where a direct measuring point was available.

Several situations have been listed in the following table (Table 10) to judge the application of a neural network in distributed fault diagnosis.

Table 10 List of neural network experiments to detect the fault in a typical scaled down network (Case study 3) with selective measuring points

NO	Experiment detail	Diagnosis result
1	All measuring points in Bus 1 are turned off	Detected: Fault in Motor11 with possibility of0.69003
2	All measuring points in Bus 1 and Bus 2 are turned off	Detected: Fault in Motor11 with possibility of 0.6265
3	All measuring points in Bus 3 including motors 11 are turned off	Suggested: Fault in Motor6 with possibility of 0.23617 (Not correct). Also suggested: Motor 9: 0.16, Motor 10:0.16, Motor 11:0.16 and Motor 12:0.16 out of 1.
4	All measuring points of Bus 3 except the faulty one turned off.	Detected: Fault in Motor11 with possibility of 0.72503
5	All measuring points of Bus 1 and the measuring points of the faulty motor are turned off	Suggested: Fault in Motor 6 with possibility of 0.20452 also suggested fault in Motor 11 with possibility of 0.139 as the second option
6	All measuring points of Bus 2 and the measuring points of the faulty motor are turned off	Detected: Fault in Motors 5 6 7 8 and 11 with possibility of 0.18452

Results of several experiments with a neural network have been summarised in Table 10. These experiments clearly demonstrate the possibility of fault finding when a set of measuring points is turned off. This can cover situations where measuring points have been replaced to save the installation cost or they are turned off due to failure in wiring or automation systems. The diagnostic system may point to a wrong motor in case of major failure in measuring systems. However an early detection of can be considered. Further calculation and considering change of the diagnostic topography due to missing measuring points may provide more accurate results.

7.5 Practical experiments

Here the test-bed explained in chapter 5 has been implemented to verify attenuation and propagation of fault signals in a real world situation. Electric motors initially set to work in an isolated mode and then they have been connected together via a power network with unmeasured quantities fault signals. As explained before the experiment is not providing a perfect environment to provide an accurate calculation for propagation of fault indices due to the following reasons:

All measurements are asynchronous. Therefore, current signals of electric motors in each experiment may differ from the next experiment on the same electric motor.

1. All motors have to be turned off and on to change the system configuration. Each startup process may change mechanical characteristics of electric motors that potentially result in a change in quality of operation of electric motors.
2. All network characteristics, such as impedance of connecting cables during experiments are considered unknown. Therefore a black box approach is the best option to verify propagation of fault signals.

Besides, of all shortcomings explained in 1, 2 and 3, the experiment can verify propagation of fault signals from one location to another location. Two sets of experiments have been employed to evaluate concept of signal propagation: stand-alone operation of each motor and parallel operation of all motors.

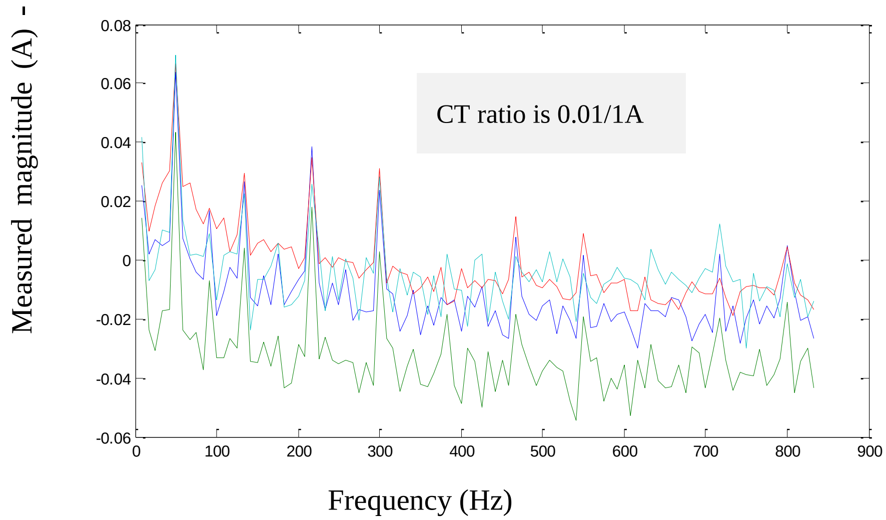


Figure 75 Frequency spectrums of electric motors in the scaled down system in isolated situation

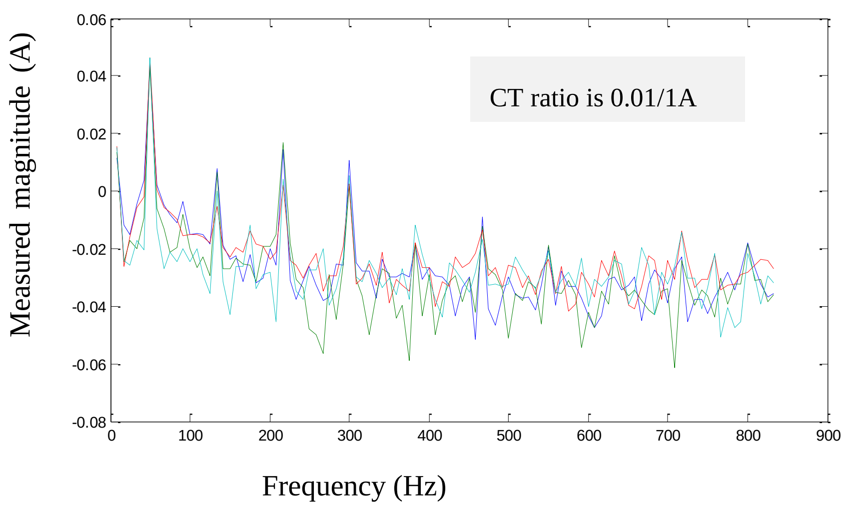


Figure 76 Frequency spectrums of electric motors in the scaled down system in parallel mode

As shown in Figure 75 and Figure 76, frequency spectrums of electric motors in parallel mode are not the same as they were in isolated situation. This change is due to propagation of fault signals in the power network.

