Application of Magnetic Fields To Aid The Detection and Diagnosis of Induction Motor Drive Faults

by

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Thesis submitted for the degree of

DOCTOR OF PHILOSOPHY

Of the

University of Wales

January 2009

University of Wales Institute Cardiff
DECLARATION

The work submitted in this thesis is the result of the candidate’s own investigations, except where otherwise indicated.

This work has not been accepted in substance for any other degree, and is not being submitted currently for any other degree.

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D.M. Holifield
Acknowledgements

Any analysis would reveal that I should concentrate my acknowledgements on one person, my supervisor David Holifield. Despite many other commitments, he always found time to meet and explore my ideas. His help, enthusiasm, and encouragement has, for me, made the essential difference between completion and non-completion of this thesis.

Several other people within UWIC helped me to pursue this research, and I would particularly like to thank technician-demonstrators Mike O’Keeffe and Dennis Flynn for their help with the practical activities associated with this research.

I would also very much like to acknowledge the help and guidance that I have received from my second supervisors; Dr. Tarsem Sihra and Dr. Amar Bousbaine.

Last but not least, I would like to thank my wife Hazel for her continued patience and understanding.
Abstract

A novel approach to the collection of fault related data associated with induction motor drives is presented. The stator to rotor magnetic flux of an induction motor is monitored by a number of strategically positioned search coils, each wound around a single stator pole. The data collected is in the form of time records of the induced voltage in the coils and is subsequently used to form the data base for a fault detection and diagnosis strategy.

Voltage waveforms obtained from a single coil and from two coils connected in series are obtained whilst the system is subjected to a range of applied electro-mechanical faults. The applied faults are applied both to the mechanical load and to the induction motor itself. A comparison is made of the efficacy of using two search coils compared to employing a single coil for fault detection.

The fault related data is collected under both steady-state and accelerating running conditions. Strictly the acceleration period waveforms are non-stationary, however, since the time dependant frequency changes are relatively slow, the author applied the FFT technique to both steady-state derived data and the acceleration period derived data. Processing is carried out on both the time domain and the corresponding frequency domain data.

The non-stationary nature of the acceleration period records is taken into account and the Wigner-Ville technique is employed to establish a time-frequency-distribution. Amplitude-time-frequency 3-D representations are produced, from which the amplitude versus time activity of a typical acceleration period component frequency is presented.
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Chapter 1

Critical Information Survey on Failure Diagnosis in Induction Motors

1.1 General Introduction

Induction motors are commonly used in a wide variety of industrial applications. It is estimated [1] that 40 – 50% of generated power is consumed by induction motor driven plant. Due to their simple design and to modern production techniques induction motors are considered to be reliable and robust, however failures do occur and may consequently result in loss of production or unsafe operating conditions.

This research forms the basis of a strategy providing an alternative to the currently employed sources of data employed in fault detection on induction motor drives. The research, as described in this thesis, employs a number of search coils to monitor the stator to rotor magnetic flux of an induction motor. The induction motor is connected to a geared load and the field related collected data is to form the basis for a fault detection and diagnosis strategy.

This chapter presents a general description of the current strategies commonly employed for fault detection and diagnosis. This chapter also introduces the basic methodology employed in this research, and provides a brief description of the measurement system, the hardware employed, the faults applied, and examples of some typical results obtained.
1.2 Condition Monitoring Strategies and Literature Review

A number of strategies can be employed in order to maintain the availability and safe operation of both induction motors and associated plant being driven by them. The strategies include either a breakdown, scheduled or condition-based maintenance strategy. This research concentrates on the condition based or predictive maintenance approach which entails providing assessment of machine condition based on measured data.

There are many commercially available tools and accepted techniques available to monitor the condition of induction motors and associated machinery. This is of particular importance where environmental, duty, and installation factors may combine to accelerate motor and/or plant failure. It has been found [2] that many of the available commercially produced condition monitoring products are not cost effective for small to medium induction motor driven systems. However, critical induction motor applications are found in all industries and employ induction motors of all horsepower ratings.

Some key drivers to employing a condition monitoring technique to induction motor driven plant, especially in critical applications, include:

- Increased plant reliability
- Increased plant availability
- Reduced maintenance costs
- Reduced spares inventory
- Reduced lost production and increased income generation.
- Reduced knock-on effects
- Improved safety

Condition monitoring (CM) is widely employed in order to detect the onset of faults on induction motors and associated machinery. The fault condition will ideally be detected at an incipient stage which will potentially reduce those costs associated with unplanned breakdowns.

The types of faults being monitored by CM are often referred to as ‘soft’ or ‘drift’ faults where components drift outside their normal operating characteristics due to factors such as wear and operational stresses. Drift faults are subject to an increasing level of severity until they reach an unacceptable level, at which point the system no longer operates within satisfactory performance limits. The role of CM is to detect and diagnose these faults before they reach an unacceptable level. In general CM can either be applied to condition checking which results in an alarm activation if a pre-set limit is reached, or trend monitoring where the machine condition is continuously monitored and recorded.

In all cases CM entails measuring a systems performance and seeing if the system is doing what it should do. Systems to which it is appropriate to apply a CM strategy are analogue in nature and can exhibit a wide range of performance characteristics from good to acceptable to poor to unacceptable etc. Binary systems are those whose performance is classified as either good or bad, satisfactory or unsatisfactory, without any grey area in between. Binary systems undergo catastrophic failure due to the occurrence of a ‘hard’ fault and are therefore unsuitable for CM.
It is preferable to perform CM under normal operating conditions and with normal operational inputs rather than applying special test signals to the system. This saves the expense and complexity of injecting special test signals such as low-levels of pseudo-noise added to the normal operational input signals. In all cases a systems ‘healthy’ response is established when the monitored system is known to be performing correctly. It is possible to perform CM under both transient and steady state conditions, since these two conditions are invoked under normal switch on and run conditions respectively.

A brief summary of some of the techniques employed in order to perform condition monitoring follows.

1.2.1 Vibration Monitoring and Analysis

This is a widely used technique for determining machine condition by capturing and analysing a time record of the output of a vibration transducer. Vibration transducers, commonly piezo-based accelerometers, are mounted at suitable locations on a machine structure. The output of these transducers gives the acceleration of vibration from which, if necessary, both the velocity and displacement of vibration can be determined. The overall vibration level can be plotted and trended and assessed against predetermined criteria to permit initial judgements to be made on machine condition. Vibration monitoring is one of the most widely used methods of condition monitoring employed in industry. Monitoring can be periodic often consisting of manual checks of vibration activity taken from selected machines and employing hand-held units. Alternatively monitoring can be continuous using permanently installed vibration transducers and associated equipment. Continuous monitoring and
real time analysis of data is particularly important for continuous process machines
performing critical applications. These machines may need to be shut down very
soon, possibly seconds, after fault dependent vibration increases to an unacceptable
level either through a sudden or gradual fault development.

Machinery which contains moving parts will, even under healthy-state conditions,
vibrate at a range of frequencies which are governed by the nature of the vibration
source. Machines commonly include one or more rolling elements such as gearboxes,
shafts, and bearings, all of which exhibit a particular effect upon the vibration signal
[1] [10] [11] [12] [18]. If any of these components starts to fail, its’ vibration
characteristic will change, which forms the basis of techniques employed to detect and
analyse the changes.

If diagnosis of a fault condition is required then a vibration time record will have to
undergo some form of frequency analysis. The resulting spectrum yields information
about the frequency components making up the vibration signal time record and is
most often presented as amplitude versus frequency. The effect upon the spectrum due
to any particular faulty component can be determined, i.e. a healthy-state spectrum
obtained by measurement or by analysis of machine and component dynamics. In any
case the basis of detection is to perform a trend analysis and of diagnosis is to
compare each current time record and its’ spectrum to the known healthy-state time
record and its’ spectrum [1] [10] [11] [12] [18]. The deviations from the healthy-state
spectrum will be dependant upon which type of fault is present on the system, and it is
this fact that makes diagnosis possible.
Another important characteristic of vibration is ‘phase’, which refers to the position of a vibrating part with reference to a fixed point or another vibrating part. As a rule, phase measurements are not taken during normal routine vibration measurements, but can provide valuable information when a problem has been detected.

Modern systems typically employ an FFT algorithm [31] [32] which processes a time record of vibration activity to produce a spectrum showing vibration levels over a range of frequencies. This overall vibration level is useful since it may be used to detect all the defects which may be present in a machine, e.g. unbalance, faulty bearings, misalignment etc.

Particular machine faults will affect one or more discrete spectral peaks and the spectral peaks can be examined to provide the means for fault detection. Which peaks will be affected by a particular fault can be established by a number of means which include a compilation of vibration data from similar machines running under a range of known fault and healthy-state conditions. In addition faults on rotating machinery such as misalignment, unbalance, bearing faults produce vibration peaks at known predictable frequencies. A number of texts provide information and tables which state the expected vibration frequencies resulting from a number of faults on rotating machinery [30]. For the rotating system components forming the basis of this research, chapter 1 section 1.4 and chapter 2 section 2.4 of this thesis present the expected vibration frequencies associated with a range of common faults such as shaft misalignment, worn gear teeth, damaged bearings, load imbalance and dynamic eccentricity. A knowledge of the expected position and magnitude of peaks in the
vibration spectra can be employed in the detection and diagnosis of faults which may develop during system operation.

The role of expert systems in vibration analysis is rapidly being expanded, some integrated systems can now acquire and analyse data, both off-line and in real time as consistently as an experienced analyst.

1.2.2 Using Acoustic Emission (AE)

Vibration techniques were originally developed to analyse the dynamic motion of structures and has been adapted to provide the basis for fault detection and diagnosis. In contrast acoustic emission [3] [5] [6] was originally developed as a method of Non-Destructive Testing (NDT) where ‘sounds’ generated by cracks in materials were detected using sensitive surface contacting transducers. To improve the signal to noise ratio of the detected signal it was necessary to monitor at higher frequencies. If a machine fault generates only low frequency vibrations then vibration analysis would be preferred. If however higher frequencies are generated, by for example a high level of misalignment and/or unbalance, then acoustic emission may be considered. It can be shown [3] [5] [6] that because of the improvement in SNR of an acoustic emission signal compared to that of a vibration signal it is often possible to detect faults using simpler (time domain) signal processing than the frequency domain processing used with vibration signals.

Toutountzakis and Mba [6] presented, in a paper, observations of acoustic emission (AE) that demonstrates the applicability of AE to gear health diagnosis. The paper states that the source of AE is attributed to the release of stored elastic energy that
manifests itself in the form of elastic waves that propagate in all directions on the surface of a material. Frequencies associated with AE activity cover a broad frequency range of between 20 KHz to 1 MHz. The paper presents the behaviour of AE to changes in speed or process in real time. Furthermore, the paper demonstrates that gear defect can be diagnosed from the bearing casings.

1.2.3 Thermographic Monitoring and Analysis

Thermographic analysis uses the heat generated, transmitted, or reflected by a machine to determine the condition of the machine. An infra red camera can be employed to detect infra red radiation from the surface of an object. Typical monitoring points would include areas around rotating machine bearing housings, supply cables and connections, control gear fuse holders etc. Infra-red monitoring is non-intrusive and can be performed under normal machine operating conditions. Infrared scanning can be used effectively for almost any system in which surface heat distribution is representative of operating condition.

During a survey an infra red image of a machine’s heat distribution is stored and a digitised photographic-like heat contour image can be produced for reporting purposes. The colour map given in the image ranges from dark blue representing cooler areas through red, orange, yellow and finally to white which represents the hottest areas, see figure 1.1. The actual temperature range which these colours represent can be selected using the camera ranging functions provided. Crosses can be placed at appropriate locations on the image, each cross location is labelled and the temperature at the position of each cross can be displayed for reporting and analysis purposes. The following figure illustrates the colour representation of surface
temperatures within the set temperature range, typically 30 °C to 60 °C. The ambient temperature is also logged and a typical value would be in the region of 8 °C.

![Colour Chart Representing Surface Temperatures](image)

**Figure 1.1 Colour Chart Representing Surface Temperatures**

This method can be employed with equal effect to monitor both the condition of the induction motor and the plant being driven [1].

Chalifaux and Northrup [4] states that Infrared Thermography (IRT) inspections are identified as either qualitative or quantitative. The quantitative inspection attempts the accurate measurement of the temperature of the item under test. This requires detailed knowledge and understanding of the relationship of temperature and radiant power, reflection, emittance, and environmental factors, as well as the limitations of the detection instrument. Qualitative measurements are time-consuming, and are not normally required for condition monitoring purposes.

The qualitative inspection is interested in relative differences, hot and cold spots, and deviations from normal or expected temperature ranges. Qualitative inspections are significantly less time-consuming since the thermographer is not concerned with highly accurate temperature measurement.

Instruments that perform infrared detection detect electromagnetic energy in the short wave (3 to 5 microns) and long wave (8 to 15 microns) bands of the electromagnetic
spectrum. A short wave instrument is best for inspections of electrical and mechanical equipment, although when taking readings in situations subject to solar reflections shiny surfaces may appear to be hotter than they really are. IRT instruments are normally portable, are sensitive to within ±0.2 ºC over a -100 to +3000 ºC, and accurate to within ±3%. In addition, the instrument must be capable of storing thermographic images for later analysis.

Thermography is limited to line of sight and care must be taken to account for material colour, material geometry, and environmental factors such as solar heating and wind effects.

1.2.4 Tribology

This method is limited to machines which incorporate an oil lubrication system and is a technique which provides information on the oils’ chemistry, wear, and contamination. Lubricant analysis involves both the monitoring of the lubricant itself and the lubricant-debris. Whilst lubricant monitoring determines the effectiveness of the lubricant, debris analysis provides valuable information on the condition of a machines’ wearing surfaces, such as bearings and slide-ways. Many off-line, spectroscopic and morphological techniques exist to analyse lubricant condition and wear metal debris.

Destructive modes of wear such as scuffing, fretting and surface fatigue is inherent in the operation of all machines, and can ultimately lead to component failure. By monitoring the quantity and nature of wear debris it is possible to obtain an indication of the condition of the various machine components which are in contact with the
lubricant. For the many failures of lubricated surfaces which are progressive in nature, rather than sudden, the method also enables a useful advanced warning of machine failure to be obtained.

Over the past two decades on-line oil monitoring techniques have been developed [8]. Inductive oil debris monitors are useful for the characterisation of both ferrous and non-ferrous particulate and have high detection efficiencies. Adding particle size, shape, and curvature monitoring on-line can contribute to early detection.

1.2.5 Model Based and Simulation Techniques.

This technique requires as many variables and system parameters as possible to be taken into account in order to construct a detailed mathematical model of the system under observation [11] [14] [16]. Once the dynamic behaviour of the system has been adequately modelled it should be possible to detect faults by detecting any differences between measured and predicted responses. These differences are called residuals and they must be sensitive to faults but not to system input or disturbance changes. Faults are detected when predetermined threshold levels assigned to each residual are reached. Modelling uncertainties which may result from system nonlinearities, system parameter uncertainties, disturbances and other measurement noise has hitherto limited the use of model-based fault diagnosis in industrial applications. The application of neural networks offers the potential for broadening the industrial acceptance of model-based fault diagnosis. Isermann and Balle [14] review the recent trends in model-based fault detection and diagnosis.
An analytic technique for modelling the magnetic noise in induction machines, which allows the air gap radial magnetic forces to be expressed as functions of the space harmonics due to rotor eccentricity is presented in a paper by Byington et al [7]. The mathematical model for a particular motor type and rating was employed to simulate the sound pressure resulting from the noise produced by the motor running under both a healthy-state and with an applied dynamic eccentricity fault condition. The noise pressures were also measured under actual running conditions and it is verified that the model is able to successfully represent motor operating condition. The sound pressure spectrum contained spectral peaks in the range 0 to 4000 Hz. This model can therefore form the basis of a fault detection and diagnosis technique where the results obtained from measurements taken during motor operation can be compared to the generated system models for a variety of running conditions.

1.2.6 Motor Current Signature Analysis (MCSA)

This is a non-invasive technique in which the motor supply current is monitored and its spectrum used to detect and diagnose the presence of faults present in Induction Motor Drives. MCSA can be performed under both transient (switch-on) and steady state (running) conditions and can be used to diagnose electromechanical faults such as [1] [9] [18]:

- Broken Rotor Bars
- Rotor Eccentricity
- Shorted Stator turns
- Bearing Faults
- Drive Shaft Misalignment etc
An induction motor drive is a complex electrical and mechanical system for which vibration from both load and motor sources can result in disturbances to the airgap flux waveform which in turn can induce current components in the motor stator winding [29]. These components can be detected by monitoring the current in a supply cable line conductor via a current transformer. The current ‘signature’ is then processed and analysed to provide a basis for fault diagnosis. The processing commonly entails obtaining the frequency spectrum of the current time record using a FFT algorithm [31] [32] to produce a current signature. The literature search carried out in support of this research reveals that the types of faults for which MCSA is most widely used to detect are electromechanical faults on the motor itself. Similarly vibration analysis is most widely used to detect mechanical faults on both the motor itself and the mechanical parts of the drive. In practice, for induction motor drives, an integrated approach is most often adopted for condition monitoring and subsequent fault detection, where typically both current and vibration signatures are combined and employed in diagnosis.

However a number of researchers [1] [15] [21] and [29] for example claim that it is possible to successfully detect and diagnose mechanical faults in both the motor itself and the immediate drive system by using MCSA alone.

1.3 Using Stator-Pole-Face Mounted Search Coils

This research employs coils to monitor the magnetic flux in the stator of a 4 kW, 415 V, 50 Hz, 4-pole, 1425 r.p.m. squirrel cage induction motor. Researchers, including Voitto Kokko [29], state that measurement of flux by magnetometers and Hall effect sensors are not reliable enough for condition monitoring purposes. Hall effect devices
have a high temperature dependency and also require an external power supply. In addition the reliable lifetime of these sensors is probably lower than that of induction motors. It is stated [29], however, that flux coil, or search coil, sensors can reach adequate reliability for useful condition monitoring of induction motor drives. The useful frequency range of a flux coil sensor is stated [29] as approximately 0.2 Hz to 15 kHz, a range that is more than adequate for this research.

This research is based upon the author’s hypothesis that the condition, healthy or otherwise, of the induction motor driven system, described in this thesis, can be determined by using a number of strategically positioned search coils, each sensitive to the state of the induction motor stator to rotor air-gap flux. Three search coils, each consisting of ten turns, were wound onto the stator pole teeth at the positions illustrated in figure 1.2. The starts and finishes of the three search coils were identified, labelled, and brought out via the motor terminal box to a terminal block.

![Figure 1.2 – Search Coil Positions](image-url)
It has already been well reported that electromechanical faults on the motor can be
detected and diagnosed by MCSA [1] [2] [15] [17] [18]. It is the author’s hypothesis
that the stator flux can be used to detect not only electromechanical faults which
develop on the motor itself but also a range of mechanical faults present on the
immediate mechanical system connected to the motor. This basic idea is supported by
a number of researchers including Dailly [17] and in particular Korde [19] and
Thomson [20] which states; “When MCSA was initially applied in industry in the
early1980s to diagnose broken rotor bars it was observed that current components
could also be induced due to the mechanical load or drive train characteristics”. This
seems reasonable since faults on the connected load which are mechanical in nature
will be exhibited as vibration, rubbing etc, the energy for which must be provided by
the supply. It is therefore reasonable to assume that mechanical load faults will have
the measurable effect of modulating both the supply current and the resulting stator
flux.

A condition monitoring and fault diagnostic strategy based upon measuring the axial
magnetic flux produced by induction motors is reported by Voitto Kokko [29].
Their paper describes the basic theory and axial flux measurement system employed
during the reported research. The paper also states that the effects of motor faults
such as rotor dynamic eccentricity or broken rotor bars, as considered in this research,
and the effects of disturbances in mechanical loading and vibration can be detected in
the resulting disturbances in the measured flux. The magnetic coil to measure axial
flux was mounted external to the motor and was axially centred on the end of the
motor. Their measurements were taken with the motor loaded and running in steady
state operation.
During this research the stator to rotor air-gap flux rather than axial flux was monitored so that the sensitivity of the search coils to flux changes could be optimised with respect to mounting location. It is also the author’s hypothesis that monitoring stator flux via a number of search coils wound around a number of stator poles and strategically placed to monitor stator to rotor air-gap flux will add an extra dimension over MCSA. This is because the effects of system electromechanical and mechanical faults on each coil will be coil position dependant as well as being flux magnitude and shape dependant. It is therefore a important proposal of this paper that combining the concurrently recorded information from more than one coil will provide an extra position dependant information source that is not present when employing MCSA. Unlike current monitoring however, where current can be monitored anywhere along the supply cable, physical access to the motor vicinity itself must be possible. It was however a relatively straightforward process to wind the search-coils with a required ten turns and to provide a convenient means of connection to each coil. The following figure 1.3 illustrates the fact that each search coil is subjected to a position dependent modulation as a result of both motor and load mechanical faults. In addition to fault dependent supply current fluctuations, mechanical faults will produce a vibration based activity which will be reflected back to the induction motor rotor. This means that for both motor and load mechanical faults which result in increased vibration, there will be a resulting fault dependent fluctuation in rotor motion. It is these fluctuations which will affect each coil output slightly differently, depending upon the coil position. The flux, $\Phi$ webers, linking the search coils is subject to variation as the ferrous material of the rotor changes its proximity to the stator pole face around which the search coil is wound. It is the authors’ opinion that when the proximity of the rotor relative to the pole face is changed this will result in corresponding changes in search
coil output voltage, the changes will be dependent upon the particular fault condition present.

![Search Coil Modulation Diagram](image)

**Figure 1.3 --- Search Coil Modulation**

It may also be noted that research has been carried out, including Thomson [26], into employing a single search-coil mounted outside the motor frame, and employed to monitor the motor axial flux in order to provide fault detection and diagnosis [26] [29]. It is claimed [26] that it is possible to monitor the axial leakage flux for the detection of shorted turns; air-gap eccentricity; and broken rotor bars.
A report on the use of axial magnetic flux to detect faults on induction motors [29] states that it is possible to detect shorted turns; rotor asymmetry; broken rotor bars; broken end ring; supply voltage asymmetry; eccentricity; and Dynamic eccentricity. This paper also states that Hall-effect sensors are not reliable enough for condition monitoring purposes, but measurements by flux coil sensors can reach adequate reliability. The useful frequency of a flux coil sensor is from about 0.2 Hz to 15 kHz, which is perfectly adequate for condition monitoring of those electrical or mechanical faults that commonly occur on induction motor drives. Time based signals can be used to study rapid disturbances of flux caused by mechanical loading [29], and as proposed by this research, fault induced flux modulations.