In order to analyse the waveform, initially all local maximums of current waveform will be categorized and then all measuring points will be compared with expected locations of industrial faults and the associated speed will be calculated for any rational assumption.

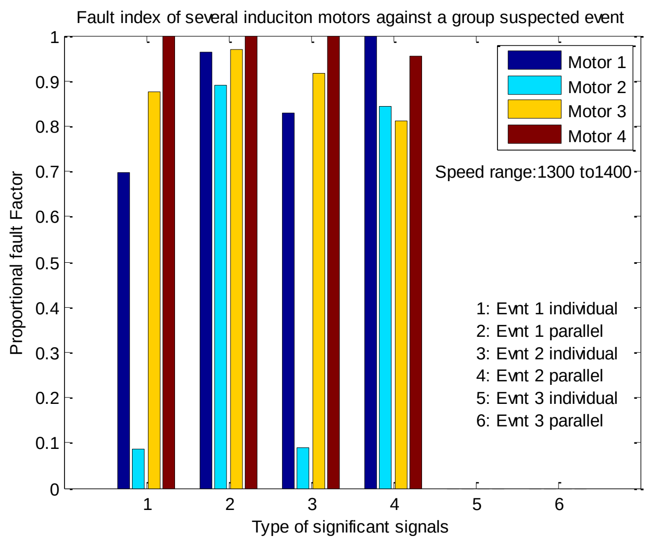


Figure 77 Fault indices for four electrical motors in both individual and parallel running- The suspected speed is 1300 to 1400RPM

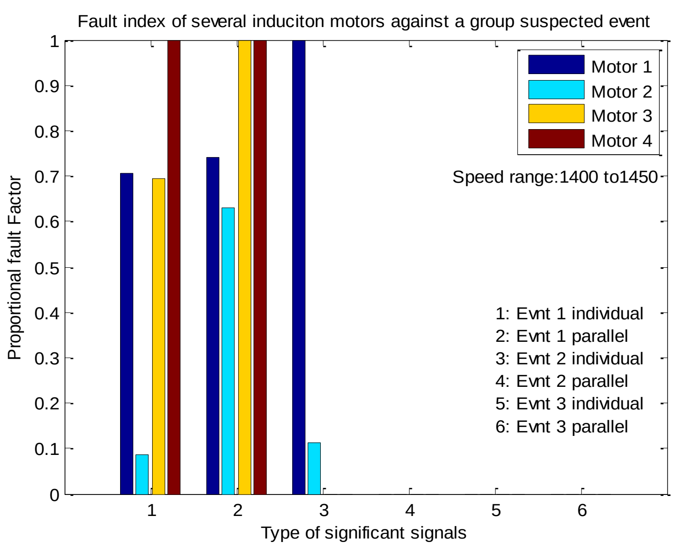


Figure 78 Fault indices for faults in for four electrical motors in both individual and parallel running- Suspected speed is 1400 to 1450RPM

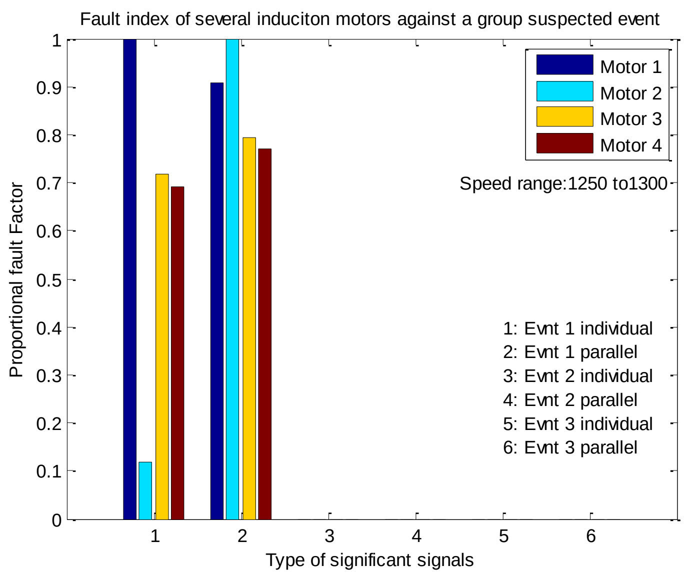


Figure 79 Fault indices for four electrical motors in both individual and parallel operation- The suspected speed is 1250-1350RPM.

As shown in Figures 77, 78 and 79 there is a significant change in value of fault indices while diagnostic speed varies. Looking at fault indices, Motor 4 can be considered as associated with a minor fault. This is the correct judgement as, Motor 4, has some degree of malfunction with fault 1 that is caused by imperfect installation of the motor. The motor's speed is 980RPM while other motors ran on speed range 1400 to 1450RPM. The fault index of Motor 3 is very close to the fault index of Motor 4. Considering the size of Motor 4, it can be concluded that the signal is caused by Motor 4.

Inconsistent increment of proportional fault indices may confuse the simulation. As discussed in 1, 2 and 3 the main reason of inconsistent increment/decrement of fault indices is the asynchronous measurement taken to measure fault signals.

7.6 Conclusion

A number of methodologies using distributed fault diagnostic approaches have been employed to improve reliability of industrial fault diagnosis. As demonstrated in this chapter, in most cases in-network fault diagnosis provided more accurate results. Fault indices demonstrated association of each motor with suspected faults. Propagation patterns describe the direction and origin of fault representatives and artificial neural network interprets fault indices using a training process. This combination attempts to take advantage of all possible indicators to point to the origin of fault signals. Besides the improvement, each solution is limited to a range of situations and came with some inherent shortcomings.

Chapter 8:

CONCLUSIONS AND RECOMMENDATIONS

8.1 Introduction

This chapter summarizes the key features of the Distributed Fault Detection and Diagnosis and describes the main findings of this research. Evaluation and judgement of the research have been followed with a set of recommendations to improve the reliability of diagnostic systems.

In this thesis, initially inherent shortcomings of individual fault diagnoses have been discussed. A diagnostic methodology has been proposed to formulate and utilize propagation of fault frequency components around the network and provide a more accurate diagnosis for in-network induction motors. An industrial scaled down distributed power system has been employed to generate data for a number of situations. This data have been used to formulate and evaluate the concept of distributed diagnosis.

Here a set of research contributions, their strength and limitations and thesis recommendation for further experiments and investigations are listed as follows.

8.2 Evaluation of research tasks and scope of future work

This project has successfully demonstrated the benefit and the necessity of in-network diagnosis as a replacement for individual diagnosis. Propagation of fault indices across the distributed power system causes serious interference in frequency components of current signals of electric motors. This interference can be interpreted as an observation of the status of remote equipment. Here a collaborative decision making methodology has been proposed to diagnose faults of all in-network electric motors considering all available observations.

More attention has to be paid to network topography to improve reliability of diagnosis. Taking advantage of topographical solutions in distribution networks may facilitate the processes of diagnosis and provide higher accuracy results.

8.2.1 Simulation Models

A scaled down industrial system has been utilized to observe behaviour of power networks against the occurrence of mechanical faults in electrical motors. Motor faults have been modelled by imperfect equivalent representatives of fault patterns as illustrated in previous research studies. Analysing the behaviour of more complicated motors with a higher number of components is an interesting assignment to develop and evaluate the concept of distributed signature analysis. Taking advantage of dynamic models of mechanical faults is an interesting task to match up propagation patterns with the dynamic extension of mechanical faults over a period of time.

8.2.2 Scaled down practical model

Here, a basic scaled down industrial system with limited numbers of electrical motors has been utilised to verify the concept of signal propagation. Results of practical experiments clearly demonstrate transmission of fault signals due to connection with other electric motors. Taking advantage of synchronous measurements for a long term situation where actual industrial faults occur is a better verification process and is recommended for further developments.

8.2.3 Numerical solutions to interpret fault information

The artificial neural network offers easier simplification of complicated situations and is capable of cancelling the network bias due to normal operation of electric motors or the interference of environmental noises. Here, a numerical solution based on ANN has been successfully implemented to utilize fault indices and diagnose the fault location in different situation. A more comprehensive study can evaluate the application of different types of neural networks to provide a more reliable diagnosis. Other methods of smart decision making such as fuzzy logics, Genetic algorithm and the Bayesian approach may suggest a general solution of fault diagnosis as well.

8.2.4 Expandability and Transportability

Accuracy of results of diagnosis is dependent on reliability of data acquisition systems, accuracy of fault indices and complexity of network configuration. As discussed previously, the concept is not limited to a set of faults. Therefore, including a pattern of new faults can provide the capability of diagnosing that fault. Further developments in theory of motor current signature analysis and quality of data acquisition systems will emerge to improve the reliability of distributed fault diagnosis.

The concept of distributed diagnosis and in-network fault detection has been employed to provide a more reliable diagnosis for electrical motors with direct measuring points and to take advantage of all observations to estimate the status of motors without any direct measuring point. This approach may offer higher reliability in other methods of diagnosis where fault signals propagate within a given network.

8.2.5 Quantifying success of experiments

As discussed in chapter 7, accuracy of distributed diagnosis is function of network topography, severity of faults, and level of noise and size of electrical motors. Forming a proper index to represent the network topography and quantifying the success of industrial experiments, emerges to improve the reliability fault diagnosis in different industrial networks.

8.3 Future developments in industrial fault diagnosis

Concerning reliability of fault diagnosis in industrial situations, we recommend the following research tasks to improve the functionality and reliability of in-network fault diagnosis:

- Rotor unbalanced and rotor asymmetry faults have been taken as an example to analyze in-network fault diagnosis. Including other types of motor faults such as eccentricity faults, broken bars and interterm faults in the proposed framework would be an interesting research task.
- An example of a scaled down industrial power system has been simulated to formulate propagation of fault signals and evaluate the concept of distributed fault diagnosis. Including transformers and electrical drives in the simulation model and investigating the nonlinear attenuation of fault signals due to saturation of the transformer in higher frequencies would be an interesting research task.
- The thesis utilizes a simplified model of electrical motors and motors faults to investigate the propagation of fault signals. Taking advantage of the dynamic model of electrical machines and the mechanical model of faults and analysis of fault indices using load flow approach during steady state and transient behavior of electrical motors provides the opportunity to diagnose the fault immediately after the incidents.
- A simple model of an artificial neural network has been taken as an example to evaluate the potential to employ numerical calculation to interpret fault indices. However the research does not cover a comprehensive study to select an optimum neural network for distributed fault diagnosis in industrial situations. Making use of other metrologies of numeric, statistic and intelligent data analysis are other areas of future expansion for research in this field.