Consequently, for this research, it was decided to employ search coils to monitor stator flux, since, as stated immediately above, they are suited to the study of the rapid fluctuations that would occur in the stator flux due to the modulation resulting from both energy fluctuations required by fault conditions and due to actual perturbations within the field due to rotor radial and axial movements resulting from faults on the induction motor driven system.

References, including [18] [21] and in particular [26], present current monitoring systems as being reliable in detecting a wide range of system faults and, in particular, as being a strategy that is employed and offered by companies for use in an industrial environment. This is a real measure of the success of the technique in that it is considered reliable by industry. It is the author’s opinion that the stator flux is potentially capable of detecting the same or similar range of faults as does current monitoring.
The system employed for this research comprises the aforementioned search coils monitoring stator pole face flux, an adjustable load torque, a reduction gearbox which is belt coupled to a drive shaft. The drive shaft is directly coupled to a 4 hp, 3-phase, 4 pole induction motor employing a direct-on-line starter.

The system, an adapted ‘Spectraquest’ test rig is typical of many induction motor drives employed in industry is illustrated in figure 1.4.

Figure. 1.4 --- The Test Rig

1.4 Root Cause Analysis of Fault Effects.

The faults applied to the system for the purpose of this research will have two predominant effects upon the outputs obtained from the search coils. The applied faults will require fault related modulations to the energy taken from the supply and hence the current and stator to rotor flux pattern. In addition any fault related radial or
axial movement or vibrational activity in the load will be reflected back to the rotor and will result in fault related rotor positional perturbations. The fault induced rotor positional perturbations will have an effect on the reluctance of the motor magnetic circuit and hence will produce fault related perturbations in the magnetic flux linking the search coils. These stator to rotor flux perturbations will be reflected in the induced emfs produced in the search coils.

This section presents a brief description of the significant features and effects resulting from the application of the listed faults employed during this research. The cause and effects of each of the applied faults is considered, particular attention being paid to the fault effects which can be employed to provide fault related search coil data.

1.4.1 Worn Gear Teeth

The belt driven gearbox, illustrated in figure 1.4 houses a bevelled reduction gearbox with a 1.5:1 speed ratio. The gear-train and the gearbox fault applied during this research is described and illustrated, figure 2.3.6, in chapter 2. Fault free gear trains exhibit a meshing frequency given by the product of the shaft speed and the number of gear teeth [12]. There is only a single pair of bevelled gears in this case and the primary gear, with 18 teeth, is driven at 1425 revolutions per minute, therefore:

$$f_m = \frac{1425 \times 18}{60} = 427.5 \text{ Hz}$$

In addition there will be meshing frequency sidebands produced, an expression for the total meshing frequencies produced given by:
Meshing frequencies \[ \pm f_m \pm N \cdot f_{sh} \quad \text{Hz} \]

where \( f_{sh} \) is the shaft frequency, and \( N \) (sideband number) = 1, 2, 3, … etc.

These frequencies will produce spectral peaks, as sidebands, for this research, at the frequencies given by:

\[ 427.5 \pm N \times 23.75 \quad \text{Hz}, \quad \text{where} \ N = 1, 2, 3, \ldots etc \]

### 1.4.2 Load Shaft Misalignment and Load Unbalance

The misalignment fault condition is described and illustrated in chapter 2, figure 2.3.5. Shaft misalignment [12] occurs when the shaft centrelines of two directly mating components meet at angles and/or are offset from one another. Misalignment produces both axial and radial vibration amplitudes with dominant frequencies ranging from 1 x shaft speed to 4 x shaft speed [11] [12] [13]. The misalignment fault condition is described and illustrated in chapter 2, figure 2.3.5.

Load unbalance [11] [12] occurs when the centre of mass differs from the centre of rotation, in this research resulting in a heavy spot on the rotating disc. This heavy spot produces a centrifugal force at a frequency equal to 1 x rotational speed. The unbalance amplitude will increase by the square of the shaft rotational speed.

It may be noted that during this research, only one fault was applied to the motor and rig at any one time. In consequence, for the purpose of establishing the effectiveness
of the use of suitably positioned search coils, only spectral peak amplitudes were considered. This strategy enabled the search coil strategy for the detection of each single applied fault to be evaluated. If, as may be case in practice, both faults are present at any one time, then since both unbalance and misalignment produce peaks at 1 x shaft speed then it will be necessary to obtain phase readings. This would allow the two faults to be distinguished since misalignment produces radial amplitudes across couplings of 180° phase difference. Unbalance produces radial amplitudes with 90° phase difference between horizontal and vertical directions. The matlab FFT routine, produces a complex FFT, from which the phase versus frequency can readily be obtained.

1.4.3 Motor Rotor Dynamic Eccentricity

Rotor eccentricity was applied to the test rig induction motor as described in chapter 2 of this thesis. Rotor eccentricity in induction motors takes two forms, static eccentricity and dynamic eccentricity. Static eccentricity is where the rotor is displaced from the stator bore centre but is still turning upon its own axis. Dynamic eccentricity is where the rotor is turning upon the stator bore centre but not on its own centre. The causes of either type of rotor eccentricity include incorrect bearing positioning during assembly, worn bearings, bent rotor shaft etc.

Eccentricity causes a force [22] [23] on the rotor which tries to pull the rotor even further from the stator bore centre. The magnetic pull is the result of Maxwellian pulls [24] which affect elements of the surface of stators and rotors of electrical machines. In the case of static eccentricity this is a steady pull in one direction. In the case of dynamic eccentricity, the form of eccentricity considered in this research, eccentricity
produces an unbalanced magnetic pull (UMP) which acts on the rotor and which rotates at rotor speed [22] [23] [24]. Figure 1.5 illustrates the difference between static and dynamic eccentricity, where the rotor centre is shown in relation to the stator bore centre. It can be seen that in static eccentricity the rotor will rotate about its’ own axis and its’ positional offset with respect to the stator bore centre is fixed in time. However, with dynamic eccentricity the rotor will still rotate about its’ own axis but its’ positional offset with respect to the rotor will rotate about the stator bore centre, illustrated in the figure at times $t_1$ to $t_5$.

![Diagram of Rotor Eccentricities](image)

**Figure 1.5 --- Rotor Eccentricities**

Both forms of eccentricity cause excessive stressing of the machine and increases bearing wear as well as producing a possible rotor-to-stator rub with consequential
damage to stator windings and rotor cage and cores. Eccentricity produces an increase in the magnetic flux pulsations at the iron surfaces, the consequence of which is to produce the radial forces which act upon the stator and rotor structures.

Thomson [20] and Thomson et al [21] state that dynamic eccentricity produces airgap field components rotating at $f_s \pm f_r$ Hz with corresponding $p \pm 1$ pole pairs in addition to the usual $p$ pole-pair field. Note that $f_s$ is the supply frequency, $f_r$ is the rotor frequency of the rotor, $s$ is the slip, and $p$ is the fundamental pole-pair of the motor.

The following expressions can be used to determine rotor rotational speed and rotational frequency ($\omega_r$).

\[
\omega_r = (1 - s) \frac{\omega_s}{p} \text{ rad sec}^{-1} \quad \text{and} \quad f_r = (1 - s) \frac{f_s}{p} \text{ Hz}
\]

It may be seen that the motor can be modelled in terms of rotating airgap field harmonics and stator and rotor surface magneto-motive force (MMF) harmonic waves [21] [22] [23] and [24]. An expression for the airgap field components is given [22] as:

\[
b_s(y, t) = \frac{\mu_0 J_s}{k_{pg}} \cos(\omega t - pky)(1 + \delta_s \cos(ky) + \delta_d \cos(\omega t - ky))
\]

where $b$ is the airgap field, $g$ is the normal airgap length, $k$ is the inverse of the average airgap radius, $y$ is the distance round the airgap circumference from some base point (such that $ky =$ angle round the airgap from the base point), $\delta_s$ is the degree
of static eccentricity, $\delta_d$ is the degree of dynamic eccentricity and $\omega_r$ is the rotor rotational speed.

Expanding and rearranging the stator airgap field is given by the following fourier series [22].

$$b_s(y, t) = \sum_{k=-p}^{p} B_S \cos(\omega t - pky)$$

$$+ \sum_{k=-1}^{p+1} B_S \cos(\omega t - (p - 1)ky)$$

$$+ \sum_{k=-1}^{p+1} B_S \cos((\omega - \omega_r)t - (p - 1)ky)$$

$$+ \sum_{k=-1}^{p+1} B_S \cos((\omega + \omega_r)t - (p + 1)ky)$$

Where

$$B_S^p = \frac{\mu_0 J_s}{kpg}; \quad B_S^{p\pm1(s)} = \frac{\mu_0 J_s}{2kpg}; \quad B_S^{p\pm1(d)} = \frac{\mu_0 J_s}{2kpg} \delta_d$$

The last two terms in the above equation give the field terms due to the presence of dynamic eccentricity. The difference in the field components for static and dynamic eccentricity is due to the rotational velocity, $\omega_r$. The expression is valid for motors of 2 pole pairs and above, a motor with a single pole pair representing a special case.
For the operating conditions present during this research the slip was 0.05 and the expected field frequencies could therefore expected to include components in the range $f_s \pm f_r$ Hz, i.e. $50 \pm 23.75$ Hz. Benbouzid, Viera and Theys [28] takes into account slot passing frequency components, an expression for which is given in chapter 3.

1.4.4 Motor Broken Rotor Bars

Rotor bar faults [12] [25] are mainly a breakage of joints between rotor bars and cage end rings as a result of pulsating load or direct on line starting. The current will increase in the remaining bars with an increased risk of more fractures. Rotor bar faults lead to torque pulsations, speed fluctuations, vibrations, changes in the magnetic field, and overheating. As described in chapter 2 of this thesis, three rotor bars were ‘broken’ by sawing through the cage close to the rotor end ring. Thomson [1] and Korde [19] describe the classical induction motor twice slip frequency due to broken rotor bars in the induction motor rotor cage. The twice slip frequency will give the frequency of the current sidebands symmetrically located about the main spectral peak at supply frequency in the current spectrum. The current spectrum sidebands around the main current spectral peak is given by $\pm 2s_f s$ Hz., where $s$ is the slip and $f_s$ the supply frequency.

There is a cyclic variation [20] of current that causes a torque pulsation at twice slip frequency ($2sf_s$) and a corresponding speed oscillation. This speed oscillation will induce an upper sideband current [20] component at $f_s(1 + 2s)$ in the stator winding. This upper sideband is also enhanced by the third harmonic of the flux waveform. For
the motor employed during this research the side bands due to broken rotor bars will be:

$$\pm 2sf_s = \pm 2 \times 0.05 \times 50 = \pm 5 \text{ Hz.}$$

These sidebands will grow in magnitude if a broken or loose rotor bar fault develops.

There are several harmonics in the stator to rotor air gap caused by stator phase currents and the rotating magnetic field [29]. The rotating mmf induces base frequencies and higher harmonics in the rotor currents and causes flux frequencies that are related to the slip of the motor. The stator windings and rotor cage bars are positioned within slots in the motor magnetic circuit. The magnetic permeance variation of stator and rotor slots cause high frequency fluxes due to the presence of slot openings. In addition Stein et al [27] describes the effects of broken rotor bars upon the motor air-gap flux frequency components. These flux frequency components can be determined [29] from the following expression (ref chapter 3 of this thesis):

$$f_{rb} = f_s \frac{k \times (1 - s) \pm sf_s}{p} \text{ where: } s = \text{slip}; \ k = \text{integer}$$

As presented in table 3.3 chapter 3, this expression gives flux frequency components which include those in the range 73.75 Hz to 168.75 Hz.

**1.4.5 Motor Faulty Drive-End Bearing**

The motor drive bearing fault was applied as described in chapter 2, i.e. damaged inner surface of the outer raceway. Ball bearings pass across the defect on the outer race and produce impacts of ball pass frequency due to outer race defect (BPFO). Figure 1.6 illustrates the main constructional features of a ball bearing as used for this
research. The frequencies produced by an outer cage defect (BPFO) range from the fundamental BPFO at the shaft rotational frequency to N x BPFO, where N is the number of balls in the bearing.

Figure 1.7 illustrates the impact frequencies [9] [12] that would be expected from a damaged ball bearing. A damaged outer cage being the particular fault applied for the purpose of this research. The bearing used during this research contained 9 balls and therefore the expected frequencies would lie in the range between 1 times BPFO and 9 times BPFO. The contact angle $\beta$ referred to in figure 1.6 is relevant to an ‘angular contact bearing’, for this research a plain bearing was employed therefore $\beta = 0$ and $\cos \beta$ is equal to 1 in the given formulae.

Figure 1.6 --- Damaged Ball Bearing Outer Race

The bearing data sheet provided the pitch diameter of 52.1 mm and the ball diameter was measured as 8.6 mm. The expected impact frequencies, in the case of this research would therefore be in the order of:
\[
\frac{9.1425 \times (1 - 8.60 \times 1)}{2 \times 60/52.1} \approx 90 \text{ Hz}
\]

These impact frequencies would produce both modulations in supplied energy and field perturbations as previously proposed. Reference [12] also states that vibrations occur at higher frequencies, up to a few kHz or so, often related to radial resonances in bearings.

\[
\text{Contact Angle } \beta
\]

\[
\begin{align*}
\text{Ball Dia (BD)} \\
\text{Pitch Dia (PD)}
\end{align*}
\]

\text{For Outer Race Defect, BPFO:}
\[
f (\text{Hz}) = \frac{n f_r}{2} \left(1 - \frac{\text{BD}}{\text{PD}} \cos \beta\right)
\]

\text{For Inner Race Defect:}
\[
f (\text{Hz}) = \frac{n f_r}{2} \left(1 + \frac{\text{BD}}{\text{PD}} \cos \beta\right)
\]

\text{For Ball Defect:}
\[
f (\text{Hz}) = \frac{\text{PD}}{\text{BD}} f_r \left[-\left(\frac{\text{BD}}{\text{PD}} \cos \beta\right)^2\right]
\]

\(n = \text{number of balls} ; \ f_r = \text{relative revs/sec between inner & outer races}\)

\textit{Figure 1.7 --- Impact Rates f (Hz) In Ball Bearings}
1.5 Acquisition of Fault Related Data.

This research concentrated upon acquiring a data bank of time records of the e.m.f.s produced in the search coils. It would have been desirable to simultaneously obtain both vibration and current time records under the same range of fault conditions so that the success or otherwise of the search coil method could be benchmarked against these two well established and Industry accepted condition monitoring techniques. However, time and resource limitations determined that this was impractical and in any case, although desirable, not strictly necessary for successful and useful outcomes resulting from this research.

The system was tested under both healthy-state and a range of fault conditions and during both acceleration and steady state periods. The range of applied faults included faults on both the induction motor itself and the driven mechanical load, the system being illustrated in figure 1.4. above. The number of records of each fault condition taken under accelerating conditions was limited to 20 in order to cut down the number of starts required for each of the time-record sets.

The range of faults placed on the system and considered during this research are typical of those faults that occur in practice [1] [2] [9] [10] [20] [29] and include:

- faulty motor drive end bearing
- rotor dynamic eccentricity
- broken rotor bars
- load drive shaft misalignment
- unbalanced load
- damaged gear wheel teeth.
Simulink, dSPACE , Controldesk and the dSPACE DS1104 controller board were employed during this research as a multi-channel data acquisition system for the initial collection of data. Controldesk and the DS1104 boards are supplied by dSPACE Ltd for use as a control and instrumentation package. Its use in this research has been adapted as a means of collecting, storing, and displaying the time records obtained from the coils.

In every case the dSPACE development system is used to record and store a number, typically 50 to 150, of time records of coil output voltage waveforms each of 0.1 second duration. All time records are saved in a matlab format and matlab m-file code was developed and used in order to process the data and obtain a spectrum. The time records for each fault condition are time synchronous averaged in order to eliminate any random components present in each of the individual time records. Any cyclic components representative of the condition of the rotating system are retained and will contain the information used to detect and diagnose the health condition of the system. A spectrum of the time synchronous averaged time record representing each fault condition is then obtained by employing matlab code to load the saved 150 time records into the matlab workspace and linear averaging them. The averaged time record is then saved in a folder and loaded into the matlab workspace when required for further processing to obtain spectra etc.

Figure 1.8. illustrates a typical time record obtained under steady state speed conditions. The record presented results from a time synchronous average of 150 such records, and the resulting spectrum (figure 1.9) of the averaged time record. These are
typical components of the basic database used to provide the basis for fault detection and diagnosis undertaken during this research.

Figure 1.8.  **Typical Steady State Record**  **Linear Averaged Time Record**

Figure 1.9 -- **Spectrum of Averaged Healthy-State TimeRecord**
Figure 1.10 illustrates a controldesk screen image of a typical time record obtained as
the motor accelerates from rest to its target steady-state speed. It was found by trial
and error that a record duration of 0.1 seconds was sufficient to allow the motor to
attain its steady state speed.

Figure 1.10  --  Typical Acceleration TimeRecord

1.6 Evaluation of Fault Related Data.

Once sufficient data in the form of time synchronised time records and their
respective spectra had been obtained, a range of strategies for fault detection and
diagnosis was employed. These strategies were then evaluated and compared with
each other. An appropriate combination of strategies was then adopted to provide the
most statistically robust fault detection and diagnostic capability. The strategies
employed during this research are briefly introduced in this introduction as follows
and are dealt with in greater detail in the body of this thesis.
Fault data collected under steady state running conditions can be effectively processed by employing the FFT algorithm to produce a spectrum for every condition healthy-state or faulty that formed part of this research. The FFT algorithm approach has been used very successfully to produce a spectrum for data collected under steady state conditions. In addition to data collection under steady state conditions this research, however, also entailed the collection of data under start-up conditions, with the motor starting from rest and accelerating up to its steady state speed. It has been found [31] [34] [35] that the frequencies of interest during the transient start-up period are non-stationary and employing the traditional FFT routine may result in a poor resolution in the frequency domain (see chapter 4).

In order to process the non-stationary data obtained during start-up a number of approaches have been adopted by researchers which include using a short time Fourier transform (STFT) [34] [35], Wavelet Packet Decomposition (WPD) [31], and a Wigner-Ville distribution (WVD) [35]. Wavelet Decomposition and Wigner-Ville distribution produce a three axes result with a time, frequency and amplitudes forming a three dimensional mesh. This research adopted the Wigner-Ville method to determine the effectiveness of the coils to detect and diagnose faults from transient data obtained as the motor accelerated from a standing start toward the steady state running speed.

1.7 Pattern Recognition Techniques

This research compares the time and frequency domain patterns obtained under healthy-state conditions with those derived under the listed electrical and mechanical fault conditions. The time and spectral patterns used in this research were derived by
using both matlab toolboxes and a time-frequency toolbox [35] [36] [37] to carry out
the following analytical mathematical functions:

- Coherence and Variance of those time records collected under both steady-
  state and at acceleration periods. A number of coil combinations were
  employed as described in this thesis.
- Auto and cross-correlation techniques applied to the time records collected
  under both steady-state and acceleration periods, for a number of coil
  combinations.
- The above techniques were also applied to the spectra of each time record.
- A Wigner-Ville spectrum and time-frequency representation of the time
  records taken from the coil combination of coilA in series with coilB.

Each of the processes listed immediately above forms the basis in this research for
determining time domain and frequency domain plots which can be employed to form
the basis of comparison between healthy-state and a range of fault conditions, and to
subsequently detect and diagnose those faults placed on the system. The parameters
from which comparisons are made include features such as peak amplitudes at
particular frequencies, peak ratios, number and position of peaks, etc.

Coherence, variance and correlation techniques applied to the records obtained from
coil and coil combinations are employed to provide the basis in this research for
determining a numerical value in order to aid fault detection and diagnosis of a range of faults.

1.8 A Final Note.

The results obtained during this research are encouraging and show that it is possible to employ stator pole mounted search coils to reinforce and improve the reliability of existing, well reported, strategies for fault detection. Furthermore it will also been demonstrated that the position of the strategically placed search coils can indeed provide alternative and additional position dependent fault data when compared to those techniques based upon current monitoring alone.
Chapter 2
Data Acquisition and Research Methodology

2.1 Introduction

This chapter presents and describes the system hardware, the methodology, the matlab code and the dSPACE /Controldesk development system employed to produce, collect, store and perform some initial pre-processing upon the raw time domain data collected from the search coils. This data was collected whilst the motor was operating under both a steady-state constant speed condition, and under an accelerating from standstill condition. For every healthy-state and faulty condition considered during this research, and under both steady state and accelerating conditions, the pre-processing involved the Fourier Transformation of a time synchronous averaged time domain data file, each representing a named fault condition, into its’ equivalent amplitude spectrum in the frequency domain (see chapters 3 and 4).

In addition, for the data collected under accelerating conditions, the Wigner-Ville method [34] [35][36] was employed to produce time-frequency-amplitude two dimensional and three dimensional plots, (see chapter 6). Matlab m-files were written and employed to load the recorded data files, and to perform an FFT upon all time domain fault related data files collected under both steady state and accelerating conditions to arrive at a conventional spectrum for every fault condition applied. In addition, for every fault condition, the Wigner-Ville algorithm was employed with the time domain data files collected under accelerating conditions in order to arrive at a fault related time-frequency distribution plot. Further processing of the steady state and acceleration results to provide the basis for fault discrimination is presented and described in chapter 5 and chapter 6. An example of the
essential features of one of the matlab m-code files employed during this research, under steady state conditions, is included in this chapter.

2.2 The Search Coils

A number of coil constructional configurations were tried before arriving at a configuration which gave an acceptable output. A number of coil pitches ranging from 12 stator slots (120° arc) to a single stator slot were investigated and it was subsequently found that the single stator pole tooth pitch produced the most resolute fault data. Using a coil wound with ten turns of 0.24 mm diameter varnished copper wire, wound around a single stator tooth resulted in a suitable coil e.m.f. of 10 volts a.c. peak to peak. It was necessary to terminate each of the coils with a terminating resistor to avoid the coil burning out due to the current transformer (CT) effect. For this purpose resistors, each of value 1 kΩ, was found to be appropriate. The coil configuration is illustrated in figure 2.1. The initial omission of the resistor did in fact result in two of the original coils burning out and becoming open circuit.

The result of a literature search carried out by the author of this thesis resulted in finding three short references to the use of a single stator-pole-face mounted search coil [21] [22] and [23]. These papers briefly mention the use of coils wound in the stator slots to sense the air-gap flux to identify dynamic eccentricity in large induction motors.