APPENDIX I: MCSA FORMULATIONS

Fault type 1: Rotor Asymmetry as described in [23]:

$$f_{as} = f_0\left[k\left(\frac{1-s}{p/2}\right) \pm s\right] \tag{I-1}$$

Fault type 2: Rotor Unbalance as described in [23]:

$$f_{rs} = f_0\left[k\left(\frac{1-s}{p/2}\right) \pm 1\right] \tag{I-2}$$

Fault type 3: Broken bar as described in[23]:

$$f_{bq} = f_0(1 \pm 2f_0) \tag{I-3}$$

s: Motor slip

p: Number of poles

k: Harmonic order of fault symptom; k=1,2,3,…

f_0: Fundamental frequency

APENDIX II: DETAILS OF SIMULATION MODEL

EH1

Component	Detail
Motor 1	Squirrel cage motor, 10Hp, 400V
Motor 2	Squirrel cage motor, 10Hp, 400V
Motor 3	Squirrel cage motor, 10Hp, 400V
Motor 4	Squirrel cage motor, 10Hp, 400V
Motor 5	Squirrel cage motor, 10Hp, 400V
Motor 6	Squirrel cage motor, 10Hp, 400V
Motor 7	Squirrel cage motor, 10Hp, 400V
Motor 8	Squirrel cage motor, 10Hp, 400V
Motor 9	Squirrel cage motor, 10Hp, 400V
Motor 10	Squirrel cage motor, 10Hp, 400V
Motor 11	Squirrel cage motor, 10Hp, 400V
Motor 12	Squirrel cage motor, 10Hp, 400V
B1-B0	$0.6 + j0.6\ \Omega$
B2-B0	$0\ \Omega$
B3-B0	$0.6 + j0.6\ \Omega$
M1-B1	1Ω

Component	Detail
M2-B1	1Ω
M3-B1	1Ω
M4-B1	1Ω
M5-B2	1Ω
M6-B2	1Ω
M7-B2	1Ω
M8-B2	1Ω
M9-B3	1Ω
M10-B3	1Ω
M11-B3	1Ω
M12-B3	1Ω
Supply bus/Generator	450V, 0.2+j0.04 Ω
Static load	P=1kW; Q=200Var (inductive)

EH2

Component	Detail
Motor 1	Squirrel cage motor, 10Hp, 400V
Motor 2	Squirrel cage motor, 10Hp, 400V
Motor 3	Squirrel cage motor, 10Hp, 400V
Motor 4	Squirrel cage motor, 10Hp, 400V
Motor 5	Squirrel cage motor, 10Hp, 400V
Motor 6	Squirrel cage motor, 10Hp, 400V
Motor 7	Squirrel cage motor, 10Hp, 400V
Motor 8	Squirrel cage motor, 10Hp, 400V
Motor 9	Squirrel cage motor, 10Hp, 400V
Motor 10	Squirrel cage motor, 10Hp, 400V
Motor 11	Squirrel cage motor, 10Hp, 400V
Motor 12	Squirrel cage motor, 10Hp, 400V
B1-B0	$0.9 + j0.2\ \Omega$

B2-B0	$0\ \Omega$
B3-B0	$0.8 + j0.6\ \Omega$
M1-B1	1Ω
Component	**Detail**
M2-B1	1Ω
M3-B1	1Ω
M4-B1	1Ω
M5-B2	$0.7 + 0j.2\Omega$
M6-B2	$1 + j0.6\Omega$
M7-B2	$1.2 + j0.7\Omega$
M8-B2	$1.4 + j0.5\Omega$
M9-B3	$1 + j0.5\Omega$
M10-B3	1Ω
M11-B3	1Ω
M12-B3	1Ω
Supply bus/Generator	450V, 0.2+j0.04 Ω
Static load	P=1kW; Q=200Var (inductive)

EH3, EH31, EH4, EH5 AND EH6

Component	Detail
Motor 1	Squirrel cage motor, 10Hp, 400V
Motor 2	Squirrel cage motor, 50Hp, 400V
Motor 3	Squirrel cage motor, 20Hp, 400V
Motor 4	Squirrel cage motor, 5.4Hp, 400V
Motor 5	Squirrel cage motor, 20Hp, 400V
Motor 6	Squirrel cage motor, 20Hp, 400V
Motor 7	Squirrel cage motor, 5.4Hp, 400V
Motor 8	Squirrel cage motor, 5.4Hp, 400V
Motor 9	Squirrel cage motor, 5.4Hp, 400V
Motor 10	Squirrel cage motor, 10Hp, 400V
Motor 11	Squirrel cage motor, 20Hp, 400V
Motor 12	Squirrel cage motor, 5.4Hp, 400V
B1-B0	$0.9 + j0.2\ \Omega$

B2-B0	$0\ \Omega$
B3-B0	$0.8 + j0.6\ \Omega$
M1-B1	1Ω
Component	**Detail**
M2-B1	1Ω
M3-B1	1Ω
M4-B1	1Ω
M5-B2	$0.7 + 0j.2\Omega$
M6-B2	$2 + j0.6\Omega$
M7-B2	$1.2 + j0.7\Omega$
M8-B2	$1.4 + j0.5\Omega$
M9-B3	$1 + j0.5\Omega$
M10-B3	1Ω
M11-B3	1Ω
M12-B3	1Ω
Supply bus/Generator	450V, 0.2+j0.04 Ω
Static load	P=1kW; Q=200Var (inductive)

APPENDIX III: MATLAB PROGRAMS

SHOWONEOF

This program calculates the frequency spectra of a sample of currents of all electrical motors. Both linear and logarithmical illustrations have been used. Logarithmic demonstration provides a good illustration of changes and linear demonstration helps in calculating the actual value of the signal in each frequency point.

```
function showonef(q,mmk)
hold off;
forxy=1:12
xx=q(xy,:);
xys=num2str(xy);
xys=strcat('M# ',xys);
%L=length(xx);
L=25000;
 NFFT = 2^nextpow2(L);
Y = fft(xx,NFFT)/L;
%Y(1:100)=0.0001;
 Y0 = abs(Y);
Fs =25000;                    % Sampling frequency
   f = Fs/2*linspace(0,1,NFFT/2);
Ls=length(Y0);
   Lf=length(f);
Ll=min(Lf,Ls);
  subplot(6,2,xy)

dlim=fix(f(mmk))-1;
  plot(f(1:mmk),Y0(1:mmk),'blue');
  Y0=log(Y0);
```

```
  hold on;
   plot(f(1:mmk),Y0(1:mmk),'red');
   text(1,-8,xys);
xlim([0,dlim]);
%xlabel('Frequency Hz')
%ylabel('Magnitude(A)')
%tt=strcat('Motor NO',num2str(xy));
%title(tt);

end;
legend('Linear', 'Logarithmic')
```

SHOWSPECT.M

This program uses bars to illustrated magnitude of dedicated fault frequencies. Initially frequency spectrum will be generated using the method explained in showoneof and then fault frequency points have been filtered by manipulating the matrix of frequency spectrums.

```
%function yu2(data)
f1=65;  %variable frequency points
f2=48;
f3=78;
f4=28;
q=eh1;
clear ff1ff2ff3ff4;
forxy=1:12
xx=q(xy,:);
%L=length(xx);
L=50000;
 NFFT = 2^nextpow2(L);
Y = fft(xx,NFFT)/L;
cc=(100/(f(100)));
%Y(1:100)=0.0001;
 Y0 = abs(Y);
Fs =25000;                    % Sampling frequency
   f = Fs/2*linspace(0,1,NFFT/2);
Ls=length(Y0);
   Lf=length(f);
Ll=min(Lf,Ls);
% subplot(3,3,i)
% Y0=log(Y0);
%plot(f(1:1300),Y0(1:1300));
%  xlabel('Frequency Hz')
%ylabel('Logarithmic Magnitude (A)')
```

```
%title('Frequency spectrum of current in of Motor 1');
ff1(xy)=max(Y0(fix(cc*f1)),Y0(1+fix(cc*f1)));
ff2(xy)=max(Y0(fix(cc*f2)),Y0(1+fix(cc*f2)));
ff3(xy)=max(Y0(fix(cc*f3)),Y0(1+fix(cc*f3)));
ff4(xy)=max(Y0(fix(cc*f4)),Y0(1+fix(cc*f4)));
end;
f1m=num2str(max(ff1));
f2m=num2str(max(ff2));
f3m=num2str(max(ff3));
f4m=num2str(max(ff4));
%f1m=strcat('f1 is:',f1m);
%f2m=strcat('f2:',f2m);
%f3m=strcat('f3',f3m);
%f4m=strcat('f4:',f4m);
ff1=ff1/max(ff1);
ff2=ff2/max(ff2);
ff3=ff3/max(ff3);
ff4=ff4/max(ff4);
ff=[ff1;ff2;ff3;ff4];
bar(ff');
%hold on;bar(ff2,'red');
%hold on;bar(ff3,'green');
%hold on;plot(ff4,'blue')

%plot(ff1,'o')
%hold on;plot(ff2,'ro')
%hold on;plot(ff3,'go')
%hold on;plot(ff4,'bo')
legend(strcat(num2str(f1),'Hz'),strcat(num2str(f2),'Hz'),strcat(num2str(f3),'Hz'),strcat(num2str(f4),'Hz'));
xlabel('Measuring points')
ylabel('Rational value of significant frequencies')
title('Rational value of significant frequencies at each measuring point');
text(4,0.9,num2str(f1));text(7,0.90,f1m);
```

```
text(4,0.85,num2str(f2));text(7,0.85,f2m);
text(4,0.8,num2str(f3));text(7,0.80,f3m);
text(4,0.75,num2str(f4));text(7,0.75,f4m);
text(3,0.95,'Frequency');
text(6.5,0.95,'Maximum Value');
hold off;
```