It is further proposed in this research that the use of search coils used in the manner described will, in addition to electromechanical induction motor faults, make it possible to detect a number of mechanical faults on the driveshaft and gearbox connected to the motor.
There is, however, no reference in this particular paper to any significance in simultaneously collecting data from a number of coils positioned around the stator as described in this thesis. The author of this thesis considers that concurrently employing more than one coil will prove to be a factor that will provide an information source in addition to that of independently monitoring the e.m.f. induced from all three of the coils while under fault conditions.

It is the authors’ opinion that the concurrent monitoring of at least two search coils provides information in addition to that obtained either by stator current monitoring, or by monitoring one coil only. Factors which support this contention include the following:

i. Variations in running conditions, normal or faulty, result in variations of loading. These variations of load will require corresponding variations in the energy supplied to the motor and therefore corresponding modulation of supply current.

ii. Fault conditions producing variations in loading result in corresponding variations in rotor current. These rotor currents produce a rotor magnetic field which must interact with the stator field influencing the search coil induced e.m.f.s. Fault conditions, even those external to the motor itself, result in some form of eccentric displacement of the rotor. Although largely constrained and limited by the motor bearings, it is the authors’ contention that a sufficient value of fault induced eccentricity is transmitted to the rotor and this eccentric motion is measurable using the search coils. Further it is proposed that at any instant of time the eccentricity influences each coil differently. Simplistically this is because the rotor can, in fact, be moving toward one coil and away from another coil at any instant in time. The fault induced relative eccentric motion of rotor with respect to each coil is complex in nature and no attempt is made.
in this thesis to perform a detailed analysis, but to limit the treatment to processing of
the results obtained as described.

iii. In addition to the effects of any rotor eccentricity effecting the rotor magnetic field
and the stator or search coil magnetic field interaction, it is proposed that any
conductive mass, in this case the rotor, when travelling through a magnetic field will
distort that field. Therefore even if we ignore the rotor current and flux produced by
the normal transformer action between stator and rotor, then any fault induced motion
transmitted to the rotor will have an effect upon stator field and subsequently the coil
induced e.m.f.s.

The first factor described above will apply with equal relevance to both supply current and
search coil monitoring. However it is the authors’ opinion that the second and third of the
above factors add an extra dimension when employing the search coil method of monitoring.
This is because the coils outputs are affected by the rotor motion as described. It is believed
that this extra spatial dimension results in a measurable advantages when compared to the
results obtained when current monitoring is solely employed. It will also be demonstrated
that the advantages will be enhanced when more than one search coil is used to
simultaneously record coil outputs. This thesis will deal particularly, but not exclusively,
with a presentation and comparison of those results obtained from a single coil and from two
coils connected in series.

It is the authors’ proposition that the techniques employed for this research will provide a
technique which will compare favourably to that of the well tried and tested current
monitoring technique. In fact the multi-coil based fault detection and diagnosis technique
proposed in this research represents a significant extension to the use of a single search coil [21] [22] [23].

It is also worthy of note in this thesis, that a number of coil pitches of varying widths of up to 120 degrees of motor stator were tried. Subsequent trials showed that none of the coil pitches employed resulted in as much fault information as did the single stator tooth pitch, which demonstrated the greatest sensitivity to the effects of the fault conditions applied during this research.

The output voltage of the search coils is equal to the derivative of the flux and will contain both low frequency and high frequency components. The high frequency components are generated as a result of stator and rotor slots as they pass the stator pole face. These high frequency flux components are due to the fact that the slots cause a variation in magnetic permeance as stator and rotor slots pass one another. It is shown [21] that any given search coil is most sensitive at the higher frequencies and that a resonant peak will typically occur at about 15 kHz. This research is most interested in maximum flux frequencies well below the quoted resonant frequency of 15 kHz.
The sensitivity of a coil can be increased by increasing either or both of the number of coil turns or the diameter of the coil. In this case the number and area of coil turns was limited by the space available in stator slots and by the fact that the coil has better fault resolution when wound around one stator tooth pitch only.

2.3 The Motor and Test Rig

The test rig employed during this research consisted of an adapted Spectraquest [registered trademark] test rig.

The original 185 W, 415 V, 50 Hz, 2815 r.p.m. induction motor supplied with the Spectraquest rig was replaced with a 4 kW, 415 V, 50 Hz, 1425 r.p.m. squirrel cage induction motor which contained 36 stator and 32 rotor slots. The replacement motor, having a full load per unit slip of 0.05, is more typical of the type of small induction motor widely employed in industry. The squirrel cage motor employed during this research was started direct-on-line and was coupled to the drive shaft via a torsionally flexible coupling. The torque load supplied with the rig, even at maximum setting, was only sufficient to place a relatively light 750 W of load onto the larger replacement motor. For the purpose of this research, which was to establish that faults could indeed be detected and diagnosed with the search coils, it was considered that a load of 750 W was sufficient. Indeed it was felt that in order to avoid magnetic saturation of the stator tooth, that it was preferable that any fault condition was monitored under relatively light loading conditions. The following figure 2.2. shows the Spectraquest test rig, fitted with the 4 kW motor, employed during this research.
2.4 The Applied Faults

The details of the six applied faults considered during this research are described and illustrated in figures 2.3.1 to 2.3.6.

2.4.1 Dynamic Eccentricity

Airgap dynamic eccentricity fault was applied by angle-grinding 0.25 mm from the outer surface of the motor drive end bearing outer raceway. This resulted in a reduction in the bearing outer diameter from 62 mm to 61.5 mm. and figure 2.3.1 illustrates the resultant
absolute minimum and maximum dynamic eccentricity produced. The maximum percentage
dynamic eccentricity being 25%. It has been shown [1] [22] [23] that airgap eccentricity can
produce flux and current components as described in chapter 1 of this thesis.

![Dynamic Eccentricity Diagram](image)

Figure 2.3.1 --- Dynamic Eccentricity

### 2.4.2 --- Damaged Motor Drive End Bearing

The motor drive end bearing comprised a standard deep groove ball bearing (6206), the
constructional details of which include an inner and an outer raceway, a cage, and 9 ball
bearings. The bearing fault was applied by ‘spark eroding’ a 4mm hole in the outer raceway.
When the faulty bearing was installed this hole was positioned at the bottom. When operating
with the faulty bearing in place, each of the ball bearings traversed the 4 mm hole shown in
figure 2.3.2.
2.4.3 --- Damaged Rotor Bars

As described in chapter 1 of this thesis, the effect of broken rotor bars is to produce fault related sideband peaks in the current spectrum at ± 2sf, either side of the supply frequency f_s. The fault peak level is a function of the fault severity and is dependant upon the number of rotor slots, 32 in this case, and the number of broken rotor bars. For the purpose of this research three rotor bars were ‘broken’ by sawing through the cage close to the rotor end ring.
2.4.4 --- Load Shaft Misalignment Fault

The spectraquest rig allowed the load bed to be rotated independently from the motor bed. Figure 2.3.4 illustrates the level of misalignment which was applied to the shaft for the purpose of this research.

2.4.5 --- Load Shaft Unbalance Fault

In order to produce an imbalance condition a weight of 23 grams was placed, as shown in figure 2.3.5, in a position approximately halfway between the induction motor and the drive belt pulley (ref fig 2.2)
2.4.6 --- Gearbox Fault

The gear box comprised a single pair of gearwheels as illustrated in figure 2.3.6. The gear ratio was 1.5:1, the number of drive cog gear teeth being 27 and the load cog gear teeth 18. For the purpose of this research a hand held grinder was employed to produce the effect of wear on each of the 18 teeth of the load cog gear by grinding approximately 0.5 mm of material from each tooth.
2.5 The Data Acquisition System

The dSPACE and Controldesk [both registered trademarks] control and development system, available at UWIC, was employed to provide the means of obtaining and displaying time records of the search coil outputs. Each set of acquired data obtained for all of the fault conditions considered during this research were saved in a suitable folder and were thus available for later use within the MATLAB environment as described in this thesis. The data acquisition system, see figure 2.4, consisted of A/Ds, amplifiers, and sinks in the form of oscilloscopes and was modelled with Simulink from within the dSPACE real-time interface environment, and coded using the MATLAB real-time workshop (RTW) builder function. The amplifiers, each of gain ten, included in each channel were required because the dSPACE A/D input channels automatically apply an attenuation factor of value ten, which needs to be compensated for when used as a data acquisition system as was the case for this research project. The RTW builder automatically generates the required C++ code required to realise the hardware function using a dSPACE DS1104 controller board. The model file was then saved as datamod1.mdl and the C++ file as datamod1.sdf. The dSPACE Controldesk development desktop interface was then employed to download the C++ code to a DS1104 controller board resident on a PC motherboard. The coil outputs were physically connected to the DS1104 board using an I/O panel supplied by dSPACE.

Although available resources, in the form of dSPACE and Controldesk, were employed for this research, alternative data acquisition systems which produce either MATLAB or comma-separated variable, i.e. x.mat or x.csv, are readily available for purchase and application.

This same dSPACE/Controldesk model was used regardless of whether data was to be collected from each single coil and corresponding trigger input, or whether coils were
actually physically interconnected as was the case for connecting coils A and B in both phase
and antiphase, and in which case channel 5 was used throughout, and was accessed either by
generating a single variable matrix, or by using matlab code to extract column Y(3) of a
multi-variable matrix.

Figure 2.4 --- The Data Acquisition Model

Each of the four 12-bit ADCs employed for this research were capable of converting
voltages within the range ± 10 volts with a signal to noise ratio of >80 dB. The resolution of
the data acquisition system was therefore determined as follows:

1 Quantum = input voltage range / 2^n , where n is number of ADCs bits

= 20 ÷ 2^{12} volts

≈ 5 mV
This meant that the system used for this research was capable of logging changes in the input voltage waveform with a resolution better than 2.5 mV. So changes in amplitude present in the spectrum of greater than about 2.5 / √2 mV, i.e. greater than 1.77 mV would represent valid changes in the input waveform due to the effect upon the input waveform and due to the presence of those faults and fault levels applied for the purpose of this research.

The amplifiers of gain 10 were included because the dSPACE ADC inputs automatically attenuated the input signals by a factor of 10 and although not absolutely necessary it was decided to compensate for this. It was also decided to extend the model so that not only the basic three coil signals could be collected, but the sum and difference of coil A and coil C concurrent outputs could be determined and stored for later processing. As has already been stated it was felt that this was important since it was proposed that concurrent information from more than one coil could yield information in addition to that which could be obtained from any of the individual coils acting alone. In addition to summing and subtracting coil A and coil C outputs via the model it was also decided to obtain the sum and difference of the information from coil A and coil B by actually physically connecting these two coils in both series opposition and series addition and repeating the collection of data for both connections and under the same set of fault conditions.

This meant that the advantages, if any, of collecting synchronised data from more than one coil could be established empirically both by interconnecting through the model or by making actual physical interconnections. Interconnecting via the model, if proven to be effective, would of course allow a degree of flexible connectivity, particularly if it subsequently proves useful to have various combinations of interconnections. Various interconnection patterns are not, however, pursued further during this work.
Regardless of whether collecting data from single coils or from a series combination of two coils the same model was used in every case, the variables (single coil or coil combination) required to be displayed and subsequently stored were selected when editing the controldesk plotter settings and the capture data settings. When using the coil combination a single variable time record was produced and represented either an additive or subtractive series coil connection. When collecting data from single coils, a time record with five variables on the vertical axis was produced. As stated these variables were extracted as and when required using a specially written matlab m-file.

The dSPACE controldesk was then employed to acquire, display, and store any combination of the three inputs connected to the acquisition system model illustrated in figure 2.3. The controldesk instrumentation panel as displayed on the computer screen is illustrated in figure 2.5 which illustrates both a single voltage plot taken with coil A and coil B physically connected to be in phase with each other, and a composite plot which shows the five voltage waveforms resulting from, coilA, coilB, coilC, coilA-C, and coilA+B.

In both cases, multi or single input, as illustrated in figure 2.5, these particular plots of coil output voltage waveforms were obtained under steady-state motor-running conditions. As previously stated, the multivariable plot, shown on the right of figure 2.5, required each variable to be separated for subsequent analysis, the separation was carried out within the matlab code and allowed the data from any single coil or coil combination to be obtained and subsequently processed. For multi-input plotting the controldesk software creates a matlab matrix with one column for each of the voltages recorded.
The plots taken under steady state conditions, and shown in figure 2.5, being for both single and multi-variable and obtained using the dSPACE controldesk, illustrate a typical single time record from the total number of 150 time records taken and stored with the motor running at steady state speed and obtained under every fault condition considered during this research. Each set of 150 files were stored in a suitably named matlab folder as matlab.mat files named rec000.mat to rec150.mat which meant that they could be used within the matlab environment without any need for further pre-processing or editing. The taking of the 150 records necessary for each fault condition also proved to be a tedious and error prone procedure, the repetition of which was avoided by recording a controldesk macro. To avoid this repetition a macro recording feature provided in controldesk was employed. A macro taking 10 records was recorded and then edited to eliminate unnecessary time delays and extended to enable 50, 100 or 150 records to be acquired. Under steady state speed
conditions it was considered appropriate to take 150 records under each condition. The 150 stored files then being available for time synchronous averaging. The number of steady state records taken at each fault condition, in this case 150, was decided upon as a result of typical recommendations included in papers read during the literature search carried out in support of this research. A number of time records, each of which are synchronous with the trigger, will average periodic signal components to their mean value, whilst noise or non-synchronous signal components will average toward zero. In general, the improvement in signal-to-noise ratio is proportional to the square root of the number of independent averages. In dB, the equation is:

$$\frac{\text{signal}}{\text{noise}} = 20 \log (N)^{1/2} \text{ dB} \quad (\text{where N is number of records, 150 here})$$

This represents an improvement in signal to noise of 20 or more.

In order to apply time synchronous averaging it was necessary to trigger each of the 150 individual plots to commence at some synchronised point. For this reason the model included a dedicated trigger input channel to which was connected a trigger signal source. The trigger point used under steady state conditions was derived from the output of coilA and fed into the dSPACE analogue-to-digital channel 8. The raw coil output did, however, contain too much noise to be used directly as a reliable trigger signal. To overcome this problem the coil signal was passed through a simple passive RC low pass filter with a corner frequency of approximately 60 Hz, 50 Hz being the fundamental frequency induced in the search coils. The filtered and relatively noise free signal was then available for triggering, see figure 2.6. This improved to be very effective, resulting in only a few ‘mis-triggered’ time records, and being so few in number that the synchronous averaging process made their effects upon the
final averaged waveform negligible. It may also be noted that the filtered trigger signal was
phase shifted from the coil output from which it was derived, but this did not matter since the
magnitude of the phase shift remained constant for each of the 150 records taken under every
fault condition considered and were therefore able to be used for time record
synchronisation.

The dSPACE 1104 (I/O) Input/Output channels 5 to channel comprise 4 12-bit analogue to
digital (A/D) converters. To avoid any possibility of aliasing when recording data it was
decided to include anti-aliasing filters. The anti-aliasing filters each comprised a low pass
passive filter with a corner frequency set at approximately 1200 Hz. This was considered
appropriate since it was considered that the frequencies of interest would all fall within a
1000 Hz upper limit.

As well as collecting fault data under steady state conditions, as previously described above,
this research also collected data under accelerating motor conditions where the motor was
accelerated from rest to its steady state speed under a given load and fault condition. Trial
and error established that a time record of 0.1 seconds was adequate to allow both the test rig
motor to accelerate to a steady state speed under all of the applied fault conditions employed during this research, and to result in an acceptable resolution in the frequency or spectral domain.

When taking readings during the acceleration period it was found that the coil outputs could not be used to provide the synchronising trigger pulses. In this case, as an alternative, it was decided to connect a slave relay coil in parallel with the direct-on-line starter contactor coil. Thus on start-up the relay provided a trigger signal as illustrated below in figure 2.7. This arrangement proved not to be entirely satisfactory in synchronising the time records recorded during the acceleration period since there was some variation in the operating time of the slave relay. However a sufficient number of synchronised records were produced which enabled a valid and reliable evaluation of results obtained under accelerating conditions to be made.

Because of the electrical and mechanical stress placed upon the starter itself when subjected to repeated starts, it was decided that for the acceleration period time records it would be necessary to limit the number of starts and therefore the number of time records to 20 for time synchronous averaging purposes. It was considered that this was at least sufficient to allow a useful initial appraisal of the ability to collect data during the acceleration period, and to enable the presence of the range of those faults applied during this research to be detected and diagnosed.

![Starter Derived Trigger Signal](image)

**Figure 2.7 --- Starter Derived Trigger Signal**
Figure 2.8 illustrates a typical acceleration period time record in which five variables, coilA, coilB, coilC, coilAplusC, and coilAminusC were plotted in controldesk. As for the steady state condition, a Matlab programme, was employed to separate the variables from the multivariable plot for individual processing to provide the individual spectrum of each. The results and analysis of the results obtained during acceleration periods are presented in chapter 3 of this thesis.

Figure 2.8 is a typical example of a 5-variable time record taken under accelerating conditions for the 4 kW, 415 V, 50 Hz, 1425 r.p.m. squirrel cage induction motor used in this research. Of the five variables shown colour coded in fig 2.8, three variables were obtained from the coil A (red), coil B (blue), Coil C (green). The remaining two plots were obtained by adding (orange) and subtracting (light blue) the outputs from coil A and coil B.

![Figure 2.8 --- Typical Acceleration --- 5 Variable Time Record](image-url)
The trigger function settings such as trigger level and the polarity of edge triggering were selected in controldesk.

In addition to using the trigger signal for the time synchronous averaging of the three 150 time record sets taken from each of the coils and for each fault condition, an important feature of the trigger signal was that it ensured that simultaneous and synchronised records of the signals from all of the search coils were able to be obtained. That is, concurrent synchronisation of the three coil outputs was obtained as well as sequential synchronisation of each of the 150 time records from each of the individual coils. This was considered to be very important since, as stated, it is the authors’ opinion that simultaneous data obtained from coil combinations, and added together in the simulink module, could yield further fault detection and diagnosis information than that which could be obtained from gathering data from each single coil at different times. This, in effect would provide the equivalent information that would be collected by physically interconnecting coil combinations and collecting a single channel sample from the combination rather than from single coils. The author proposes that employing a single trigger signal to obtain data concurrently from each of the search coils would result in extra fault dependant information. It is proposed that this is because, at any instant of time, the instantaneous particular fault effect being experienced by each coil will differ as a consequence of coil position only. Furthermore, it is proposed that since, over a period of time, each coil will experience the identical ( or at least very similar ) fault effects, that information is lost by collecting data under identical conditions but at different times for each coil. However collecting concurrent data from more than one coil, with the coils either physically interconnected, or connected by the matlab/dSPACE model will provide data that includes the slight variations in fault effect due to coil position alone. It is the authors’ opinion that it is this additional critical difference that adds an extra
dimension to the use of more than one coil for fault detection when compared to using a single current or coil monitoring strategy.

2.5.1 Determination of Model Sample Step Size

The model, as illustrated in figure 2.8, was described by invoking both simulink and the real time interface (RTI) applications packages which are both provided on a matlab platform. The simulink comes as standard with the matlab package, and the real time interface was obtained from dSPACE and purchased as a part of their controldesk development system. Before the model can be built in the dSPACE real time workshop (RTW), the required sampling step size must be entered. The following criteria were applied when deciding upon the number of samples, N, to be taken over the duration of the time record.

The motor used during this research was a 4 hp 1500 rpm motor fed from a symmetrical three phase 50 Hz supply. The voltages induced into the stator mounted search coils had a fundamental frequency of 50 Hz whilst the shaft rotated at a frequency of 25 Hz. It was therefore decided to make the duration of all time records equal to 0.1 second since, for a data sampled system, the lowest frequency that can successfully be sampled, \( f_{\text{low}} \), is given by the reciprocal of the time record duration [31].

In this case: \( f_{\text{low}} = \frac{1}{0.1} = 10 \text{ Hz} \).

This is sufficiently below the minimum frequency of 25 Hz present on the system due to the shaft speed \( \leq 1500 \text{ revs per min} \). Another consideration when deciding upon a suitable time record duration is the effect upon frequency resolution in the spectrum. When employing an FFT algorithm to obtain a spectrum the lowest frequency that can successfully be sampled
will also give the resolution in the frequency domain. Again it was considered that a resolution of 10 Hz was acceptable for defining individual peaks within the spectrum.

For a data sampled system, where \( N \) samples are taken in the time record duration, the highest frequency that can be successfully sampled is given by:

\[
f_{\text{high}} = \frac{N}{2} \cdot f_{\text{low}} \text{ Hz.}
\]

For the purposes of this research, it was considered that the number of gear train teeth and rollers in the motor bearings would have most influence upon the choice of the highest frequency signal component to be satisfactorily sampled. This would typically be in the order of a kilohertz or less. In fact, at the beginning of this research, before any in-depth analysis was carried out, it was decided to take advantage of the capability of the system to sample at a far greater rate than is absolutely necessary for fault detection. In fact to cover the possibility of there being any useful higher frequency components than was initially expected, it was decided to make the highest frequency to be sampled as high as 20 kHz.

Therefore in this case:  
\[ f_{\text{high}} = 20 \text{ kHz} \]

So: 
\[
N = \frac{2 \cdot f_{\text{high}}}{f_{\text{low}}} = \frac{2 \times 20,000}{10} = 4000 \text{ samples}
\]

This agrees with the Nyquist criterion for a \( f_{\text{high}} \) of 20 KHz since 4000 samples in 0.1 seconds is equivalent to a sampling frequency of 40 kHz, which is twice the frequency of the highest frequency which is able to be successfully sampled. In any case, even as is often the
In practice, it is a rule of thumb that the required sampling frequency is required to be up to 10 times the highest signal frequency component of interest, then the number of samples taken in 0.1 second still allowed signal components of up to 4 kHz to be successfully and effectively sampled.

### 2.5.2 Matlab Fast Fourier Transform

During this research the matlab fast fourier transform (FFT), and is based upon a discrete form of the famous fourier integral. This integral is used for determining the frequency content of any signal and in any case is particularly useful for determining the frequency content of non-periodic functions. The approach is to assume that any function \( f(t) \) is periodic in the limit as time, \( t \), becomes infinite, and the integral expression used is quoted as follows:

\[
F(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) \exp^{-j\omega t} \, dt
\]

The matlab function [36] \( Y = \text{fft}(x) \) implements the transform given for vectors of length \( N \) by:

\[
Y(k) = \sum_{k=1}^{N} y(k) \exp\left(\frac{-j\pi}{N}\right)
\]

\( Y = \text{fft}(x) \) returns the discrete Fourier transform (DFT) of vector \( X \), computed with a fast Fourier transform (FFT) algorithm. Matlab can operate on multidimensional vectors and
matics, but for the purpose of this research all data for analysis is processed into a one-dimensional vector format. Each vector employed during this research, representing the healthy-state and/or faulty data records, consists of a one dimensional vector comprising 4001 elements. So that the FFT routine algorithm is executed with maximum speed and efficiency the data records are padded out with zeroes to give a vector length equal in value to a power of 2, i.e. from 4001 to 4096 in this case.