SPPY.M

This program compares fault frequencies of the spectrum with frequency patterns of three known fault events. This program considers each frequency point as associated with all suspected faults and calculates the speed that is associated with this involvement. The fault frequency point will be considered if the calculated speed is in range of acceptable speeds otherwise it will be rejected and then compared against the next significant fault. sppy may return association with none or more than one fault for each single frequency- magnitude point.

```
function [m1,m2,m3,fsign]=sppy(frn0,mag,vmax,vmin)
cf=1;f0=50;Q=1;K=1;vs=1500;KQ=1;p=4;kk=2;m1=0;m2=0;m3=0;
   clear speedfsign;
fsign(1)=0;
      speed(1)=0;
for n=15:-1:1
   k=n;
   s=((frn0/f0)-(2*k/p))/(1-(2*k/p));%4
v=(1-s)*vs;

if v>vmin
if v<vmax
fsign(kk)=1;
      speed(kk)=v;kk=kk+1;
      m1=mag/kk;
end
end
s=((2*k/p)-(frn0/f0))/ (2*k/p+1); %5
v=(1-s)*vs;
if v>vmin
if v<vmax
fsign(kk)=2;
```

```
        speed(kk)=v;
kk=kk+1;
        m1=mag/kk;
end
end
s=1-n*((frn0/(cf*f0)-n)/(K*Q));%6
v=(1-s)*vs;
if v>vmin
if v<vmax
fsign(kk)=3;
        speed(kk)=v;kk=kk+1;
        m2=mag/kk;
end
end

s=1-n*((n+(frn0/(cf*f0))))/KQ;%1
v=(1-s)*vs;
if v>vmin
if v<vmax
fsign(kk)=4;
        speed(kk)=v;kk=kk+1;
        m2=mag/kk;
end
end

s=1-n*(((frn0/cf*f0)-n)/(k*Q+n));%2
v=(1-s)*vs;
if v>vmin
if v<vmax
fsign(kk)=5;
        speed(kk)=v;kk=kk+1;
        m3=mag/kk;
```

```
end
end
s=1-((((frn0/(cf*f0))+n)/(k*Q-n))*n);%3
v=(1-s)*vs;
if v>vmin
if v<vmax
fsign(kk)=6;
    speed(kk)=v;kk=kk+1;
    m3=mag/kk;
end
end

end;
dyy= find(speed>0);
%fkk=fsign(dyy);
dyy=speed(dyy);
%dyy=[dyy;fkk];
%dyy=sum(dyy)/(length(dyy));
%disp(dyy');
end
```

PATARZ.M

This program calculates the frequency spectrums using the same way explained in **showoneof**. Then employs the concept of local maximums to identify fault frequency points in the waveform and finally pass frequency-magnitude points to SPPY.

```
function [f1 f2 f3]=patarz(y0,vmax,vmin)
%frr=d25;vmax=1900;vmin=3000;rtt=1;
ijj=size(y0); ijj=ijj(2);
for ij=1:ijj
y1=y0(:,ij);
m1=0;m2=0;m3=0;
L=2500;
 NFFT = 2^nextpow2(L);
Fs =25000;                    % Sampling frequency
%f = Fs/2*linspace(0,1,NFFT/2);
%FFT
        Y = fft(y1,NFFT)/L;
%Y(1)=[];

%Y=Y-Y0; % test %%%%%%%%%%%%%should be removed
f = Fs/2*linspace(0,1,NFFT/2);
pyy= (2*(abs(Y(1:NFFT/2))));
%f=f(1:1000);pyy=pyy(1:1000);
%pyy(90:106)=0;pyy0(90:106)=0;%50HZ
%pyy(1:5)=0;

%pyy=pyy(1:1960);
%f=f(1:1960);
%FFT
  fr0=pyy;
[pks,locs]=findpeaks(fr0);
```

```
flocs=f(locs);
locs22=flocs;pks2=pks; %use the same variable to make it easier
%plot(locs,pks)
%[pks1,locs1]=findpeaks(pks);
%locs11=locs(locs1);

%[pks2,locs2]=findpeaks(pks1);

%locs22=locs11(locs2);

itt=1;

whileitt<length(locs22)
if pks2(itt)>(max(pks2)/2000)
itt=itt+1;

else
    pks2(itt)=[];locs22(itt)=[];
%disp(itt)
end;
end

%fl=flocs;
 hold on
%ps=length(pks2);

xmm=length(locs22);
locs22(xmm)=[];pks2(xmm)=[];

% pks2=10*log(pks2);
%two lines removed to increase the speed
% plot(locs22,pks2,'bo')
```

```
%plot(locs22,pks2)
%%%%%%%%%%%%Spp; to diagnose the points

% rts=num2str(rt); %ms=num2str(m);

for stt=1:length(pks2)
pktf=pks2(stt);
sttf=locs22(stt);
% if sttf>0
        [m1b,m2b,m3b,fsign]=sppy(sttf,pktf,vmax,vmin);%#ok<NASGU> %spp(frn0,vmax,vmin)
        m1=m1+m1b;m2=m2+m2b;m3=m3+m3b;
%m1=max(m1,m1b);m2=max(m2,m2b);m3=max(m3,m3b);
%if (length(fsign)>1)% avoide returning zeros

%fsigns=num2str(fsign);speeds=num2str(speed);

% strs=strcat('detected at,sensor:',rts,' ,time:',ms,' ,speed:',speeds ,' ,type:',fsigns);
% disp(strs);
% end; %avoid returning zeros
%  end;
end;
%%%%%%%%%%%%%%%%%%%%%%%%

% end;% end of time variation
% pause(0.1);
  hold off;
%showing faults power
%m1s=num2str(m1);
%m2s=num2str(m2);m3s=num2str(m3);
%dds=strcat('Sensor',rts,'   F1:',m1s,',  F2:',m2s,'  F3:',m3s);
f1(ij)=m1;f2(ij)=m2;f3(ij)=m3;
%disp(dds)
```

```
%showing faults power
%m1=0;m2=0;m3=0;
end;

end%end of sensor variation

% frn0= fix(cf*(f0*(k*Q*((1-sl)/(n))-n)));%1
```

CHALLENGE1.M

This program organizes workspace variables which were generated by simulation models and prepares them for further processing using Patarz.

```
clear smtsm1;
vmax=1450;%Variable
vmin=1430;%Variable
J=1;
%
smt(:,1)=i1(2500:5000);
smt(:,2)=i2(2500:5000);
smt(:,3)=i3(2500:5000);
smt(:,4)=i4(2500:5000);
smt(:,5)=i5(2500:5000);
smt(:,6)=i6(2500:5000);
smt(:,7)=i7(2500:5000);
smt(:,8)=i8(2500:5000);
smt(:,9)=i9(2500:5000);
smt(:,10)=i10(2500:5000);
smt(:,11)=i11(2500:5000);
smt(:,12)=i12(2500:5000);

%sm1(:,1)=i1;
  [b1,b2,b3]=patarz(smt,vmax,vmin);
%b1=b1./max(b1);
%b2=b2./max(b2);
%b3=b3./max(b3);
%[a1,a2,a3]=patarz(sml,vmax,vmin);
%a1=a1./max(a1);
```

```
%a2=a2./max(a2);
%a3=a3./max(a3);
sp1=num2str(vmin);
sp2=num2str(vmax);
   bar([b1;b2;b3])
%bar([a1;b1;a2;b2;a3;b3])
sq=strcat('Fault index of several induction motors against a group suspected event');
title(sq);

xlabel('Type of fault signals');
ylabel('Proportional fault Factor');
legend(12,'Motor 1', 'Motor 2','Motor 3','Motor 4','Motor 5','Motor 6','Motor 7','Motor 8','Motor 9','Motor 10','Motor 11','Motor 12');

sq1=strcat('Speed range:',sp1,' to ',sp2);
text(4.5,-.2,sq1);
text(5,.4,'1: Evnt 1 individual');
text(5,.35,'2: Evnt 1 parallel');
text(5,.3,'3: Evnt 2 individual');
text(5,.25,'4: Evnt 2 parallel');
text(5,.2,'5: Evnt 3 individual');
text(5,.15,'6: Evnt 3 parallel');
```

CHART1.M

This program provides a graphical solution to demonstrate propagation of fault indicators and find the faulty motor. Challenge1 produces the required data for this program.

```
%challenge1;
hold off;
for z=1:3
for x=1:4
for y=4:-1:(x+1)
%bar([b1;b2;b3])
% subplot(3,1,1), bar([b1;b2;b3])
% disp(x),disp(y);
% 0.2 is a set point assigned by the network topography as discussed in the theory chapter
if (b1(4*(z-1)+x)+b1(4*(z-1)+y)>0)
if (b1(4*(z-1)+x)>1.1*b1(4*(z-1)+y)); hold on;
        plot((z+(x-1)*0.2),y,'.');hold on;
         line([(z+(x-1)*0.2),(z+(y-1)*0.2)],[x,y],'Color','red','LineWidth',2)
elseif (1.1*b1(4*(z-1)+x)<b1(4*(z-1)+y))
      hold on;
      plot((z+(x-1)*0.2),y,'rO');
      hold on;
      line([(z+(x+1)*0.2),(z+(y-1)*0.2)],[x,y],'Color','blue','LineWidth',2);
else
         line([(z+(x)*0.2),(z+(y-1)*0.2)],[x,y],'Color','y','LineWidth',2);
end;
end;
end;%for
end;%for
end;%for
%bar([a1;b1;a2;b2;a3;b3])
```

```
    bb1=sum(b1(1:4));bb2=sum(b1(5:8));bb3=sum(b1(9:12));
if(bb1>bb2)
        line([1,2],[2.5,2.5],'Color','g','LineWidth',4,'LineStyle','<');
      line([1,2],[2.5,2.5],'Color','g','LineWidth',4);
else
         line([1,2],[2.5,2.5],'Color','g','LineWidth',4,'LineStyle','>');
      line([1,2],[2.5,2.5],'Color','g','LineWidth',4);
end;

if(bb2>bb3)
        line([2,3],[1.5,1.5],'Color','g','LineWidth',4,'LineStyle','<');
      line([2,3],[1.5,1.5],'Color','g','LineWidth',4);
else
         line([2,3],[1.5,1.5],'Color','g','LineWidth',4,'LineStyle','>');
      line([2,3],[1.5,1.5],'Color','g','LineWidth',4);
end;

if(bb1>bb3)
        line([1,3],[3.5,3.5],'Color','g','LineWidth',4,'LineStyle','<');
      line([1,3],[3.5,3.5],'Color','g','LineWidth',4);
else
         line([2,3],[3.5,3.5],'Color','g','LineWidth',4,'LineStyle','>');
      line([1,3],[3.5,3.5],'Color','g','LineWidth',4);
end;

sq=strcat('Propagation pattern of fault indices ');
title(sq);

xlabel('Supply Bus #1,#2 and #3');
ylabel('Induction motors');
```

```
%legend(12,'Motor 1', 'Motor 2','Motor 3','Motor 4','Motor 5','Motor 6','Motor 7','Motor 8','Motor 9','Motor 10','Motor 11','Motor 12');
xlim([0.5,4]);ylim([0.5,4.5]);
hold on;
for i=1:3
for k=1:4
    no=num2str(4*(i-1)+k);
    mm=strcat('M ',no);
text(i,k,mm);
end;
end;

text(0.8,4.3,'----Bus 1----');
text(1.8,4.3,'----Bus 2----');
text(2.8,4.3,'----Bus 3----');
```