Having employed the FFT algorithm the frequencies included in the resulting spectrum will comprise those discrete values given by $1/TR$, $2/TR$, $.........0.5N/TR$, and since $N=4000$ in this research, it is evident that any signal component frequency present in the data signal would be available in the resulting spectra.

### 2.6 Obtaining Steady State And Acceleration Spectra

With the motor running at steady-state speed and for every fault and healthy-state condition considered during this research, three sets of readings were taken. For every applied fault each of the three sets of acquired data consisted of 150 time records. In order to demonstrate that the results obtained could be repeated, each of the three sets taken under every fault condition were independently obtained at different times. In all cases a fault was applied, readings taken, the fault removed or changed, the fault eventually re-applied and the taking of readings repeated. This ensured that the taking of each of the three sets of readings for every condition were separated by the taking of one of the three sets of readings for every other healthy-state and faulty condition. The one exception to this was the broken rotor bars fault, which was left until last since this fault, once applied, could not be rectified. This meant that, for this particular fault alone, the three sets of readings were taken contiguously.
Similarly, records were taken under motor accelerating conditions, although for practical reasons, the number of time records at each fault condition was limited to twenty or less and the number of data sets limited to two.

Chapters 3 and 4 present some resulting steady state and acceleration spectra for a sample number of the healthy-state and fault conditions which were carried out during this research. The spectra presented in chapter 3 and chapter 4 resulted from taking time records as described both with a mechanical load connected to the motor and with the motor uncoupled from the mechanical load. A close inspection of these figures demonstrates that there are indeed measurable and reliable differences between the fault and healthy-state spectra.

Furthermore, the spectra demonstrate that there are indeed visible and measurable differences which, as will be shown later in this thesis, are entirely dependent upon the fault condition of the test rig during the taking of the time records. It is also shown in chapter 3 that under both healthy-state and the full range of fault conditions applied during this research that the results are repeatable. Indeed it will be demonstrated that the spectra obtained for each of the sets of readings when obtained under the same fault and/or healthy-state condition are extremely similar to one another. It will also be demonstrated that the variation in spectra as a result of the fault condition is acceptably consistent for every set of coil readings taken. It will therefore be proposed, that it has been demonstrated that the spectra obtained in the described manner, provide repeatable and reliable information regarding the health condition of the system under test. It is important to emphasise here that the taking of each of the set 1 of readings were not immediately followed by the taking of set 2 readings, and for the steady state condition, of set 3 readings. A fault was applied, data was obtained, a different fault applied, data taken etc until all fault data had been taken and stored in appropriate folders. It is worth noting that a typical 150 records taken with controldesk, for each system steady state
running condition, required approximately 10 M Bytes of storage space. The fault conditions were then reapplied and the process repeated. Indeed, a typical sequence of results with the Spectraquest rig connected to the motor, were obtained according to the following typical pattern:

i. Set 1 of readings taken under healthy-state condition ;  
ii. Set 1 of readings taken under dynamic eccentricity fault conditions ;  
iii. Set 1 of readings taken under drive-end bearing fault conditions ;  
iv. Set 2 of readings taken under healthy-state condition ;  
v. Set 2 of readings taken under dynamic eccentricity fault conditions ;  
vi. Set 2 of readings taken under drive-end bearing fault conditions ;  
vii. Set 3 of readings taken under healthy-state condition ;  etc

Procedures similar to the above were adopted throughout this research, an exception being the sets of readings taken under broken rotor bars fault conditions. For this particular fault condition the three sets of readings were taken immediately after each other.

The fault conditions under which the coil induced voltages were recorded are listed as presented below. The resulting spectral plots for a selection of set 1 and set 2 data is presented in chapter 3, accompanied by an initial appraisal of the results obtained. The faults applied to the system under test are listed and briefly described as follows:

1. **Coil A --- Induction Motor Only  [ Without SpectraQuest Rig ]:**  
   i. Healthy-State  
   ii. Faulty Motor Drive End Bearing  (Spark Eroded 4 mm Hole In Outer Cage)
iii. Broken Rotor Bars  
   (Hacksawed Through Rotor Cage)

iv. Motor Dynamic eccentricity  
   (Ground Cage of Motor Drive End Bearing)

2. **Coil A --- Induction Motor With SpectraQuest Rig Connected:**

v. Healthy-State

vi. Faulty Rig Gearbox  
   (Broken Geartooth)

vii. Load Shaft Misalignment  
    (Offset Rig Bed)

viii. Load Shaft Unbalance  
     (Attached Weight to Rim of Flywheel)

3. **Coil A Connected In -Phase With Coil B ; [Motor Only]**

4. **Coil A Connected In Anti-Phase To Coil B ; [Motor + Spectra Rig]**

5. **Coil A Output Added To Coil C Output ; [Motor Only]**

6. **Coil A Connected In - Phase With Coil B ; [Motor + Spectra Rig]**

The list of fault conditions for coil connection patterns 3 to 6 above are the same as those for connection patterns 1 and 2, i.e. as those for coil A only. For cases 3, 4 and 6 listed above, coilA and coilB were physically connected. For case 5 above, the addition and subtraction of the outputs from coil A and coil C was carried out via the system model. A detailed analysis of the results under every fault condition listed above was carried out and a full report of the results obtained when employing the data for fault detection and diagnosis is included later in this thesis.

2.6.1 **Calibration Time Record And Its’ Spectrum**

The matlab, m-file code, presented below is typical of that employed to provide a spectrum of the data acquired with the controldesk system. As illustrated by the preceding flowchart
the presented matlab code loads the 150 time records taken under steady state conditions, performs a row by row matrix average, and then performs a FFT algorithm on the averaged record. In order to confirm code efficacy in operation a test pattern was used, in this case a 50 Hz 10 V pk to pk sinewave voltage was employed. The test voltage itself also provided the source of the trigger signal. Figure 2.9 illustrates that under the conditions described, the average of 150 records is identical to a typical, randomly chosen, time record plot. The resulting spectrum demonstrates that the spectral peak resulting from the averaged time record does occur at the expected 50 Hz frequency.

![Typical plot](image1) ![Averaged plot](image2) ![Spectrum of Av](image3)

**Figure 2.9 --- Calibration Plots**

### 2.6.2 Programme Flowchart and Matlab Code:

The following flowchart, figure 2.10, illustrates the programme structure to enable:

i. 150 previously recorded time records to be loaded from matlab workspace.
ii. Upon request, to display a time plot of any individual record.
iii. To time synchronous average the 150 records.
iv. To plot the time synchronous averaged waveform.
v. To use the fast fourier transform routine (FFT) to produce a spectrum.
vi. To display a linear amplitude continuous and line spectral plots.
vii. To display a logarithmic amplitude spectral plot.
Figure 2.10 --- Flowchart To Load Records and Produce Spectra

1. Input Record, Number To Plot
2. Calculate time-synchronous average

- Plot another record?
- Save averaged time domain record
- Display averaged time Domain record
- Apply FFT to obtain spectrum Of averaged record

3.
The Matlab Code:

%*************************************************************************
%  LOAD 150 RECORDS PREVIOUSLY RECORDED AND SAVED IN WORKSPACE
% TIME SYNCHRONOUS AVERAGE; DISPLAY; CREATE LINEAR/LOG SPECTRA
% Simulink model step size set to 0.1 /4000
%*************************************************************************

% Prepare vector for frequency axis

% Display linear amplitude continuous spectral plot

% Display linear amplitude Line spectral plot

% Display logarithmic amplitude continuous spectral plot

END
disp(' ')
disp('To make sure that you are in the correct directory..... PRESS ANY KEY')
pause

disp(' ')

disp('This program requires that 150, 5 x variable time records have been obtained using dSPACE')
disp('and saved in this directory')
disp(' ')

%Prompt for filename
name = input('Type the filename as entered in ControlDesk > ','s');
disp(' ')

%Load the 150 data records each of 6 channels data Y1 to Y5 and time X
ycoil = [];
final = [];

for i = 1:150
    s = ['00' num2str(i)];
s = s(length(s) - 2:end);
filename = [name s];
load (filename);

%Create ycoilA matrix (measured data) where each column represents one record capture i.e. 4001 row by 150 column matrix (150 records)
% e.g. access col 3 of 5-col matrix where recxxx is a 1x5 structure
eval(['ycoil = [ycoil ',filename,'.Y(3).Data.'']);
end

eval(['x = ',filename,'.X.Data'';']); % create time vector

numsamples = length(x);
disp('THE NUMBER OF SAMPLES TAKEN IS GIVEN AS FOLLOWS:     ') ; numsamples

if number > 110
    z = [];
    quest = 121;
disp(' ')
    while quest > 110
        disp(' ')
        choice = input('Enter record number to plot OR zero to average > ');  
        disp(' ')

    end
    disp(' ')
end
num = ['00' num2str(choice)];
num = num(length(num) - 2:end);
rectoplot = [name num];
eval(['z = [z ',rectoplot,'.Y(3).Data'';']);

if  choice ~= 0
    plot(x,z); % Added to plot Typical Record
    ylabel('Signal Magnitude '), grid on
    xlabel('Time [secs]')
    title('Typical Plot Of Coil A Healthy-State Time Record')
end
quest = input('Plot any further time records ?  Y / N > ','s');
disp(' ')
end

disp('PRESS ANY KEY TO PROCEED TO AVERAGE')
end

%*************************************************************************
%*************************************************************************
% Take time synchronous average of 150 col 4001 row matrix
ycoilA_av = mean(ycoil,2);
Coil_A_Av_FF_With_Spectra = ycoilA_av ;
save  Coil_A_Av_FF_With_Spectra ;
%*************************************************************************
%*************************************************************************
plot(x,ycoilA_av);
ylabel('Magnitude'), grid on
xlabel('Time [Seconds]')
title('Average Of 150 Coil A With Spectra Healthy-State Time Records')
axis ([ 0 0.1  -4  4])

pause
disp('Press any KEY to CONTINUE');
disp(' ')
pause

%*************************************************************************
%*************************************************************************
% In fft below the returned value is a vector of complex numbers
% also a weighting factor of 2*N where N is number of samples taken
finalA = fft(ycoilA_av,4096); % Pads out record with zeroes to 4096 values
%*************************************************************************
%*************************************************************************
% Get the spectrum information
% Note : 2048 used because FFT mirrored around middle of sampling interval
% i.e.in our case the first 2048 samples are relevant the rest is the same
% data mirrored
SpecfinalA  =  sqrt(finalA.*conj (finalA))/2048;
%*************************************************************************
%*************************************************************************
% Prepare the frequency vector
Freq = 40960*(0:2048)/4096 ;
disp('Now Press Any Key To Obtain FFT Magnitude Plot')

pause

% plot(Freq, SpecfinalA(1:2049));

disp('')
ylabel('Magnitude'), grid on
xlabel ('Frequency [Hertz]')
title ('Spectrum Of Averaged Coil A With Motor+Rig Fault-Free Time Record')
axis ([ 0 1000 0 0.5])
disp ('Now Press Any Key To Obtain LINE SPECTRUM Plot')
pause
disp('')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
stem (Freq,SpecfinalA(1:2049));
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

disp('')
ylabel('Line Magnitude'), grid on
xlabel('Frequency [Hertz]')
title ('Line Spectrum Of Averaged Coil A Motor+Rig Spectra Fault-Free Time Record')

%% PLOT  LOG v LINEAR

semilogy(Freq, SpecfinalA(1:2049)); % CHOICE 1

disp('')
disp('')
ylabel('Magnitude'), grid on
xlabel ('Frequency [Hertz]')
title ('Spectrum Of Averaged Coil A Motor+Rig Fault-Free Time Record')
axis ([ 0 1000 0 0.5])


2.7 Chapter Conclusion

The faults to be considered during this research (as listed in this chapter) were successfully applied to the system under test. Each fault, in turn, was applied to the system under test and the data acquisition system described in this chapter was employed to collect fault related time records concurrently from each of the search coils. Time records were obtained under the stated healthy-state and fault conditions and whilst the test rig was operating under both steady-state and accelerating from rest conditions. A number of synchronously triggered time records were obtained for each healthy-state and fault condition applied. These synchronous time records could then be time-synchronous averaged to produce a single waveform, free
from random components, which could be employed for the detection and diagnosis of the applied fault conditions. The method of providing a synchronising trigger is described and some typical time records obtained under both system steady-state and accelerating conditions is presented. The matlab code employed to perform the synchronous averaging, the fast-fourier transform algorithm (FFT), and the time and spectral plotting is included here since it is particularly appropriate to the initial processing and preparation of the collected data for use either as described particularly in chapters 4, 5 and 6 of this thesis.
Chapter 3

Preliminary Study Using Stator to Rotor Magnetic Flux as the Diagnostic Indicator

3.1 Introduction

This chapter includes some examples of the resulting spectra obtained from the application of a matlab based fast fourier transform (FFT) routine to those time records collected under steady-state speed operating conditions as outlined in the previous chapter. The results obtained, presented as spectral plots in this chapter, were produced from time records collected under a number of healthy-state and faulty conditions, again as described in the previous chapter. An initial appraisal, based upon careful inspection of the spectra of the time records obtained under each system condition, is presented in this chapter. The visual inspections provide the basis for an initial estimate to be offered as to the ability of the spectra to detect and discriminate between machine healthy-state and fault conditions. Later chapters of this thesis deal with a more detailed and analytical evaluation of the ability of the spectra to provide fault detection and diagnosis and also possible analytical processing of those spectra obtained in order to provide an automatic diagnostic strategy.

A summary of the results of the visual inspections based upon the spectra of those time records collected from coilA acting alone and from coilA and coilB connected in series, as presented in this chapter, is given later in this chapter in table 3.1 and table 3.2. and figures 3.3 to 3.6.
During this thesis the analysis and presentation of the results obtained from the collected data concentrates upon those produced from the sets of readings taken as data set 1. This was decided upon because the sheer volume of data collected made it impractical to consider the data from every data set obtained during the research. This thesis, refer fig 3.1, 3.2, 3.3 demonstrates that data independently taken at different times, under the same load and with the same system healthy or fault condition provided consistent information regarding system condition. It has been demonstrated and that any differences in the spectra obtained under the conditions described are produced by differences in system health condition alone. In this chapter, to demonstrate that different data sets are equivalent, a number of examples of the data from two sets of fault equivalent data are offered. The diagrams presented in this chapter, figures 3.1 to 3.4, when subjected to close inspection illustrate that the repeatability of all results, for all healthy state and fault conditions, was ascertained. In fact inspection of the following spectra for set1 and set2 demonstrates that it is often quite difficult to detect the small differences between the two data sets presented for each system running condition. This is considered by the author to be very encouraging since it demonstrates that the time records obtained may be employed to provide the source data for a robust and reliable fault detection strategy.

3.2 Results Using Coil A Only -- Steady State Speed

Figure 3.1, figure 3.2 and figure 3.3, each illustrating two sets of readings show that the two sets of readings obtained from coil A and taken at different times under the same fault and load condition, in this case with no rig connected, are visually very similar, and show no significant differences. Logarithmic vertical amplitude scale spectra are included to aid the evaluation of the visual inspection.
3.2.1  **CoilA -- Motor Only Healthy State**

It can be seen that the above spectra have essentially identical features, however an examination, particularly of the logarithmic spectra, does reveal subtle differences between the two spectra. For example, an observable difference occurs at approximately 430 Hz, with further smaller but still observable differences at 750 Hz, and 850 Hz. The two sets of data therefore provide convincing evidence that sets of data taken independently from each other, and for the same loading and system running conditions, provide consistent data. Some further examples of the consistent
results from set1 and set2, obtained under a variety of running conditions, are presented later in this chapter.

3.2.2 **CoilA --- Rotor Dynamic Eccentricity Fault -- Motor Only**

The following spectra of two fault equivalent but independently taken time records, shown in figure 3.2 illustrate the results obtained under a motor rotor dynamic eccentricity fault condition. Dynamic eccentricity creates a variable stator-rotor air gap, and is typically caused by worn bearing housings or end covers. For this research this fault was applied by grinding the outer surface of the outer raceway of the motor drive end bearing which produced a 0.5 mm (see chapter 2) gap between the bearing outer race and the motor end-bell bearing housing. The 0.25 mm of material ground from the outer surface of the bearing was sufficient to produce a level of dynamic eccentricity (25%) appropriate for the purposes of this research but limited to a value that allowed the motor to be operated safely with no prospect of the motor stator being damaged by the eccentric motion of the rotor. Having already established in figure 3.1 above that the fault free data comprising set1 and set2 is consistent, the following figures 3.2 to 3.4 are provided to confirm the consistency between each pair of set1 and set2 fault data presented for a dynamic eccentricity and a bearing fault.

Close inspection of figure 3.2 demonstrates that there are visibly perceptible differences between the healthy-state and fault spectra (see table 3.1). Inspection of figure3.2 reveals that the differences between healthy-state and dynamic eccentricity fault conditions are most noticeable in the linear amplitude spectra, particularly at the spectral peaks positioned at frequencies 150 Hz, 250 Hz, 450 Hz etc.
In this case those differences between the fault and healthy-state spectra show themselves with increases or decreases in peak amplitudes, rather than any obvious

**Figure 3.2** Set1 and Set2 CoilA Spectra – Dynamic Eccentricity
extra peaks occurring. It may be noted that the differences are relatively small but it can also be seen that the differences between healthy-state and fault spectra are consistent for both time record sets. The log amplitude spectra are included here since differences between set 1 and set 2 data can only be visually observed here when a very close inspection is carried out of the log amplitude spectra. This again demonstrates the consistency of the data taken under any one of the fault conditions applied during this research, and its’ ability to effectively provide a recognisable spectrum which is representative of any given system healthy-state or faulty operating condition.

### 3.2.3 CoilA --- Motor Drive End Bearing Fault -- Motor Only

The following two sets of spectra, shown in figure 3.3, present the results obtained under a motor drive-end bearing fault condition. The roller element bearing is one of the most crucial components in rotating electrical machinery and the consequence of its breakdown can prove catastrophic since it would then be possible for the rotor to breach the stator windings. For the purpose of this research the fault was applied by spark eroding a 4 mm diameter hole in the outer cage of the motor drive end bearing. For the purpose of this test the healthy-state motor drive end bearing was replaced by an identical but faulty bearing. The faulty bearing was fitted onto the motor shaft with the hole in the outer cage positioned at the bottom of the bearing so that the roller elements of the bearing entered the hole and were affected by both gravity and centripetal forces as the motor rotated.

Once more two sets of fault data, each pair (set1 and set2) taken under the same fault and load conditions was obtained. Both sets of fault data are compared to one set of
healthy-state data, in order to demonstrate repeatability of fault detection capability for the same fault independently applied. It can be seen that the two sets of motor drive end bearing fault data presented as follows have essentially the same spectral features and variations when compared to the fault free spectrum. In fact the spectral differences between healthy-state and fault spectra are particularly noticeable in the logarithmic spectrum.

Figure 3.3 Set1 and Set2 CoilA Spectra – Motor Only – Motor Bearing Fault
Close inspection of the above spectra demonstrates that there are differences between the healthy-state and fault spectra (see table 3.1). In this case, the differences between healthy-state and damaged motor drive end bearing fault conditions are immediately noticeable in the linear amplitude spectra although the differences are most easily visually observed in the log amplitude spectra. Slight differences between set 1 and set 2 fault condition data can most easily be observed when a close inspection is carried out of the log amplitude spectra, which again demonstrates the repeatability of identifiable fault data.

3.2.4 CoilA --- Load Shaft Misalignment Fault --- Motor and Rig

The following set of spectra, as presented in figure 3.4 illustrates those results obtained under a misaligned load shaft fault condition. The misalignment fault was applied by rotating the rig bed with respect to the drive motor longitudinal axis so that the load drive shaft was misaligned along the motor-load shaft axis in a horizontal plane. Once again the fault level, in this case misalignment, was limited to a value (0.65°, see chapter 2) that would not compromise future operation of the system.
It can be seen by inspection of figure 3.4 that any fault dependant differences between healthy-state and fault spectra are visually small and slightly more visible in the log amplitude spectra. Close inspection of these spectra demonstrates that there are small but nevertheless visibly noticeable differences between the spectra produced from the healthy-state and misalignment fault running conditions. In addition it can be stated that those visible differences that can be detected between the healthy-state and the fault condition are consistent in both of the sets of fault data presented, (table 3.1).

3.3 Results Of Coil A and Coil B Connected In Series

As previously stated the search coils were connected together in a number of configurations. The following spectra resulted from two of the three coils being connected together in series. The following figures 3.5 to 3.7 present the resulting spectra obtained when coilA and coilB were physically connected in series, hereafter
denoted coilAplusB. The voltage outputs from the individual coils were summed and the voltage obtained from the coil combination provided a time record of the combination of the two coils, each placed 120° apart as described. As previously stated it is proposed that the use of more than one coil will provide extra fault related information which will increase the fault detection capability of the search coil method. Tables 3.3 to 3.6 presented later in this chapter allow an initial evaluation of the advantage, if any, of employing more than one search coil. Again a more rigorous and analytic evaluation is presented in chapter 5 of this thesis.

3.3.1 CoilAplusB -- Motor With Rig Connected --- Healthy-State

For the final time in this thesis, in order to demonstrate the consistency of different data sets each taken under the same running and fault conditions, the following figure presents two sets of data for the same condition, healthy-state motor only in this case. The figure demonstrates that, as is the case for coilA acting alone, the series connection of coilA and coilB results in sets of data that are practically identical when the system is run under the same conditions. This consistency between each of the data sets, set1 and set2, was evident for all of the running conditions and coil interconnections employed during this research, and after figure 3.5 there will be no further attempt in this thesis to provide more than one set of spectra.
Once again it can be seen that the above spectra have essentially identical features, but a closer examination does reveal subtle differences between the two sets of spectra, particularly noticeable in the log amplitude spectra at approximately 850 Hz.
3.3.2 CoilAplusB --- Fault Spectra

The following figures present only one set of data but it is worth noting that, as is the case when presenting the previous sets of data, sets of data taken under the same operating conditions presented below are visually very similar, which demonstrates that they contain the same information regarding the motor running condition. Three fault conditions are presented, two with motor only running and one with the motor plus load connected.

Figure 3.6 presents typical healthy-state and fault condition spectra obtained with the load shaft uncoupled from the induction motor and the faults applied as previously described.

Inspection of the spectra in figure 3.6 reveals that the spectra produced under rotor eccentricity and motor drive-end bearing faults both have quite noticeable differences both from the healthy-state spectra and from each other (see table 3.2). These differences were essentially consistent between those sets of data taken under the same running conditions and it is this consistency of differences that enables them to be employed for fault detection purposes. In this case, especially for the eccentricity fault condition, any differences are visibly more noticeable in the linear amplitude spectrum.
Figure 3.7 presents the spectra for healthy-state and load shaft misalignment fault obtained whilst the load shaft was coupled to the induction motor.
The differences between the healthy-state and misalignment spectra can be seen in both the linear and the log amplitude spectra. It is again the author’s assertion that the differences in the spectra are consistent for different sets, and that it is indeed possible to detect the presence of the fault condition by visual examination of the spectra.
3.4 Tabulisation of Results.

3.4.1 CoilA Only

The table 3.1 presents an estimate of the value of the spectral peaks resulting from coilA only and at the stated frequencies.

<table>
<thead>
<tr>
<th>Peak Frequencies (Hz)</th>
<th>150</th>
<th>250</th>
<th>350</th>
<th>450</th>
<th>550</th>
<th>650</th>
<th>750</th>
<th>850</th>
<th>950</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak Amplitudes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthy-State (Motor Only)</td>
<td>0.475</td>
<td>0.25</td>
<td>0.16</td>
<td>0.05</td>
<td>0.047</td>
<td>0.035</td>
<td>0.037</td>
<td>NA</td>
<td>0.02</td>
</tr>
<tr>
<td>Dynamic Eccentricity</td>
<td>0.5</td>
<td>0.22</td>
<td>0.18</td>
<td>0.025</td>
<td>0.04</td>
<td>0.035</td>
<td>0.025</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Motor Bearing Fault</td>
<td>0.5</td>
<td>0.22</td>
<td>0.15</td>
<td>0.035</td>
<td>0.065</td>
<td>0.035</td>
<td>0.03</td>
<td>0.025</td>
<td>0.01</td>
</tr>
<tr>
<td>Dynamic Eccentricity ±% w.r.t. FF Peak</td>
<td>+5.3</td>
<td>-12</td>
<td>+12.5</td>
<td>-50</td>
<td>-15</td>
<td>±0</td>
<td>-48</td>
<td>New peak</td>
<td>±0</td>
</tr>
<tr>
<td>Motor Bearing Fault ±% w.r.t. FF Peak</td>
<td>+5.3</td>
<td>-12</td>
<td>-6.3</td>
<td>-30</td>
<td>+38</td>
<td>±0</td>
<td>-19</td>
<td>New peak</td>
<td>-50</td>
</tr>
</tbody>
</table>

Table 3.1 --- Table of Peak Values and % Deviations W.R.T. CoilA Healthy-State Peaks
3.4.2 CoilAplusB

Table 3.4 presents a visual estimate of the value of the spectral peaks resulting from coilA series connected to coilB and at the stated frequencies. The results are obtained from the same set of running conditions when collecting data from coilA only. This allows an initial estimate to be made as to the efficacy of employing two coils compared to data obtained from one coil only.

<table>
<thead>
<tr>
<th>Peak Frequencies (Hz)</th>
<th>150</th>
<th>250</th>
<th>350</th>
<th>450</th>
<th>550</th>
<th>650</th>
<th>750</th>
<th>850</th>
<th>950</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak Amplitudes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthy-State (Motor Only)</td>
<td>0.14</td>
<td>0.42</td>
<td>0.28</td>
<td>0.02</td>
<td>0.08</td>
<td>0.04</td>
<td>NA</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Dynamic Eccentricity</td>
<td>0.22</td>
<td>0.26</td>
<td>0.27</td>
<td>0.01</td>
<td>0.04</td>
<td>0.04</td>
<td>0.025</td>
<td>NA</td>
<td>0.02</td>
</tr>
<tr>
<td>Motor Bearing Fault</td>
<td>0.08</td>
<td>0.39</td>
<td>0.22</td>
<td>NA</td>
<td>0.1</td>
<td>0.07</td>
<td>0.02</td>
<td>0.03</td>
<td>NA</td>
</tr>
<tr>
<td>Dynamic Eccentricity ±% w.r.t. FF Peak</td>
<td>+57</td>
<td>-38</td>
<td>±0</td>
<td>±0</td>
<td>-50</td>
<td>±0</td>
<td>New Peak</td>
<td>+20</td>
<td>±0</td>
</tr>
<tr>
<td>Motor Bearing Fault ±% w.r.t. FF Peak</td>
<td>-43</td>
<td>-7</td>
<td>+21</td>
<td>No Peak</td>
<td>+25</td>
<td>+75</td>
<td>-20</td>
<td>+20</td>
<td>No Peak</td>
</tr>
</tbody>
</table>

Table 3.2 Table of Peak Values and % Deviations W.R.T. CoilA+B Healthy-State Peaks
Figures 3.8 to figure 3.11 illustrate the percentage deviations of the fault spectral peak amplitudes when calculated with respect to the appropriate fault free spectral peak amplitudes at each frequency. The graphs are obtained from source data that has been estimated in value after visual inspection of the spectral peaks. This is, of course, subject to errors of judgement, but nevertheless serves a useful purpose at this point, since it presents an acceptably accurate comparative estimate of the results obtained from both coilA acting alone and coilA and coilB connected in series.

Figure 3.8 --- CoilA Spectral Peak % Deviations Of Fault Spectra From Healthy-State

Figure 3.9 --- CoilAplusB Spectral Peak % Deviations Of Fault Spectra W.R.T. Healthy-State
Spectral Deviations --- CoilA and Motor + Rig

Figure 3.10 --- CoilA Spectral Peak % Deviations Of Fault Spectra W.R.T. Healthy-State

Spectral Deviations --- CoilAplusB and Motor + Rig

Figure 3.11 --- CoilAplusB Spectral Peak % Deviations Of Fault Spectra From Healthy-State

3.5 Spectral Frequencies of Interest.

Researchers including Da-Ming Yang, James Penman [16] and Aditya Korde [19] suggest that induction motor stator line current monitoring could be used to identify the existence of a range of both motor electromechanical faults and mechanical faults in the driven load. The fault list includes those faults considered and applied during this research. In addition to induction motor faults [19] also proposes that load faults
such as load bearing faults, gear tooth damage, worn or loose drive belts, etc can be detected by monitoring the motor supply current. The load faults listed cause pulses in the torque, and since this is reflected in the motor input current and so their presence can be observed by analysing the motor current waveform.

This research involves the use of flux waveforms rather than current waveforms for the reasons already stated. It is not easy, if at all possible, to make an accurate and sufficiently reliable prediction of the frequency content of a motors’ flux waveform when running under a range of fault and loading conditions. Dailly [17] states that even for a healthy motor, the magnetic flux will be rich in component frequencies. There are several harmonics in the air gap [17], the causes for which include:

- Stator phase currents driving the magnetic circuit toward saturation, or at least a ‘flatter portion of the B/H characteristic curve.
- Interactive field distortion produced by the rotating magnetic field. The rotating magnetic field produces harmonics in the flux wave that are related to the value of the slip of the motor.
- The permeance variation of rotor and stator slots cause high frequencies called ‘slot pass frequencies’ and as the name suggests are due to the presence of slot openings
- Winding construction, which can be different for different motors.

It is recommended that it is too unreliable to make any attempt to predict the flux waveform component frequencies with sufficient accuracy to be of use in fault detection and diagnosis. It is suggested that it is more reliable to take a reference
measurement on a healthy system. For flux measurements to be useful as a diagnostic tool, it is also necessary to make a reference measurement under every fault condition to be monitored. As described, this research has used the search coils to obtain a set of flux dependant signatures, each representing a particular fault condition of the system under test.

Although this research has taken reference flux waveform measurements at each healthy-state and fault condition, some frequency content predictions were employed to provide at least some evaluation of the flux waveforms collected. The following formulas can be used to provide a basis for predicting the number and frequency of fault dependant spectral peaks which may be expected to appear in the flux spectra. This is included here since it is considered useful to enable at least an estimate of the reliability of the data collection and processing methods employed during this research to be made.

3.6 Expected Typical Flux Frequency Components

The following equations were employed to determine the typical frequencies of the components of the stator to rotor flux waveform for sine wave supplied motors in both normal and failure mode operation. These equations can then be employed to provide the basis of an estimation of whether the signal from the search coils contains fault condition dependant information in the frequency range that may be expected.

Healthy machine [16]

Air gap flux caused by each phase of the stator current:

\[ f_{\text{gap}} = k f_s \] ; where \( f_s \) is supply frequency and \( k \) = odd integer
Flux frequencies due to stator slot pass frequencies:

\[ f_{sp} = f_s \left( \frac{Q_s \pm 1}{p} \right) ; \quad Q \text{ is the number of stator slots} \]

**Faulty Machine**

Broken rotor bar [27]:

\[ f_{rb} = f_s k(1 - s) \pm sf_s \quad \text{where: } s = \text{slip}; \quad k = \text{integer} \]

Dynamic Eccentricity [28]:

\[ f_{de} = f_s \left( \frac{k(1 - s)}{p} \right) \pm 1 \]

where: \( s = \text{slip}; \quad p = \text{pole pairs}; \quad \text{and } k = \text{odd integer} \)

Taking into account rotor slot pass frequencies:

\[ f_{de} = f_s \left( \frac{nQ_r \pm l)(1 - s)}{p} \right) \pm k \]

where \( Q_r = \text{Number of rotor slots} \) and \( k = \pm 1, \pm 3, \pm 5, \ldots \)

**External Vibration** [Riley]:

\[ f_{ev} = kf_s \pm f_{vib} \]

where: \( f_{vib} = \text{mechanical vibration frequency} \) and \( k = \text{integer} \)

Using the above equations for the frequency flux waveform components, table 3.3 presents a small but representative selection of the frequencies that would have been expected during this research for the 3-phase, 50 Hz, 4-pole, 1425 rpm induction motor employed. The calculations for external vibration assume that the misalignment vibration frequencies are the same as shaft rotational speed, and the gear tooth
vibration frequencies are due to the gear train meshing frequency (10 x 25 Hz) and its sidebands. It may be noted that not all frequencies have been included in the table of calculated values.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Hz @ k = 1</th>
<th>Hz @ k = 2</th>
<th>Hz @ k = 3</th>
<th>Hz @ k = 4</th>
<th>Hz @ k = 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>50, 855, 950</td>
<td>150</td>
<td>250</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Broken Rotor Bar</td>
<td>73.75</td>
<td>97.5</td>
<td>121.25</td>
<td>145</td>
<td>168.75</td>
</tr>
<tr>
<td>Dynamic Eccentricity</td>
<td>73.75 to 855</td>
<td>121.25</td>
<td></td>
<td>118.75</td>
<td></td>
</tr>
<tr>
<td>Misalignment</td>
<td>100</td>
<td>150</td>
<td>200</td>
<td>250</td>
<td>300</td>
</tr>
<tr>
<td>Gear Tooth</td>
<td>300 &amp; 855</td>
<td>350</td>
<td>400</td>
<td>450</td>
<td>500</td>
</tr>
</tbody>
</table>

Table 3.3 --- Typical Low Frequency Components

The calculated frequencies for values of k up to 5 provide an estimate of the expected frequency range of the air-gap flux waveform that can be expected for the system under a variety of healthy-state and faulty conditions. Inspection of the spectra produced from the data collected in this research confirms that the actual frequency content of the data flux spectra obtained does fall within the range of the predicted values. This indicates that the data collected from the coils is suitable to be used for the purposes as described in this thesis.

3.7 An Initial Appraisal Of Steady State Results:

This initial appraisal is based upon a visual inspection only of the five examples of spectra presented earlier in this chapter in figures 3.2 to 3.4 and figures 3.6 and 3.7. It
is worth noting that the examples of those data sets used to produce the spectra presented in this chapter were chosen from a larger data base as being typical of those obtained during this research.

No attempt is made in this chapter to accurately quantify the ability of the data as presented to detect and diagnose the applied fault conditions considered during this research. However some initial and, in the authors’ view, useful preliminary estimates have been submitted here resulting from a simple visual inspection of the spectra here presented. The entries in tables 3.1 and 3.2 are submitted as the result of a visual inspection of the example spectra, the value of each table entry being subject to errors of judgement when inspecting the appropriate spectrum. However, for the purpose of providing the basis of an initial, valid if not accurate, estimate of the ability of the coils to detect a faulty condition, the visual estimate of spectral amplitudes is sufficiently fit for purpose. It is also possible to form the basis of a comparative estimate between the ability of a single coil, or alternatively of two interconnected coils, to provide sufficient fault dependant data. Inspection and comparison of tables 3.1 and 3.2, and of figures 3.3 to 3.6 provides promising initial indications that there is a significant improvement in fault detection capability when coilA and coilB were series connected when compared to using coilA alone.

Inspection of the spectra presented in this chapter reveals an immediate and very important observation that for all five sets of spectra there are repeatable and therefore reliable differences between the healthy-state spectra and the spectra for each of the fault conditions presented. The research results lead the author to suggest that the amplitude, position, shape and number of the differences in spectral peaks are largely, if not entirely, dependent upon which of the faults was applied. Although not fully
presented in this chapter, it is of vital importance to restate the fact that the same essential differences between set1 and set2 of the same fault condition were repeated across the three independently obtained sets of data. It is proposed that this verifies the authors’ opinion that the data obtained from the search coils does indeed represent the fault condition of the system under test. The three sets of readings did exhibit very slight variations from one another, a situation which is to be expected when taking independent sets of data, which required the same fault condition to be re-applied when required. However the differences between data sets for the same fault proved very small when compared to the differences in the spectra obtained under the stated fault conditions. The fault dependent differences were readily and unmistakably recognisable in all three sets of data. In this and subsequent chapters, the ability of the coils to detect onboard motor faults and those faults external to the motor, i.e. load shaft misalignment, load unbalance, and faulty gearbox has been convincingly demonstrated. The sensitivity of the coils to both onboard motor faults and external load faults will be dealt with more fully in later chapters of this thesis.

Another general observation that can be made is that the interconnection of coils, whether a physical connection or effected via the system model, does in fact, generally result in greater and more visible differences between the healthy-state and fault spectra in the majority of cases. Inspection of tables 3.1 and 3.2 illustrate this point, and the spectral differences are particularly noticeable for those faults placed on the motor load rather than the motor itself. In any case, even for the few cases presented in this chapter where the interconnection of coils does not afford any noticeable additional information, there is at least no visible reduction in the amount of information obtained than from one coil acting alone. At this stage, of course, these observations are based upon visible inspections, each of which is subject to some
error of judgement, and no attempt is made in this chapter to accurately quantify the
ability of the data to form the basis of a fault detection and diagnostic strategy. Later
sections of this thesis describe the methods employed to quantify and evaluate the
ability of the coils to provide fault detection and diagnosis. It is however, the authors’
opinion that it has already been demonstrated in this chapter that the spectra produced
during this research show significant promise that they could by themselves be
employed to develop an effective and reliable method of fault diagnosis. The authors’
opinion that stator flux monitoring can be used for successful condition monitoring is
particularly valid if the results presented here are combined with the results obtained
from other fault detection methods some of which are described in chapter 1 of this
thesis. It is also worth noting that the faults applied were considered to be of a level
which would be classed as light to moderate in level. All faults, other than the broken
rotor bars, were rectified a number of times, and the system resumed operation in a
healthy-state and reliable operating condition.

The figures presented in this chapter demonstrate that the results obtained under a
particular fault condition are both observable and repeatable. As previously described
each of the spectral sets are produced at different times, with the particular fault
condition being reintroduced to take a further set of fault data independently from the
first set. For example if the spectra presented in figure 3.3 for the faulty motor drive
end bearing are closely inspected it can be seen that there are indeed essentially the
same differences between both of the fault spectra and the spectra for the equivalent
fault free condition. The figure demonstrates that the general shape for the two
presented sets of fault spectra presented in figure 3.3 are essentially equivalent, and
that even to the eye the same fault information can be relatively easily recognised in
both the figure 3.3 set 1 and set 2 spectra.
As stated, the results of adding or subtracting the induced voltages in coil A and coil C was carried out via the data acquisition model instead of actually physically connecting the coils as was the case for coil A and coil B. The results obtained, although not presented in this chapter, were comparable to the case with coil A and coil B physically connected to one another as described. This demonstrates that triggering the start of data acquisition into all of the data acquisition channels eliminates the absolute necessity of physically connecting the coils. This research investigate both the results obtained from the physical interconnection of coils, and the concurrent acquisition of data from the three search coils provided, and it was found that no appreciable difference was apparent.

3.8 Chapter Conclusion

Evidence has been provided in this chapter which supports the author’s opinion that obtaining stator to rotor magnetic field flux measurements from one or more search coils enables reliable fault dependent data to be obtained. Further chapters of this thesis will contain a description of the techniques employed to perform a more detailed and robust fault detection method.
Chapter 4

Acceleration Spectra and Their Application

4.1 Introduction

This chapter includes some examples of the resulting spectra obtained from those time records taken under motor accelerating conditions as outlined in chapter 2. As was the case of the results presented for the steady state running conditions presented in chapter 3, the results presented in this chapter, i.e. those obtained under motor accelerating conditions, were obtained as a result of the motor and rig being operated under a number of healthy-state and faulty conditions as previously described in chapter 2 of this thesis.

An appropriate acceleration time period time record duration was established by trial and error, and consequently for this application a record duration of 0.1 second was found to be appropriate. Two typical 0.1 second time records taken as the motor accelerated from rest to full speed are presented in figure 4.1., and their corresponding spectra, obtained by employing the matlab FFT routine, are presented in figure 4.2. as follows.

It can be seen from figure 4.1 that the two data sets, i.e. set1 and set2 of data presented for the motor-only healthy-state case are essentially equivalent. Having demonstrated that each pair, set1 and set2, of the acquired time records are consistently representative of the same load and fault condition, it is now not intended to present more than one data set for each motor-rig fault and load condition. Figure 4.2 presents the time record and resulting spectrum when a rotor dynamic eccentricity
fault is present. Inspection and comparison with either of the two fault free spectra reveals that there are indeed significant differences in spectral peaks.

Figure 4.1. -- Motor Only -- Healthy-State 0 – 0.1 s Acceleration Time Record and Spectrum

Figure 4.2. -- Motor Only -- Dynamic Eccentricity 0 – 0.1 s Acceleration Time Record and Spectrum
At this point it is once more worthy of note that for every healthy-state or fault operating condition of the motor and load, the time records and the resulting spectra for each and every condition was found to be repeatable, as was the case for the steady state results reported in chapter 2. Indeed variations between sets of data obtained under equivalent conditions, taken at different times, as described in chapter 2, produce results with differences that are insignificant when compared with those differences apparent between the spectra when obtained under those different fault conditions employed during this research.

In fact, the results obtained under motor accelerating conditions produce non-stationary waveforms [34] [35] [36] and it is suggested by a number of researchers that a simple FFT based technique may have to be replaced by a more elaborate technique which results in amplitude versus both frequency and time and frequency, the so called time-frequency-response. Rajagopalan et al [35] in particular states that “there has not been much research in the area of fault diagnostics of motors operating under non-stationary conditions”. Weidong and Mechefske [33], state that the well known FFT technique does not result in as good a resolution in the spectra than that which would be obtained by employing an alternative technique for non-stationary waveform analysis. The technique employed during this research to take into account the non-stationarity of the records obtained during motor acceleration is dealt with in greater detail in chapter 6 of this thesis.

Despite the claimed limitations concerning poor resolution in the spectra when a standard FFT based technique is employed for the non-stationary data obtained during motor acceleration, a comparative inspection of figure 4.1 and figure 4.2 indicates that
the results obtained by employing standard FFT techniques to produce spectra did, at least in the case of this research, produce spectra whose features could indeed be usefully employed to represent the condition of the motor under a variety of healthy-state and fault conditions. It is the authors’ opinion that this is due to the fact that the rate of acceleration of the motor is relatively low and that the frequency change with respect to time has a relatively small value and that although a time-frequency-response analysis would be preferred a reasonable spectral resolution would be produced in this case when the simple FFT is employed. Figures 4.1 and 4.2 present the time records and their resulting FFT produced spectra for the stated conditions, and as already stated, it can be clearly seen that there are readily discernable differences between them. This was also found to be the case for the entire range of data obtained at the stated fault conditions considered as part of this research. Since differences were both discernable and representative of motor-rig condition it was subsequently decided to proceed with the strategy employed for steady state operation and to present the results obtained by employing the standard FFT routine in this chapter.

An initial appraisal of the results, based upon a visual inspection of the spectra obtained from the time records collected under each applied fault condition, is also presented in this chapter. The visual inspections carried out provided the basis for an initial estimate to be offered as to the ability of the method employed to be able to detect and discriminate between machine fault conditions. A summary of the results based upon visual inspections of the results obtained for coilA acting alone and for coilA and coilB connected in series, is presented in this chapter in tables 4.1 to 4.4.
After having initially produced a variety of FFT produced spectra it was subsequently decided to partition the time records obtained during this research into two regions, viz 0 to 0.05 seconds and 0.04 seconds to 0.1 seconds. This was carried out in order to demonstrate that the first half of the acceleration time-record, i.e. 0 to 0.05 second contained the greatest amount of fault related information. The process of partitioning the time records into two regions was carried out by adding appropriate code to the matlab m-file employed for the purpose. Partitioning the time records in this manner produces two independent data sources which may subsequently be employed to provide supporting evidence when an attempt is made to use the data to determine which of the given healthy-state or fault conditions is actually present. The remaining plots presented in this chapter both for coil A acting alone and for coil A and coil B connected in series all adhere to these two time regions.

4.2 **Coil A Spectra -- Motor Plus Load Rig**

The plots for the two above stated time regions. 0 to 0.05 second and 0.04 to 0.1 second are presented in figures 4.3.1 to 4.10.2.

Inspection of the time record plots demonstrates that there are differences in the waveforms produced for both time regions when the time records under each fault operating condition is compared. Once again the nature of the differences in time record frequency content is most apparent in the frequency domain. As previously stated the results obtained were repeatable for equivalent fault and running conditions. Differences in spectral peaks are significant and discernable and demonstrate that differences are more noticeable than was the case for those results obtained under equivalent fault steady-state running conditions and presented in chapter 3.
Of equal importance, inspection of the spectra presented in figures 4.3.1 to 4.10.2, reveals that the spectral peaks can be employed to diagnose a fault condition. Chapter 5 will include a quantitative analysis of the fault discriminating capabilities of the data obtained from coilA in series with coilB, ie coilAplusB, under accelerating conditions.