CHALLENGECON2.M

This program automatically runs a number of simulation models to generate the data to train the Neural Network model.

```
clear b1yb2yb3y;
clear smtsm1;
vmax=1470;
vmin=1410;
J=1;
%
sy=1;
forjk=[1,4,7,10,12,13]
jks=num2str(jk-1);
ff=strcat('eh3',jks);
disp(strcat('eh3',jks));
sim(ff)
smt(:,1)=i1(72500:75000);
smt(:,2)=i2(72500:75000);
smt(:,3)=i3(72500:75000);
smt(:,4)=i4(72500:75000);
smt(:,5)=i5(72500:75000);
smt(:,6)=i6(72500:75000);
smt(:,7)=i7(72500:75000);
smt(:,8)=i8(72500:75000);
smt(:,9)=i9(72500:75000);
smt(:,10)=i10(72500:75000);
smt(:,11)=i11(72500:75000);
smt(:,12)=i12(72500:75000);

%sm1(:,1)=i1;
```

```
xx=1;
forjj=vmin:10:vmax
  [b1,b2,b3]=patarz(smt,jj+11,jj);
  b1z(sy,xx,:)=b1;
  b2z(sy,xx,:)=b2;b3z(sy,xx,:)=b3;
  xx=xx+1;
%b1=b1./max(b1);
%b2=b2./max(b2);
%b3=b3./max(b3);
%[a1,a2,a3]=patarz(sml,vmax,vmin);
%a1=a1./max(a1);
%a2=a2./max(a2);
%a3=a3./max(a3);
end;
disp('OOOOOOOOO');sy=sy+1;
end;
save;
```

NNEXSOME4.M

This program forms a feed forward neural network model to interpret fault indicators and allocate fault locations.

```
clear ptnet2yx1y1;
%clc;
%vvv(2,1)=1;vvv(3,2)=1;vvv(4,3)=1;vvv(5,4)=1;vvv(6,5)=1;vvv(7,6)=1;vvv(8,7)=1;vvv(9,8)=1;vvv(10,9)=1;vvv(7,10)=1;vvv(12,7)=1;vvv(13,12)=1;

%net2=newff(p,t,5);% 5 hidden layer
bb=b1z(6,:,:);bb=reshape(bb,7,12);

bb= sqrt(sum(bb.^2));%ffffff

vx=[0 0 0 0 0 0 0 0 0 0 0 1];
net2=newff(bb,vx,5);% 5 hidden layer

%jk=[1,4,7,10,12,13]

%for j=1:3:13
  j=1;
disp(j);
  bb=b1z(j,:,:);bb=reshape(bb,7,12);
  bb= sqrt(sum(bb.^2));%ffffff
vx=[0 0 0 0 0 0 0 0 0 0 0 0];
net2.trainParam.goal = 0.01;% error target
net2 = train(net2,bb,vx);
y=sim(net2,bb);
%end;
```

```
%for j=1:3:13
   j=2;
disp(j);
   bb=b1z(j,:,:);bb=reshape(bb,7,12);
   bb= sqrt(sum(bb.^2));%ffffff
vx=[0 0 1 0 0 0 0 0 0 0 0 0];
net2.trainParam.goal = 0.01;% error target
net2 = train(net2,bb,vx);
y=sim(net2,bb);
%end;


%for j=1:3:13
   j=3;
disp(j);
   bb=b1z(j,:,:);bb=reshape(bb,7,12);%Fault representatives
   bb= sqrt(sum(bb.^2));%Calculate Fault indices
vx=[0 0 0 0 0 1 0 0 0 0 0 0];
net2.trainParam.goal = 0.05;% error target
net2 = train(net2,bb,vx);
y=sim(net2,bb);
%end;


%for j=1:3:13
   j=3;
disp(j);
   bb=b1z(j,:,:);bb=reshape(bb,7,12);

  bb= sqrt(sum(bb.^2));%ffffff
```

```
vx=[0 0 0 0 0 0 0 0 1 0 0 0];
net2.trainParam.goal = 0.01;% error target
net2 = train(net2,bb,vx);
y=sim(net2,bb);
%end;
bb=b1z(5,:,:);bb=reshape(bb,7,12);
bb= sqrt(sum(bb.^2));%ffffff
y1=sim(net2,bb);
%plot(x1,y1)
y1=abs(y1);
y1=y1/(sum(y1));
bar(abs(y1));
xlabel ('Measuring points')
ylabel ('proportional possibility')
% b1z(jk+1,xx,:)=b1; jk: fault in subsystem; xx::fault index
%
bb=b1z(5,:,:);bb=reshape(bb,7,12);
bb= sqrt(sum(bb.^2));%ffffff
bc=bb;
y1=sim(net2,bc);
%plot(x1,y1)
y1=abs(y1);
y1=y1/(sum(y1));
bar(abs(y1));
xlabel ('Measuring points')
ylabel ('Proportional possibility')
xf=find(y1==max(y1));xf=num2str(xf);
xm=max(y1);xm=num2str(xm);
xxx=strcat('Detected: Fault in Motor',xf,' with possibility of', xm)
 text(0.5,0.4,xxx);
text(0.5,0.35,'out of 1')
```

TESTNN.M

This program employs the trained network explained in **nnexSome4.m** as an offline neural network to and uses fault indices of each simulation Case study to signify the fault location.

```
bb=b1z(5,:,:);% variable
bb=reshape(bb,7,12);
bb= sqrt(sum(bb.^2));%ffffff
bc=bb;
bc([5,6,7,8,11])=0; % measuring points to turn off.
y1=sim(net2,bc);
%plot(x1,y1)
y1=abs(y1);
y1=y1/(sum(y1));
bar(abs(y1));
xlabel ('Measuring points')
ylabel ('Proportional possibility')
xf=find(y1==max(y1));xf=num2str(xf);
xm=max(y1);xm=num2str(xm);
xxx=strcat('Detected: Fault in Motor ',xf,' with possibility of', xm)
 text(0.5,0.4,xxx);
text(0.5,0.35,'out of 1')
```

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