**Figure 4.3.1**  
CoilA -- Motor + Rig --- Healthy-State
Figure 4.3.2 CoilA -- Motor + Rig --- Misalignment Fault

Figure 4.4.1 CoilA -- Motor + Rig --- Gearbox Fault
Figure 4.4.2  CoilA -- Motor + Rig  --- Load Shaft Unbalance

Figure 4.5.1  CoilA -- Motor Only  --- Healthy-State
Figure 4.5.2  CoilA -- Motor Only --- Drive End Bearing Fault

Figure 4.6.1  CoilA -- Motor Only --- Dynamic Eccentricity Fault
**Figure 4.6.2**  
CoilA -- Motor Only --- Motor Rotor Bars Fault  

**Figure 4.7.1**  
CoilA -- Motor + Rig --- Healthy-State  

Time Record  
0 to 0.05 s  

Spectrum  
0 to 1000 Hz  

Time Record  
0.04 to 0.1 s  

Spectrum  
0 to 1000 Hz
Figure 4.7.2  CoilA -- Motor + Rig --- Misalignment Fault

Figure 4.8.1  CoilA -- Motor + Rig --- Gearbox Fault
Figure 4.8.2  CoilA -- Motor + Rig --- Load Unbalance

Figure 4.9.1  CoilA -- Motor Only --- Healthy-State
**Figure 4.9.2**  
CoilA -- Motor Only  ---  Motor Drive End Bearing Fault

**Figure 4.10.1**  
CoilA -- Motor Only  ---  Dynamic Eccentricity Fault
In a similar manner to that for coilA the plots for coilAplusB for the two previously stated time regions. 0 to 0.05 second and 0.04 to 0.1 second are presented in figures 4.11.1 to 4.18.2.

Once more inspection of the time record plots demonstrates that there are differences in the waveforms produced for both time regions when the time records under each fault operating condition is compared. Once again the nature of the differences in time record frequency content is most apparent in the frequency domain. As previously stated the results obtained were repeatable for equivalent fault and running conditions. Differences in spectral peaks are significant and discernable and demonstrate that differences are more noticeable than was the case for those results obtained under

### Figure 4.10.2  
CoilA -- Motor Only --- Motor Rotor Bars Fault

---

4.3  **CoilAplusB Spectra -- Motor Plus Load Rig**

In a similar manner to that for coilA the plots for coilAplusB for the two previously stated time regions. 0 to 0.05 second and 0.04 to 0.1 second are presented in figures 4.11.1 to 4.18.2.

Once more inspection of the time record plots demonstrates that there are differences in the waveforms produced for both time regions when the time records under each fault operating condition is compared. Once again the nature of the differences in time record frequency content is most apparent in the frequency domain. As previously stated the results obtained were repeatable for equivalent fault and running conditions. Differences in spectral peaks are significant and discernable and demonstrate that differences are more noticeable than was the case for those results obtained under
equivalent-fault steady-state running conditions and presented in chapter 3.

Again of equal importance, inspection of the spectra presented in figures 4.11.1 to 4.18.2 reveals that the spectral peaks can be employed to diagnose a fault condition. As previously stated Chapter 5 will include a quantitative analysis of the fault discriminating capabilities of the data obtained from coilA and coilB connected in series (coilAplusB) under accelerating conditions.

A final note here is to propose that a visual inspection of the spectra presented and figures 4.19 to 4.22 indicates that the results for coilAplusB are superior to those from coilA acting alone. Verification of this assertion will be undertaken in chapters 5, 6 and 7.

<table>
<thead>
<tr>
<th>Time Record</th>
<th>Spectrum</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 to 0.05 s</td>
<td>0 to 1000 Hz</td>
</tr>
</tbody>
</table>

Figure 4.11.1  CoilAplusB -- Motor + Load Rig --- Healthy-State
Figure 4.11.2  CoilAplusB -- Motor + Load Rig  ---  Misalignment Fault

Figure 4.12.1  CoilAplusB -- Motor + Load Rig  ---  Gearbox Fault
Figure 4.12.2  CoilAplusB -- Motor + Load Rig --- Load Unbalance Fault

Figure 4.13.1  CoilAplusB -- Motor Only --- Healthy-State
Figure 4.13.2  CoilAplusB -- Motor Only --- End Bearing Fault

Figure 4.14.1  CoilAplusB -- Motor Only --- Rotor Dynamic Eccentricity Fault
Figure 4.14.2  
**CoilAplusB -- Motor Only --- Broken Rotor Bars Fault**

Time Record  
0 to 0.05 s

Spectrum  
0 to 1000 Hz

Figure 4.15.1  
**CoilAplusB -- Motor + Load Rig --- Healthy-State**

Time Record  
0.04 to 0.1 s

Spectrum  
0 to 1000 Hz
Figure 4.15.2  CoilAplusB -- Motor + Rig --- Misalignment Fault

Figure 4.16.1  CoilAplusB -- Motor + Load Rig --- Gearbox Fault
Figure 4.16.2  CoilAplusB -- Motor + Rig --- Load Unbalance Fault

Figure 4.17.1  CoilAplusB -- Motor Only --- Healthy-State
Figure 4.17.2  CoilAplusB -- Motor Only --- End Bearing Fault

Time Record
0.04 to 0.1 s

Spectrum
0 to 1000 Hz

Figure 4.18.1  CoilAplusB -- Motor Only --- Rotor Dynamic Eccentricity Fault

Time Record
0.04 to 0.1 s

Spectrum
0 to 1000 Hz

Figure 4.18.1  CoilAplusB -- Motor Only --- Rotor Dynamic Eccentricity Fault
Figure 4.18.2  CoilAplusB -- Motor Only --- Broken Rotor Bars Fault
4.4 An Initial Appraisal Of Acceleration Results:

As was the case in chapter 3 for the steady state conditions the initial appraisal offered here is based upon a visual inspection only of the 16 examples of spectra presented above in figures 4.3 to 4.18 and figures 4.19 to 4.22. It is also again worth noting that the examples of data used to produce the spectra presented in this chapter were chosen from a larger data base as being typical of those obtained during this research.

As was the case for the results taken under steady state conditions and presented in chapter 3 no attempt is made in this chapter to accurately quantify the ability of the acceleration data as presented to detect and diagnose the applied fault conditions considered during this research. However, once more, some initial and, in the authors’ opinion, useful preliminary estimates have been submitted in this chapter and once again resulting from a simple visual inspection of the spectra here presented. The entries in tables 4.1 to 4.4 are produced as the result of a visual inspection of the above spectra, the value of each table entry being subject to errors of judgement when inspecting the appropriate spectrum. However, for the purpose of providing the basis of an initial, valid if not accurate, estimate of the ability of the coils to detect a faulty condition, the visual estimate of spectral amplitudes is sufficiently fit for purpose and it may be clearly seen that the presence of a faulty condition measurably alters the resulting spectra from the healthy-state condition. Once more, as was the case for the results taken under steady state conditions, it is also possible to form the basis of a comparative estimate between the ability of a single coil, or alternatively of two interconnected coils, to provide sufficient and useful fault dependant data. Inspection and comparison of figures 4.19 to 4.22 again provides promising initial indications that there is an overall improvement in fault detection capability when coil A and
coilB were series connected when compared to using coilA alone. It must be noted here that in order to present the line diagrams within equal page areas that the vertical scales for coilAplusB results have a greater range than those for coilA acting alone. Partitioning the time records into two separate time regions did also result in higher resolution spectra than those which were obtained by employing the complete time record. It is proposed that this is because the frequency variations are not so pronounced within the limited time ranges used.

Once more the research results lead the author to suggest that the amplitude, position, shape and number of the differences in spectral peaks are largely, if not entirely, dependent upon which of the faults was applied. Although not fully presented in this chapter, it is of vital importance to restate the fact that the same essential differences between equivalent fault conditions were repeated across the two independently obtained sets of data taken under motor accelerating conditions. It is again proposed that this verifies the authors’ opinion that the data obtained from the search coils does indeed represent the health-state or fault condition of the system under test. The differences between data sets taken under the same load conditions and with the same healthy-state or fault condition proved very small when compared to the differences in the acceleration spectra obtained under the stated fault conditions. The fault dependent differences were readily and unmistakably recognisable in both sets of data. In this and subsequent chapters, the ability of the coils to detect onboard motor faults and those faults external to the motor, i.e. load shaft misalignment, load unbalance, and faulty gearbox has been convincingly demonstrated. As is the case for the steady-state operating condition the sensitivity of the coils and coil configuration to both onboard motor faults and external load faults will be dealt with more fully in later chapters of this thesis.
Once more a general observation that can be made is that the interconnection of coils, whether a physical connection or effected via the system model, does in fact, generally result in greater and more visible differences between the healthy-state and fault spectra in the majority of cases. At the very least it may again be observed from the results presented in chapters 3 and 4 that there is no visible reduction in the amount of information obtained than from one coil acting alone. Inspection of tables 4.1 to 4.4, in conjunction with the corresponding figures 4.11.1 to 4.18.2, illustrates this point. At this stage, of course, these observations are again based upon visible inspections, each of which is subject to some error of judgement, and no attempt is made in this chapter to accurately quantify the ability of the data to form the basis of a fault detection and diagnostic strategy. Later sections of this thesis describe the methods employed to quantify and evaluate the ability of the coils to provide fault detection and diagnosis. It is however, the authors’ opinion that it has been demonstrated in this and the previous chapter 3 that the spectra produced during this research show significant promise that they could, by themselves, be employed to develop an effective and reliable method of fault diagnosis which is comparable in performance to other well tried methods such as current monitoring. Once more the faults applied were considered to be of a level which would be classed as light to moderate in level

4.5 Chapter Conclusion

The figures presented in this chapter demonstrate that the results obtained under a particular fault condition are both observable and fault dependent. As previously described for the acceleration period two spectral sets were taken and were produced
at different non-contiguous times, with the particular fault condition being reintroduced to take a further set of fault data independently from the first set.

As was the case for the previous chapter and as a final comment on this chapter it is again proposed that sufficient evidence has been provided which supports the author’s belief that obtaining stator to rotor magnetic field flux measurements from one or more search coils enables fault dependent data to be obtained. It is also the case that the spectral differences obtained under accelerating conditions were more pronounced than those obtained under steady state conditions. Opportunities for collection of acceleration data would, in practice, present themselves whenever the motor was switched on, an action that, in most cases, can reasonably be assumed to take place with sufficiently high frequency for the purpose of effective condition monitoring. Further chapters of this thesis will contain a description of the techniques employed to perform a more detailed, robust and automatic fault detection exercise.
<table>
<thead>
<tr>
<th>Peak Frequencies (Hz)</th>
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<th>250</th>
<th>350</th>
<th>450</th>
<th>550</th>
<th>650</th>
<th>750</th>
<th>850</th>
<th>950</th>
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</tr>
<tr>
<td>Healthy-State</td>
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<td>0.04</td>
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<td>0.2</td>
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Table 4.1. --- Peak Values and % Deviations CoilA W.R.T. Healthy-state --- 0 to 0.05 sec
| Peak Frequencies  
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<th>(Hz)</th>
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<td></td>
<td></td>
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</tr>
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| Peak Frequencies  
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</tr>
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Table 4.2. --- Peak Values and % Deviations CoilA W.R.T. Healthy-State --- 0.04 to 0.1 sec
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**Table 4.3.** --- Peak Values and % Deviations CoilA+B W.R.T. Healthy-State --- 0 to 0.05 sec
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<tr>
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<td>0.09</td>
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<td>0.03</td>
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<td>0.03</td>
<td>0.06</td>
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<td>0.08</td>
<td>0.07</td>
<td>0.03</td>
</tr>
<tr>
<td>Rotor Bars Fault</td>
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<td>0.09</td>
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<td>0.07</td>
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</tr>
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<td>Dynamic Eccentricity ±% w.r.t. FF Peak</td>
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<td>±0</td>
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<td>50</td>
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<td>75</td>
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<td>-14</td>
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<tr>
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Table 4.4. --- Peak Values and % Deviations CoilA+B W.R.T. Healthy-State --- 0.04 to 0.1
Figure 4.19  Spectral Deviations --- Motor Only --- 0 to 0.05 s

Note: Fault-Free ≡ Healthy-State
Figure 4.20  Spectral Deviations --- Motor + Load Rig --- 0 to 0.05 s

Note: Fault-Free ≡ Healthy-State
Figure 4.21  Spectral Deviations  ---  Motor Only  ---  0.04 to 0.1 s

Note:  Fault-Free ≡ Healthy-State
Figure 4.22  Spectral Deviations --- Motor + load Rig --- 0.04 to 0.1 s

Note:  Fault-Free ≡ Healthy-State
Chapter 5

Data Analysis and Feature Extraction

5.1 Introduction

The results presented so far in chapters three and four have been in the form of spectral plots showing the signal components as amplitude versus frequency. In this chapter a number of further techniques will be employed in order to aid and enable the data collected to be employed for fault detection and diagnosis. During this research a number of techniques were applied to the data records in the time domain, in particular auto and cross-correlation, variance, covariance, and coherence. Correlation and variance techniques are employed to both the time-domain waveforms and the frequency domain spectra. The coherence function is employed on the time domain records only, since the technique itself involves the use of the power spectral densities of the two waveforms employed in each case as described further on in this chapter.

As will be illustrated in this and subsequent chapters the results produced by the above listed techniques did provide data that could be reliably employed to categorise the system under test as being in one of a number of given fault and healthy-state conditions as previously described in earlier chapters. The time synchronous averaged time records and their resultant spectra obtained during this research produced a very large volume of data. In order to compress the volume of data and to aid the employment of an automatic pattern recognition technique, such as a neural network based technique, the techniques listed in the above paragraph were employed to provide some form of feature extraction. Feature extraction, in effect, performs data
compression, whereby the compressed data rather than the averaged time records or their spectra can be employed to identify the system healthy-state and fault condition. The raw data (averaged time records), whether in the time or frequency domains, is composed of 4096 time domain data samples (4001 + zeroes padding) which results in 2048 frequency domain data values (FFT produced). The compressed data for each system healthy-state and fault condition can comprise a number of representative features, typically in the order of a few tens or less [40] [41]. Yang and Penman [42] employ a neural network with 18 input nodes.

The spectra produced from the time synchronous averaged time records enabled any differences in the information present as a result of the fault and healthy-state running condition to be more easily seen with the naked eye. To enable an automated detection and diagnosis system to be implemented, the aforementioned feature extraction methods were applied to both the time domain and frequency domain records.

### 5.2 Auto and Cross Correlation

A correlation function is a measure of coincidence between two instances of a time domain signal. At any particular phase displacement between two signals the correlation measure is found by integrating the product of the signals over all time and finding the average value of the integral by dividing the integral by the duration of the signal. This process is repeated over an appropriate range of phase displacements (or lag) between the signals to give the auto-correlation function. The cross-correlation function, \( R_{xy}(\tau) \), is determined when the operation as described is performed between two different signals, each of duration T seconds. When the operation is performed between a signal and a time displaced version of itself, the procedure is known as auto-correlation, \( R_{xx}(\tau) \). If the average product is found at each time shift, then the result is
known as an auto-correlation function. The correlation function is defined mathematically as follows, where the cross-correlation function is given by:

\[ R_{xy}(\tau) = \frac{1}{T} \int_{T=0}^{T=\infty} f_x(t) f_y(t-\tau) \, dt \]

This research employs the matlab cross-correlation function, xcorr which estimates the cross-correlation and auto-correlation of a sequence. For vectors of length N, the xcorr function returns the cross-correlation sequence in a length 2(N-1), for vectors of unequal length, which is not the case in this research, the shortest vector would be automatically padded with zeroes. The matlab correlation function xcorr computes raw correlations with no normalisations.

\[ R_{xy}(m) = \sum_{n=0}^{N-m-1} x_{n+m} y_n \quad m \geq 0 \]

The output vector of product terms also contains terms for \( R_{xy}(-m) \) obtained for \( m < 0 \) by the same process mathematically stated immediately above. The resulting correlation between two sequences x and y, \( C_{xy} \), therefore has elements given by correlations by \( C_{xy}(m-N) \) where \( m = 1 \) to \( m = 2N-1 \). This means that for a sequence of say 10 elements, there would be 19 correlations resulting from shifting the sequences \pm 9 lags from the zero time shift position. In this case a time shift of one lag represents the sampling interval used when recording data.

Since the auto-correlation is a measure of the similarity between a signal and a shifted version of itself, it can be treated as a special case of the cross-correlation between two
separate signals, because in both cases the correlation is between two signals. One difference between the auto and cross-correlations is that, in general for any random signal, the autocorrelation is always a maximum at $\tau = 0$, but this is not necessarily the case for the cross correlation. However for cross-correlation where there is an equivalent predominant feature in both signals the cross-correlation measure for the time records will also be a maximum at or about $\tau = 0$ which is the situation for the time records and spectra obtained during this research.

Matlab allows a number of correlation function options to be stipulated, this research used the ‘coeff’ option provided so that the autocorrelations at zero lag are identically 1.0. When cross-correlating the separate signals forming the research data base, the correlation function also employed the ‘maxlags’ option which limited the number of correlations performed to $\pm$ No lags specified. This was found to be important since, for the averaged time records, the maximum correlation did not necessarily occur at zero lag, but for this research did occur within a range of $\pm$100 lags. In terms of time record duration, a figure of $\pm$100 lags is equivalent to correlations calculated between zero shift and $\pm$2.5 mS. This allowed for any small but non-negligible phase displacements between time records taken under different fault conditions. Inspection of the spectra obtained from the time synchronised averaged time records, taken under steady-state running condition, and collected from the search coils indicated that the 50 Hz spectral peak did not appear to contain any significant fault dependent information, or at least any fault information that may have been present was ‘swamped’ by the main 50 Hz spectral peak. Before correlation, or any other technique used in this research, was employed it was therefore subsequently decided to filter out the 50 Hz signal component. It was felt that fault dependant variations in the filtered waveform would therefore have a greater significance and could more easily
be distinguished. In fact this was bourne out by the fact that the resulting correlations between time records and between spectra showed larger variations than those initially produced from the unfiltered data. The results obtained for the unfiltered data are not presented in this thesis.

The matlab function buttord was employed to design a high pass Butterworth filter of minimum order necessary to obtain a suitable cut-off frequency and with minimum signal loss in the pass band and maximum signal attenuation in the stop band. For this research a high pass Butterworth filter of order five was subsequently employed.

Autocorrelation is normally considered to be a technique that is performed on time domain sequences or signals. This research is not seeking to use auto and cross-correlation to identify deterministic and random signal components, but is only interested in a figure that represents the similarity between two sequences, it was decided to perform the cross-correlation function to both the time domain data and the spectra produced using the FFT function as described. The filtered time domain data was cross correlated and table 5.1. illustrates a typical set of results for data taken under steady state running conditions. Inspection of this table shows that the use of cross-correlation does produce fault dependant result variations that, although small, are sufficiently significant that they could potentially be employed for fault detection and diagnosis. To enable the following tables to be completed, data from the set1 record group forms the dictionary of fault related data, and data from the set2 record group is used as the test data which was classified into a particular healthy-state or fault condition. The following tables use a green bold where the highest correlation does, in fact, result in a correct diagnosis, a red bold where a misdiagnosis occurred, in which case a bold blue highlights the expected diagnosis.
The following tables also show whether both fault detection and subsequent diagnosis was possible. It may again be noted here that although the differences illustrated are small, the differences produced for the entire data range is repeatable and consistently provides an accurate and reliable basis for diagnosis.

Note 1: In tables 5.1 to 5.17 the time records taken as set1 data forms the fault dictionary against which the actual fault condition (taken from set2) is established.

Note 2: In tables 5.1 to 5.17 Healthy-State ≡ Fault-Free ≡ F-F

<table>
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<th>Time Records</th>
<th>Fault-Free Set1</th>
<th>Dynamic Eccentricity Set1</th>
<th>Drive Bearing Set1</th>
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<td>Fault-Free</td>
<td>0.9996</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dyn Ecc</td>
<td>0.9928</td>
<td>0.9993</td>
<td>0.9811</td>
<td>0.9919</td>
</tr>
<tr>
<td>Drive Brg</td>
<td>0.9834</td>
<td>0.9807</td>
<td>0.9983</td>
<td>0.9799</td>
</tr>
<tr>
<td>Rot Bars</td>
<td>0.9945</td>
<td>0.9918</td>
<td>0.9805</td>
<td>0.9997</td>
</tr>
</tbody>
</table>

Table 5.1. -- XCorrs -- CoilA Steady State Motor Only -- w.r.t. Set1 Data

5.3 Correlation Results

5.3.1 Steady-State Correlation Results

Tables 5.2 and 5.4 present correlations of the filtered time record data obtained from coilA. Tables 5.3 and 5.5 present correlations of the filtered time record data obtained from coilAplusB. For both coilA and coilAplusB combination the system was operated under the stated fault/healthy-state condition. Inspection of these tables shows that for the fault conditions listed, detection of a fault condition was possible in all cases, however there is one instance of mis-diagnosis. For coilA an unbalance fault is incorrectly diagnosed as a misalignment fault, whilst the data obtained from coilAplusB produced a 100% detection and diagnosis success rate.
Table 5.10 and 5.12 present the results of the correlations of the spectra of the filtered
time record data obtained from coilA. Tables 5.11 and 5.13 present correlations of the
spectra of the filtered time record data obtained from coilAplusB. For both coilA and
coilAplusB combination the system was operated under the stated fault/healthy-state
condition. Inspection of these tables shows that for the fault conditions listed,
detection of a fault condition was possible in all cases, however there is one instance of
mis-diagnosis. For coilA an unbalance fault is incorrectly diagnosed as a misalignment
fault, whilst the data obtained from coilAplusB produced a 100% detection and
diagnosis success rate.

5.3.2 Acceleration Period Correlation Results

In addition to data collected under steady state speed conditions, as previously
described, time records were obtained for each of the healthy-state and fault conditions
under motor accelerating conditions. The time records obtained were for a time period
of 0.01 seconds and chapter 4 presents a selection of the time records obtained under
the accelerating conditions taken during this research. As illustrated in chapter 4, the
0.1 second acceleration plot was partitioned into two time regions, viz 0 to 0.05
seconds and 0.04 to 0.1 second. This allowed the initial 0.05 second period following
start-up to be considered separately, since it was considered to contain the most
acceleration generated fault dependant information. Cross correlations of data taken
under accelerating conditions employed the data recorded for the first 0.05 second after
the start-up trigger signal was received. It was felt that this period would yield the
more robust results, an assumption based initially upon a visual inspection of the
waveforms presented in chapter 4. Inspection of the waveforms and spectra presented
in chapter 4 reveals that the acceleration periods from 0.04 to 0.1 second also contain
visually noticeable variations in the plots for different healthy-state and fault
conditions. However this chapter will now concentrate on the 0 to 0.05 period immediately following the start-up trigger pulse.

Inspection of tables, table 5.2 to 5.17, containing the results of the auto and cross-correlations show that the results obtained under accelerating conditions can be considered more reliable and are certainly far more discriminative and reliable in their diagnosis than was the case for the results obtained under steady-state running conditions. This is extremely significant when considering fault detection and diagnostic capability since although opportunities for the taking of test data are greatest under steady-state speed conditions, the motor driven rig can, under typical usage, can be expected to be started from rest to enable effective condition monitoring to take place.

Another conclusion that can be drawn from inspection of the correlation tables is that the use of more than one coil did, for the data this research project, result in a more robust set of results, a fact that supports the author’s proposal stated in chapter 2.

The results are presented in the following tables 5.2 to 5.17, a full discussion of the results obtained from the use of applying an autocorrelation and a cross correlation technique is included at the end of this chapter.
Highest Value ≡ Best Fit ; Green ≡ Diagnosis Correct ; Red ≡ Misdiagnosis

No Detection ≡ Healthy-State (Fault-Free) Highest Value Under Fault Condition

<table>
<thead>
<tr>
<th>Time Records</th>
<th>F -F Set1</th>
<th>Dynamic Eccy</th>
<th>Drive Brg</th>
<th>Rotor Bars</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set2</td>
<td>0.9996</td>
<td>0.9940</td>
<td>0.9836</td>
<td>0.9963</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc Set2</td>
<td>0.9928</td>
<td>0.9993</td>
<td>0.9811</td>
<td>0.9919</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Drive Brg Set2</td>
<td>0.9834</td>
<td>0.9807</td>
<td>0.9983</td>
<td>0.9799</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars Set2</td>
<td>0.9945</td>
<td>0.9918</td>
<td>0.9805</td>
<td>0.9997</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.2. -- XCorrs -- CoilA Steady State Motor Only -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Time Records</th>
<th>F -F Set1</th>
<th>Dynamic Eccy</th>
<th>Drive Brg</th>
<th>Rotor Bars</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set2</td>
<td>0.9996</td>
<td>0.7544</td>
<td>0.9765</td>
<td>0.9931</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc Set2</td>
<td>0.9928</td>
<td>0.9960</td>
<td>0.7733</td>
<td>0.8175</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Drive Brg Set2</td>
<td>0.9834</td>
<td>0.9090</td>
<td>0.9299</td>
<td>0.9160</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars Set2</td>
<td>0.9945</td>
<td>0.7709</td>
<td>0.9619</td>
<td>0.9950</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.3. -- XCorrs -- CoilAplusB Steady State Motor Only -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Time Records</th>
<th>F -F Set1</th>
<th>Shaft Misal</th>
<th>Shaft Unbal</th>
<th>Gear Tooth</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9996</td>
<td>0.9983</td>
<td>0.9981</td>
<td>0.9975</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misalign Set2</td>
<td>0.9981</td>
<td>0.9994</td>
<td>0.9989</td>
<td>0.9990</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbalance Set2</td>
<td>0.9989</td>
<td>0.9992</td>
<td>0.9989</td>
<td>0.9987</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Gear Flt Set2</td>
<td>0.9984</td>
<td>0.9989</td>
<td>0.9989</td>
<td>0.9995</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.4. -- XCorrs -- CoilA Steady State Motor + Rig -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Time Records</th>
<th>F -F Set1</th>
<th>Shaft Misal</th>
<th>Shaft Unbal</th>
<th>Gear Tooth</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9993</td>
<td>0.9915</td>
<td>0.9964</td>
<td>0.9910</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misalign Set2</td>
<td>0.9959</td>
<td>0.9979</td>
<td>0.9952</td>
<td>0.9936</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbalance Set2</td>
<td>0.9948</td>
<td>0.9899</td>
<td>0.9988</td>
<td>0.9965</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt Set2</td>
<td>0.9916</td>
<td>0.9906</td>
<td>0.9971</td>
<td>0.9985</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.5. -- XCorrs -- CoilAplusB Steady State Motor + Rig -- w.r.t. Set1 Data
Highest Value ≡ Best Fit ; Green ≡ Diagnosis Correct ; Red ≡ Misdiagnosis

No Detection ≡ Healthy-State (Fault-Free) Highest Value Under Fault Condition

<table>
<thead>
<tr>
<th>Time Records</th>
<th>F -F Set1</th>
<th>Dynamic Eccy</th>
<th>Drive Brg</th>
<th>Rotor Bars</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9021</td>
<td>0.6130</td>
<td>0.5859</td>
<td>0.5606</td>
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<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc Set2</td>
<td>0.6148</td>
<td>0.9852</td>
<td>0.8733</td>
<td>0.8518</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Drive Brg Set2</td>
<td>0.6112</td>
<td>0.8355</td>
<td>0.9984</td>
<td>0.8984</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars Set2</td>
<td>0.6105</td>
<td>0.8237</td>
<td>0.9789</td>
<td>0.9983</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.6. -- XCorrs -- CoilA Acceleration Motor Only -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Time Records</th>
<th>F -F Set1</th>
<th>Dynamic Eccy</th>
<th>Drive Brg</th>
<th>Rotor Bars</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9851</td>
<td>0.9585</td>
<td>0.9389</td>
<td>0.9027</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc Set2</td>
<td>0.9044</td>
<td>0.9533</td>
<td>0.8895</td>
<td>0.9284</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Drive Brg Set2</td>
<td>0.9590</td>
<td>0.9595</td>
<td>0.9905</td>
<td>0.8848</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars Set2</td>
<td>0.8664</td>
<td>0.8967</td>
<td>0.8524</td>
<td>0.9695</td>
<td>yes</td>
<td>yes</td>
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</table>

Table. 5.7. -- XCorrs -- CoilAplusB Acceleration Motor Only -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Time Records</th>
<th>F -F Set1</th>
<th>Shaft Misal</th>
<th>Shaft Unbal</th>
<th>Gear Tooth</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9061</td>
<td>0.6710</td>
<td>0.7008</td>
<td>0.8051</td>
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<td>yes</td>
</tr>
<tr>
<td>Misalign Set2</td>
<td>0.7030</td>
<td>0.9791</td>
<td>0.9217</td>
<td>0.7992</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbalance Set2</td>
<td>0.7219</td>
<td>0.9863</td>
<td>0.9908</td>
<td>0.8707</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt Set2</td>
<td>0.6752</td>
<td>0.8958</td>
<td>0.9561</td>
<td>0.9623</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.8. --- XCorrs -- CoilA Acceleration Motor + Rig -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Time Records</th>
<th>F -F Set1</th>
<th>Shaft Misal</th>
<th>Shaft Unbal</th>
<th>Gear Tooth</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9906</td>
<td>0.8269</td>
<td>0.5752</td>
<td>0.8709</td>
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<td>yes</td>
</tr>
<tr>
<td>Misalign Set2</td>
<td>0.8671</td>
<td>0.9346</td>
<td>0.5316</td>
<td>0.8282</td>
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<td>yes</td>
</tr>
<tr>
<td>Unbalance Set2</td>
<td>0.5758</td>
<td>0.5738</td>
<td>0.9912</td>
<td>0.5677</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt Set2</td>
<td>0.8503</td>
<td>0.8429</td>
<td>0.5648</td>
<td>0.9578</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.9. -- XCorrs -- CoilAplusB Acceleration Motor + Rig -- w.r.t. Set1 Data
Highest Value ≡ Best Fit ;    Green ≡ Diagnosis Correct ;    Red ≡ Misdiagnosis

No Detection ≡ Healthy-State (Fault-Free) Highest Value Under Fault Condition

<table>
<thead>
<tr>
<th>Spectral Records</th>
<th>F -F Set1</th>
<th>Dynamic Ecc</th>
<th>Drive Brg</th>
<th>Rotor Bars</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set2</td>
<td>0.9998</td>
<td>0.9952</td>
<td>0.9940</td>
<td>0.9974</td>
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<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc Set2</td>
<td>0.9939</td>
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<td>0.9917</td>
<td>0.9938</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Drive Brg Set2</td>
<td>0.9948</td>
<td>0.9915</td>
<td><strong>0.9988</strong></td>
<td>0.9904</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars Set2</td>
<td>0.9957</td>
<td>0.9935</td>
<td>0.9921</td>
<td><strong>0.9999</strong></td>
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</tbody>
</table>

Table. 5.10. -- XCorrs -- CoilA Steady State Motor Only -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Spectral Records</th>
<th>F -F Set1</th>
<th>Dynamic Ecc</th>
<th>Drive Brg</th>
<th>Rotor Bars</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set2</td>
<td>0.9998</td>
<td>0.9008</td>
<td>0.9879</td>
<td>0.9975</td>
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<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc Set2</td>
<td>0.9278</td>
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<td>0.9180</td>
<td>0.9325</td>
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<td>yes</td>
</tr>
<tr>
<td>Drive Brg Set2</td>
<td>0.9790</td>
<td>0.9317</td>
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<td>0.9787</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars Set2</td>
<td>0.9913</td>
<td>0.9156</td>
<td>0.9808</td>
<td><strong>0.9971</strong></td>
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<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.11. -- XCorrs -- CoilAplusB Steady State Motor Only -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Spectral Records</th>
<th>F -F Set1</th>
<th>Shaft Misal</th>
<th>Shaft Unbal</th>
<th>Gear Tooth</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set2</td>
<td>0.9998</td>
<td>0.9988</td>
<td>0.9986</td>
<td>0.9983</td>
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<td>yes</td>
</tr>
<tr>
<td>Misalign Set2</td>
<td>0.9989</td>
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<td>0.9996</td>
<td>0.9996</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbalance Set2</td>
<td>0.9994</td>
<td><strong>0.9996</strong></td>
<td>0.9992</td>
<td>0.9764</td>
<td>yes</td>
<td><strong>no</strong></td>
</tr>
<tr>
<td>Gear Flt Set2</td>
<td>0.9990</td>
<td>0.9994</td>
<td>0.9995</td>
<td><strong>0.9998</strong></td>
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<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.12. -- XCorrs -- CoilA Steady State Motor + Rig -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Spectral Records</th>
<th>F -F Set1</th>
<th>Shaft Misal</th>
<th>Shaft Unbal</th>
<th>Gear Tooth</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set2</td>
<td>0.9997</td>
<td>0.9949</td>
<td>0.9980</td>
<td>0.9950</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misalign Set2</td>
<td>0.9974</td>
<td><strong>0.9989</strong></td>
<td>0.9972</td>
<td>0.9969</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbalance Set2</td>
<td>0.9963</td>
<td>0.9922</td>
<td><strong>0.9994</strong></td>
<td>0.9985</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt Set2</td>
<td>0.9947</td>
<td>0.9928</td>
<td>0.9985</td>
<td><strong>0.9996</strong></td>
<td>yes</td>
<td>yes</td>
</tr>
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</table>

Table. 5.13. -- XCorrs -- CoilAplusB Steady State Motor + Rig -- w.r.t. Set1 Data
Highest Value ≡ Best Fit ;  Green ≡ Diagnosis Correct ;  Red ≡ Misdiagnosis

No Detection ≡ Healthy-State (Fault-Free) Highest Value Under Fault Condition

<table>
<thead>
<tr>
<th>Spectral Records</th>
<th>F -F Set1</th>
<th>Dynamic Eccy</th>
<th>Drive Brg</th>
<th>Rotor Bars</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9626</td>
<td>0.8908</td>
<td>0.8537</td>
<td>0.8687</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc Set2</td>
<td>0.8212</td>
<td>0.9903</td>
<td>0.9384</td>
<td>0.9188</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Drive Brg Set2</td>
<td>0.8506</td>
<td>0.9106</td>
<td>0.9994</td>
<td>0.9937</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars Set2</td>
<td>0.8616</td>
<td>0.9046</td>
<td>0.9894</td>
<td>0.9995</td>
<td>yes</td>
<td>yes</td>
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</tbody>
</table>

Table. 5.14. -- XCorrs -- CoilA Acceleration Motor Only -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Spectral Records</th>
<th>F -F Set1</th>
<th>Dynamic Eccy</th>
<th>Drive Brg</th>
<th>Rotor Bars</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9914</td>
<td>0.9842</td>
<td>0.9737</td>
<td>0.9528</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc Set2</td>
<td>0.9263</td>
<td>0.9752</td>
<td>0.9214</td>
<td>0.9748</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Drive Brg Set2</td>
<td>0.9774</td>
<td>0.9744</td>
<td>0.9975</td>
<td>0.9211</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars Set2</td>
<td>0.9285</td>
<td>0.9668</td>
<td>0.9201</td>
<td>0.9873</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.15. -- XCorrs -- CoilAplusB Acceleration Motor Only -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Spectral Records</th>
<th>F -F Set1</th>
<th>Shaft Misal</th>
<th>Shaft Unbal</th>
<th>Gear Tooth</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9514</td>
<td>0.8241</td>
<td>0.9372</td>
<td>0.9015</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misalign Set2</td>
<td>0.9334</td>
<td>0.9878</td>
<td>0.9662</td>
<td>0.9318</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbalance Set2</td>
<td>0.8906</td>
<td>0.9926</td>
<td>0.9955</td>
<td>0.9510</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt Set2</td>
<td>0.9334</td>
<td>0.9357</td>
<td>0.9694</td>
<td>0.9884</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.16. -- XCorrs -- CoilA Acceleration Motor + Rig -- w.r.t. Set1 Data

<table>
<thead>
<tr>
<th>Spectral Records</th>
<th>F -F Set1</th>
<th>Shaft Misal</th>
<th>Shaft Unbal</th>
<th>Gear Tooth</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free Set 2</td>
<td>0.9966</td>
<td>0.9504</td>
<td>0.8454</td>
<td>0.9601</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misalign Set2</td>
<td>0.9555</td>
<td>0.9998</td>
<td>0.8605</td>
<td>0.9303</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbalance Set2</td>
<td>0.8408</td>
<td>0.8628</td>
<td>0.9978</td>
<td>0.8030</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt Set2</td>
<td>0.9317</td>
<td>0.9419</td>
<td>0.7868</td>
<td>0.9826</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table. 5.17. -- XCorrs -- CoilAplusB Acceleration Motor + Rig -- w.r.t. Set1 Data
5.4 Correlation Based m-code

The following list of code provides the essential coding features employed in acquiring data correlations. Note that Fault-Free ≡ FF ≡ Healthy-State

```matlab
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  LOAD CoilAplusBplusB TIME SERIES SETS 1 and 2 MOTOR ONLY %%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
load Coil_AplusB_Av_FF_nospec_SET1 ; load Coil_AplusB_Av_FF_nospec_SET2
load Coil_AplusB_Av_Dyn_Ecc_nospec_SET1; load
Coil_AplusB_Av_Dyn_Ecc_nospec_SET2
e tc
timevals  =  rec010.X.Data ; % file in current folder

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%       Correlation Coefficients of TIME RECORDS          %%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
 disp('Press any key for FF CoilAplusBplusB set1 Filtered TR plot') ;   pause
%%% filter of order 5 and normalised frequency to fs/2 ; i.e.  2 x fc / fs
[b, a]  =  butter(5, 100/20000, 'high');
%%%%%      Plot of Healthy-state Set1 Data  %%%%%
disp('Press any key for High Pass Filtered CoilAplusBplusB FF Set1 plot') ; pause
Coil_AplusB_Av_FF_nospec_SET1_Fltrd = filtfilt(b,a,Coil_AplusB_Av_FF_nospec_SET1);
plot(timevals,Coil_AplusB_Av_FF_nospec_SET1_Fltrd)
title('Plot of FF Filtered Set1 Time Record CoilAplusB') %i.e. autocorrelation
axis ([0  0.1  -2  2])

% % % % %   FFT of Dynamic Eccentricity Fault Data Set1 % % % % %
freq = 40960*(0:2048)/4096 ;
fft_DE_Set1 = fft(Coil_AplusB_Av_Dyn_Ecc_nospec_SET1_Fltrd,4096);
final_DE_Set1 = sqrt(fft_DE_Set1.*conj(fft_DE_Set1))/2048 ;

%%%%       EXAMPLES  FILTER DATA     %%%%%%%%%
Coil_AplusB_Av_Dr_Brg_nospec_SET1_Fltrd   =
filtfilt(b,a,Coil_AplusB_Av_Dr_Brg_nospec_SET1) ;
```

160
Coil_AplusB_Av_Rot_Bars_nospec_SET1_Fltrd = filtfilt(b,a,Coil_AplusB_Av_Rot_Bars_nospec_SET1);

% Etc

disp('Press any key for CoilAplusB DE Set2 SPECTRUM plot')
pause
freq = 40960*(0:2048)/4096;
fft_DE_Set2 = fft(Coil_AplusB_Av_Dyn_Ecc_nospec_SET2,4096);
final_DE_Set2 = sqrt(fft_DE_Set2.*conj(fft_DE_Set2))/2048;

freq = 40960*(0:2048)/4096;
fft_DE_Set2 = fft(Coil_AplusB_Av_Dyn_Ecc_nospec_SET2_Fltrd,4096);
final_DE_Set2 = sqrt(fft_DE_Set2.*conj(fft_DE_Set2))/2048;

%%% AUTOCORRELATION OF SET 1 CoilAplusB --- FF

corr_max_FF_FF_CoilAplusB_S1 = xcorr(Coil_AplusB_Av_FF_nospec_SET1_Fltrd,0,'coeff')
corr_lags_FF_FF_CoilAplusB_S1 = corr(Coil_AplusB_Av_FF_nospec_SET1_Fltrd,100,'coeff');

%%% Crosscorr CoilAplusB - FF - example of set1 v set2 - Motor Only %%%

disp('Press any key for FF set 1 v set2 correlation plots -- 2')
pause

corr_max_FF_SETS_CoilAplusB = xcorr(Coil_AplusB_Av_FF_nospec_SET1_Fltrd,Coil_AplusB_Av_FF_nospec_SET2_Fltrd,0,'coeff')
corr_lags_FF_SETS_CoilAplusB = xcorr(Coil_AplusB_Av_FF_nospec_SET1_Fltrd,Coil_AplusB_Av_FF_nospec_SET2_Fltrd,100,'coeff');
corr_maxlags_FF_SETS_CoilAplusB = max(corr_lags_FF_SETS_CoilAplusB)

%%% E.G. LOOK FOR MATCH Dyn Ecc set2 with ALL set 1 %%%
disp('Press any key for All Conditions set1 v DE set2 correlations -- 4')

pause

corr_max_FF1_DE2_CoilAplusB =
    xcorr(Coil_AplusB_Av_FF_nospec_SET1_Fltrd,Coil_AplusB_Av_Dyn_Ecc_nospec_SET2_Fltrd,0,'coeff')
corr_lags_FF1_DE2_CoilAplusB =
    xcorr(Coil_AplusB_Av_FF_nospec_SET1_Fltrd,Coil_AplusB_Av_Dyn_Ecc_nospec_SET2_Fltrd,100,'coeff');

corr_maxlags_FF1_DE2_CoilAplusB = max(corr_lags_FF1_DE2_CoilAplusB)

corr_max_DB1_DE2_CoilAplusB =
    xcorr(Coil_AplusB_Av_Dr_Brg_nospec_SET1_Fltrd,Coil_AplusB_Av_Dyn_Ecc_nospec_SET2_Fltrd,0,'coeff')
corr_lags_DB1_DE2_CoilAplusB =
    xcorr(Coil_AplusB_Av_Dr_Brg_nospec_SET1_Fltrd,Coil_AplusB_Av_Dyn_Ecc_nospec_SET2_Fltrd,100,'coeff');

corr_maxlags_DB1_DE2_CoilAplusB = max(corr_lags_DB1_DE2_CoilAplusB)

%%%%%%                  END OF DYN ECC                %%%%%%%

%%%%%%                                Take Example FFTs                                %%%%%%%

%%%%%%        Prepare Frequency Vector       %%%%%%%

Freq = 40960*(0:2048)/4096 ;

%%%%%        Spectrum FF SET1 - Motor Only        %%%%%

fft_FF_Set1 = fft(Coil_AplusB_Av_FF_nospec_SET1_Fltrd,4096); %zeroes padded
final_FF_Set1 = sqrt(fft_FF_Set1.*conj(fft_FF_Set1))/2048 ;

%%%%%        Spectrum Dr Brg SET1 - Motor Only        %%%%%

fft_DB_Set1 = fft(Coil_AplusB_Av_Dr_Brg_nospec_SET1_Fltrd,4096);
final_DB_Set1 = sqrt(fft_DB_Set1.*conj(fft_DB_Set1))/2048 ;

%%%%%        Spectrum Dr Brg SET2 - Motor Only        %%%%%
fft_DB_Set2 = fft(Coil_AplusB_Av_Dr_Brg_nospec_SET2_Fltrd,4096);
final_DB_Set2 = sqrt(fft_DB_Set2.*conj(fft_DB_Set2))/2048;

%%% CORRELATIONS of SPECTRA Motor Only %%%%
disp('Press any key for FF Set1 Spectrum Auto-Corr'); pause

XC_max_FF1_FF1_ClAplusB_FFT = xcorr(final_FF_Set1,0,'coeff')
XC_lags_FF1_FF1_ClAplusB_FFT = xcorr(final_FF_Set1,50,'coeff');
disp('Press any key for set1 v set2 Spectrum XCorr')
pause

XC_max_FF1_FF2_ClAplusB_FFT = xcorr(final_FF_Set1,final_FF_Set2,0,'coeff')
XC_lags_FF1_FF2_ClAplusB_FFT = xcorr(final_FF_Set1,final_FF_Set2,50,'coeff');
Etc

%%% LOOK FOR MATCH FF set2 with ALL Set 1 %%%
disp('Press any key for Dr Brg Set1 v FF set2 Spectrum XCorr')
pause

XC_max_DB1_FF2_ClAplusB_FFT = xcorr(final_DB_Set1,final_FF_Set2,0,'coeff')
XC_lags_DB1_FF2_ClAplusB_FFT = xcorr(final_DB_Set1,final_FF_Set2,50,'coeff');
disp('Press any key for Rot Bars Set1 v FF set2 Spectrum XCorr')
pause

XC_max_RB1_FF2_ClAplusB_FFT = xcorr(final_RB_Set1,final_FF_Set2,0,'coeff')
XC_lags_RB1_FF2_ClAplusB_FFT = xcorr(final_RB_Set1,final_FF_Set2,50,'coeff');

Etc for every fault condition considered in this research.

5.5 Covariance and Its’ Application

The matlab ‘cov’ function was employed to obtain the variance of a column vector, each element of which is produced by subtracting the data taken under a known condition from one of the column vectors acquired with the rig operating under a
simulated unknown fault condition. As was the above case for correlation, once more the raw data is filtered to eliminate the 50 Hz signal component and the filtered waveform employed to provide the basis for analysis.

The matlab ‘cov’ function, e.g. \( C = \text{cov}(x, y) \) will return the covariance of the elements in column vectors \( x \) and \( y \). The matlab ‘cov’ function is the covariance between two column vectors or matrix columns \((i)\), and is defined as:

\[
\text{Cov}(x_1, x_2) = E[(x_1 - \mu_1)(x_2 - \mu_2)]
\]

Where \( E \) is the mathematical expectation and \( \mu_i = Ex_i \)

The matlab ‘cov’ function, e.g. \( C = \text{cov}(x) \) will return the variance of a single vector. Whether operating on matrix columns, column vector pairs, or a single column vector, the matlab ‘cov’ function removes the mean from the vector before calculating the result. In the case of this research \( \text{cov}(x) \) will produce the variance of the single 4001 element vectors obtained whilst the system was placed under the stated fault conditions, and can be defined as:

\[
\text{Cov}(x) = E[(x - \mu)^2] ; \quad \text{where once again } E \text{ is the mathematical expectation}
\]

The section of m-code, the essential content and features of which are listed immediately below, illustrates the procedure for producing the column vectors employed to provide the basis for determining the state of the rig under a particular test-fault condition. The particular fault condition, although known for the purpose of this research, represents the particular operating random fault condition of the motor and rig when running within it’s normal environment and under normal operational
stresses. In the particular case demonstrated at this point in the thesis, the motor was being operated in a healthy-state condition, designated ‘FF2’. The resulting filtered data, obtained under the stated healthy-state condition was then used to determine whether the FF2 data was closest in feature to each of the stored fault data previously obtained. That is, the healthy-state test condition is compared to the stored data taken whilst the system was operating at every stored known fault condition. The data collected whilst the system was operating under a range of known conditions formed the fault-dictionary. As previously stated, the fault dictionary included data collected whilst the system was operated under healthy-state or healthy-state (FF1), dynamic eccentricity fault (DE1), faulty motor drive-end bearing (EB1), and broken rotor bars (RB1) conditions. In this case, the closest match will correspond to the lowest variance value, i.e. the lowest value is the ‘closest fit’ and would be taken to represent the condition of the system at the time the test data was obtained.

As was the case for the auto and cross correlations, the variance function is applied to both the time and frequency domain vectors and under both steady-state and accelerating conditions. In addition, as for the correlation technique under steady state conditions, a filtered version of the time record data was employed.

5.5.1 Covariance Results

The results are presented in the following tables 5.18 to 5.33, and as for the correlation function described above, a full discussion of the results obtained from the use of applying a variance based technique is included at the end of this chapter.
Lowest Value ≡ Best Fit ;     Green ≡ Diagnosis Correct ;     Red ≡ Misdiagnosis

No Detection ≡ Healthy-State (Fault-Free) Lowest Value Under Fault Condition

Coil A --- Motor Only --- Steady State

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowₓ</th>
<th>Dyn Ecc 1 minus Rowₓ</th>
<th>End Brg 1 minus Rowₓ</th>
<th>Rot Bars 1 minus Rowₓ</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>3.97 x 10⁻⁴</td>
<td>3.4 x 10⁻³</td>
<td>1.93 x 10⁻¹</td>
<td>4.8 x 10⁻³</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Eccen 2</td>
<td>3.8 x 10⁻⁴</td>
<td>7.05 x 10⁻⁴</td>
<td>1.97 x 10⁻¹</td>
<td>8.7 x 10⁻³</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>2.01 x 10⁻¹</td>
<td>2.01 x 10⁻¹</td>
<td>1.5 x 10⁻²</td>
<td>2.44 x 10⁻¹</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>8.4 x 10⁻¹</td>
<td>1.17 x 10⁻²</td>
<td>2.29 x 10⁻¹</td>
<td>1.48 x 10⁻⁴</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.18 Time Domain --- Variances of \[ \text{Stored fault data} - \text{Unknown fault data} \]

Coil AplusB --- Motor Only --- Steady State

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowₓ</th>
<th>Dyn Ecc 1 minus Rowₓ</th>
<th>End Brg 1 minus Rowₓ</th>
<th>Rot Bars 1 minus Rowₓ</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>3.49 x 10⁻⁴</td>
<td>8.66 x 10⁻²</td>
<td>3.47 x 10⁻¹</td>
<td>3.7 x 10⁻³</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Eccen 2</td>
<td>7.37 x 10⁻²</td>
<td>1.10 x 10⁻³</td>
<td>3.58 x 10⁻¹</td>
<td>5.76 x 10⁻²</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>2.69 x 10⁻¹</td>
<td>2.55 x 10⁻¹</td>
<td>3.00 x 10⁻²</td>
<td>2.79 x 10⁻¹</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>1.54 x 10⁻²</td>
<td>7.08 x 10⁻²</td>
<td>4.05 x 10⁻¹</td>
<td>4.7 x 10⁻³</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.19 Time Domain --- Variances of \[ \text{Stored fault data} - \text{Unknown fault data} \]
Lowest Value ≡ Best Fit ; Green ≡ Diagnosis Correct ; Red ≡ Misdiagnosis

No Detection ≡ Healthy-State (Fault-Free) Lowest Value Under Fault Condition

Coil A --- Motor With Rig --- Steady State

Row 1-4 Fault Time Record Collected With Test Fault Applied

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Row_x</th>
<th>Misal 1 minus Row_x</th>
<th>UnBal 1 minus Row_x</th>
<th>Gear Flt 1 minus Row_x</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>2.83 x 10^{-3}</td>
<td>6.12 x 10^{-3}</td>
<td>6.97 x 10^{-3}</td>
<td>8.81 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misal 2</td>
<td>1.10 x 10^{-3}</td>
<td>1.97 x 10^{-3}</td>
<td>3.81 x 10^{-3}</td>
<td>3.58 x 10^{-3}</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Unbal 2</td>
<td>4.64 x 10^{-4}</td>
<td>4.60 x 10^{-4}</td>
<td>4.87 x 10^{-4}</td>
<td>5.78 x 10^{-4}</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Gear Flt 2</td>
<td>5.57 x 10^{-4}</td>
<td>4.71 x 10^{-4}</td>
<td>6.80 x 10^{-4}</td>
<td>2.57 x 10^{-4}</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.20 Time Domain --- Variances of [ Stored fault data – Unknown fault data ]

Coil AplusB --- Motor With Rig --- Steady State

Row 1-4 Fault Time Record Collected With Test Fault Applied

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Row_x</th>
<th>Misal 1 minus Row_x</th>
<th>UnBal 1 minus Row_x</th>
<th>Gear Flt 1 minus Row_x</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>2.23 x 10^{-4}</td>
<td>4.70 x 10^{-3}</td>
<td>1.40 x 10^{-3}</td>
<td>3.70 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misal 2</td>
<td>2.90 x 10^{-3}</td>
<td>1.50 x 10^{-3}</td>
<td>9.96 x 10^{-4}</td>
<td>3.20 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbal 2</td>
<td>2.80 x 10^{-3}</td>
<td>8.80 x 10^{-3}</td>
<td>5.16 x 10^{-4}</td>
<td>1.20 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt 2</td>
<td>3.80 x 10^{-3}</td>
<td>8.60 x 10^{-3}</td>
<td>1.10 x 10^{-3}</td>
<td>4.98 x 10^{-4}</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.21 Time Domain --- Variances of [ Stored fault data – Unknown fault data ]
**Table 5.22** Time Domain --- Variances of [Stored fault data – Unknown fault data]

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flt-Free 2</td>
<td>0.1633</td>
<td>0.8874</td>
<td>1.0579</td>
<td>1.2219</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Eccen 2</td>
<td>0.7392</td>
<td>0.0410</td>
<td>0.3623</td>
<td>0.7213</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>1.2319</td>
<td>0.8648</td>
<td>0.0813</td>
<td>0.1043</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>1.0143</td>
<td>0.7712</td>
<td>0.0953</td>
<td><strong>0.0094</strong></td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>0.3810</td>
<td>6.8394</td>
<td>3.4356</td>
<td>4.1061</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Eccen 2</td>
<td>6.0155</td>
<td><strong>1.8305</strong></td>
<td>2.0455</td>
<td>4.5669</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>1.5744</td>
<td>2.6829</td>
<td><strong>0.3583</strong></td>
<td>2.2723</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>2.8486</td>
<td>6.7181</td>
<td>3.8253</td>
<td><strong>0.4985</strong></td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>
**Lowest Value ≡ Best Fit ; Green ≡ Diagnosis Correct ; Red ≡ Misdiagnosis**

**No Detection ≡ Healthy-State (Fault-Free) Lowest Value Under Fault Condition**

### Coil A --- Motor With Rig --- Acceleration

#### Row 1-4 Fault Spectrum of Applied Fault Time Record

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Misal 1 minus Rowx</th>
<th>UnBal 1 minus Rowx</th>
<th>Gear Flt 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>0.1214</td>
<td>0.7431</td>
<td>1.0950</td>
<td>0.3613</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misal 2</td>
<td>0.5013</td>
<td>0.0871</td>
<td>0.5321</td>
<td>0.4316</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbal 2</td>
<td>0.8936</td>
<td>0.1908</td>
<td>0.0313</td>
<td>0.4284</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt 2</td>
<td>0.9860</td>
<td>0.4342</td>
<td><strong>0.1510</strong></td>
<td>0.2098</td>
<td>yes</td>
<td><strong>no</strong></td>
</tr>
</tbody>
</table>

Table 5.24  Time Domain --- Variances of  \([ \text{Stored fault data} – \text{Unknown fault data} \])

### Coil AplusB --- Motor With Rig --- Acceleration

#### Row 1-4 Fault Time Record Collected With Test Fault Applied

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Misal 1 minus Rowx</th>
<th>UnBal 1 minus Rowx</th>
<th>Gear Flt 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>0.2522</td>
<td>8.5623</td>
<td>20.7154</td>
<td>7.2509</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misal 2</td>
<td>10.3500</td>
<td><strong>1.5703</strong></td>
<td>27.5721</td>
<td>4.7681</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbal 2</td>
<td>19.7101</td>
<td>18.5706</td>
<td><strong>0.4008</strong></td>
<td>18.3894</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt 2</td>
<td>6.7442</td>
<td>2.6833</td>
<td>20.8760</td>
<td><strong>0.5899</strong></td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.25  Time Domain --- Variances of  \([ \text{Stored fault data} – \text{Unknown fault data} \])
Lowest Value ≡ Best Fit ; Green ≡ Diagnosis Correct ; Red ≡ Misdiagnosis

No Detection ≡ Healthy-State (Fault-Free) Lowest Value Under Fault Condition

Coil A --- Motor Only --- Steady State

Row 1-4 Fault Time Record Collected With Test Fault Applied

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>3.97 x 10^{-4}</td>
<td>3.4 x 10^{-5}</td>
<td>1.93 x 10^{-1}</td>
<td>4.8 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc 2</td>
<td>3.8 x 10^{-4}</td>
<td>7.05 x 10^{-4}</td>
<td>1.97 x 10^{-1}</td>
<td>8.7 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>2.01 x 10^{-1}</td>
<td>2.01 x 10^{-3}</td>
<td>1.5 x 10^{-3}</td>
<td>2.44 x 10^{-1}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>8.4 x 10^{-3}</td>
<td>1.17 x 10^{-2}</td>
<td>2.29 x 10^{-1}</td>
<td>1.48 x 10^{-4}</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.26 Frequency Domain --- Variances of [ Stored fault Data – Unknown fault data ]

Coil AplusB --- Motor Only --- Steady State

Row 1-4 Fault Time Record Collected With Test Fault Applied

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>3.47 x 10^{-4}</td>
<td>8.66 x 10^{-2}</td>
<td>3.47 x 10^{-1}</td>
<td>3.7 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Ecc 2</td>
<td>7.37 x 10^{-2}</td>
<td>1.1 x 10^{-3}</td>
<td>3.58 x 10^{-1}</td>
<td>5.76 x 10^{-2}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>2.69 x 10^{-1}</td>
<td>2.55 x 10^{-1}</td>
<td>3.0 x 10^{-2}</td>
<td>2.79 x 10^{-1}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>1.54 x 10^{-2}</td>
<td>7.08 x 10^{-2}</td>
<td>4.05 x 10^{-1}</td>
<td>4.7 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.27 Frequency Domain --- Variances of [ Stored fault Data – Unknown fault data ]
Lowest Value $\equiv$ Best Fit ; Green $\equiv$ Diagnosis Correct ; Red $\equiv$ Misdiagnosis

No Detection $\equiv$ Healthy-State (Fault-Free) Lowest Value Under Fault Condition

Coil A --- Motor With Rig --- Steady State

<table>
<thead>
<tr>
<th>Variance</th>
<th>Row 1-4 Fault Spectrum of Applied Fault Time Record</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Row 1-4</td>
<td>$F_{\text{flt-free}}$ minus Rowx</td>
<td>$F_{\text{misal}}$ minus Rowx</td>
<td>$F_{\text{unbal}}$ minus Rowx</td>
</tr>
<tr>
<td>Fault-Free 2</td>
<td>2.84 x 10^{-4}</td>
<td>6.12 x 10^{-4}</td>
<td>6.97 x 10^{-4}</td>
</tr>
<tr>
<td>Misal 2</td>
<td>1.10 x 10^{-3}</td>
<td>1.97 x 10^{-4}</td>
<td>3.81 x 10^{-4}</td>
</tr>
<tr>
<td>Unbal 2</td>
<td>4.60 x 10^{-4}</td>
<td>4.64 x 10^{-4}</td>
<td>6.37 x 10^{-4}</td>
</tr>
<tr>
<td>Gear Flt 2</td>
<td>5.57 x 10^{-4}</td>
<td>4.71 x 10^{-4}</td>
<td>6.80 x 10^{-4}</td>
</tr>
</tbody>
</table>

Table 5.28 Frequency Domain --- Variances of [ Stored fault Data – Unknown fault data ]

Coil A plus B --- Motor With Rig --- Steady State

<table>
<thead>
<tr>
<th>Variance</th>
<th>Row 1-4 Fault Time Record Collected With Test Fault Applied</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Row 1-4</td>
<td>$F_{\text{flt-free}}$ minus Rowx</td>
<td>$F_{\text{misal}}$ minus Rowx</td>
<td>$F_{\text{unbal}}$ minus Rowx</td>
</tr>
<tr>
<td>Fault-Free 2</td>
<td>2.23 x 10^{-4}</td>
<td>4.70 x 10^{-3}</td>
<td>1.40 x 10^{-3}</td>
</tr>
<tr>
<td>Misal 2</td>
<td>2.90 x 10^{-3}</td>
<td>1.50 x 10^{-3}</td>
<td>9.96 x 10^{-4}</td>
</tr>
<tr>
<td>Unbal 2</td>
<td>2.80 x 10^{-3}</td>
<td>8.80 x 10^{-3}</td>
<td>5.16 x 10^{-4}</td>
</tr>
<tr>
<td>Gear Flt 2</td>
<td>3.80 x 10^{-3}</td>
<td>8.60 x 10^{-3}</td>
<td>1.10 x 10^{-3}</td>
</tr>
</tbody>
</table>

Table 5.29 Frequency Domain --- Variances of [ Stored fault Data – Unknown fault data ]
Lowest Value \equiv \text{Best Fit} ; \quad \text{Green} \equiv \text{Diagnosis Correct} ; \quad \text{Red} \equiv \text{Misdiagnosis}

No Detection \equiv \text{Healthy-State (Fault-Free) Lowest Value Under Fault Condition}

### Table 5.30  Frequency Domain --- Variances of [ Stored fault Data – Unknown fault data ]

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>1.60 x 10^{-1}</td>
<td>8.74 x 10^{-1}</td>
<td>1.05</td>
<td>1.22</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Eccen 2</td>
<td>7.29 x 10^{-1}</td>
<td>4.1 x 10^{-2}</td>
<td>3.62 x 10^{-1}</td>
<td>7.21 x 10^{-1}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>1.23</td>
<td>8.65 x 10^{-1}</td>
<td>8.13 x 10^{-3}</td>
<td>1.43 x 10^{-2}</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>1.01</td>
<td>7.7 x 10^{-1}</td>
<td>9.53 x 10^{-2}</td>
<td>9.40 x 10^{-3}</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

### Table 5.31  Frequency Domain --- Variances of [ Stored fault Data – Unknown fault data ]

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>3.81 x 10^{-1}</td>
<td>6.84</td>
<td>3.44</td>
<td>4.11</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Eccen 2</td>
<td>6.02</td>
<td>1.83</td>
<td>2.05</td>
<td>4.56</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>1.57</td>
<td>2.68</td>
<td>3.58 x 10^{-1}</td>
<td>2.27</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>2.85</td>
<td>6.72</td>
<td>3.83</td>
<td>4.91 x 10^{-1}</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>
Lowest Value ≡ Best Fit ;     Green ≡ Diagnosis Correct ;     Red ≡ Misdiagnosis

No Detection ≡ Healthy-State (Fault-Free) Lowest Value Under Fault Condition

Coil A --- Motor With Rig --- Acceleration

Row 1-4 Fault Spectrum of Applied Fault Time Record

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Misal 1 minus Rowx</th>
<th>UnBal 1 minus Rowx</th>
<th>Gear Flt 1 minus Rowx</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>$1.21 \times 10^{-1}$</td>
<td>$7.43 \times 10^{-1}$</td>
<td>1.10</td>
<td>$3.6 \times 10^{-1}$</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misal 2</td>
<td>$5.01 \times 10^{-1}$</td>
<td>$8.71 \times 10^{-2}$</td>
<td>$5.32 \times 10^{-1}$</td>
<td>$4.32 \times 10^{-1}$</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbal 2</td>
<td>$8.94 \times 10^{-1}$</td>
<td>$1.91 \times 10^{-1}$</td>
<td>$3.13 \times 10^{-2}$</td>
<td>$4.28 \times 10^{-1}$</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt 2</td>
<td>$9.86 \times 10^{-1}$</td>
<td>$4.34 \times 10^{-1}$</td>
<td>$1.51 \times 10^{-1}$</td>
<td>$2.10 \times 10^{-1}$</td>
<td>yes</td>
<td>no</td>
</tr>
</tbody>
</table>

Table 5.32  Frequency Domain --- Variances of [ Stored fault Data – Unknown fault data ]

Coil AplusB --- Motor With Rig --- Acceleration

Row 1-4 Fault Time Record Collected With Test Fault Applied

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Misal 1 minus Rowx</th>
<th>UnBal 1 minus Rowx</th>
<th>Gear Flt 1 minus Rowx</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>$2.52 \times 10^{-1}$</td>
<td>8.56</td>
<td>20.72</td>
<td>7.25</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misal 2</td>
<td>10.35</td>
<td>$1.57$</td>
<td>25.57</td>
<td>4.77</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbal 2</td>
<td>19.70</td>
<td>18.57</td>
<td>$4.00 \times 10^{-1}$</td>
<td>18.39</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Flt 2</td>
<td>6.74</td>
<td>2.68</td>
<td>20.88</td>
<td>$5.90 \times 10^{-1}$</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.33  Frequency Domain --- Variances of [ Stored fault Data – Unknown fault data ]
5.6 Variance Based m-code

The following list of code provides the main coding features employed in acquiring data variances. In all cases the variance function was applied to a vector formed by subtracting each of the known fault vectors contained in the fault dictionary from the particular test vector. As previously stated for the purposes of this research each test vector was obtained with the motor and rig in a known healthy-state or faulty condition.

```matlab
testpath = 'load Coil_AplusB_Av_FF_nospec_SET1';
testpath = 'load Coil_AplusB_Av_FF_nospec_SET2';
testpath = 'load Coil_AplusB_Av_Rot_Bars_nospec_SET1';
testpath = 'load Coil_AplusB_Av_Rot_Bars_nospec_SET2';
etc

disp('Press any key for FF2 Variance Test'); pause

FF2_minus_FF1 = FF2_col - FF1_col;
FF2_minus_DE1 = FF2_col - DE1_col;
FF2_minus_EB1 = FF2_col - EB1_col;
FF2_minus_RB1 = FF2_col - RB1_col;
var_FF2_minus_FF1 = cov(FF2_minus_FF1);
var_FF2_minus_DE1 = cov(FF2_minus_DE1);
var_FF2_minus_EB1 = cov(FF2_minus_EB1);
var_FF2_minus_RB1 = cov(FF2_minus_RB1);
```
% disp('Press any key for Dyn Ecc 2  Variance Test') ; pause

DE2_minus_FF1 = DE2_col - FF1_col;
DE2_minus_DE1 = DE2_col - DE1_col;
DE2_minus_EB1 = DE2_col - EB1_col;
DE2_minus_RB1 = DE2_col - RB1_col;
var_DE2_minus_FF1 = cov(DE2_minus_FF1)
var_DE2_minus_DE1 = cov(DE2_minus_DE1)
var_DE2_minus_EB1 = cov(DE2_minus_EB1)
var_DE2_minus_RB1 = cov(DE2_minus_RB1)
Etc for remaining conditions

%%%%%         Take FFTs  of Filtered Records   as for Correlation above                    %%%%

%%         Example  Spectrum Dyn Ecc SET2  - Motor Only                %%%%

fft_DE_Set2 = fft(Coil_AplusB_Av_Dyn_Ecc_nospec_SET2_Fltrd,4096);
final_DE_Set2  =  sqrt(fft_DE_Set2.*conj(fft_DE_Set2))/2048 ;
FF1_col = final_FF_Set1 ;  DE1_col = final_DE_Set1 ;   etc
FF2_col = final_FF_Set2 ; RB2_col = final_RB_Set2 ;   etc
disp('Press any key for Fault_Free Set 2 variances of differences ') ; pause

FF2_minus_FF1_spec = FF2_col - FF1_col;
FF2_minus_DE1_spec = FF2_col - DE1_col;
FF2_minus_EB1_spec = FF2_col - EB1_col;
FF2_minus_RB1_spec = FF2_col - RB1_col;
var_FF2_minus_FF1 = cov(FF2_minus_FF1)
var_FF2_minus_DE1 = cov(FF2_minus_DE1)
var_FF2_minus_EB1 = cov(FF2_minus_EB1)
var_FF2_minus_RB1 = cov(FF2_minus_RB1)

disp('Press any key for Dyn Ecc 2 variances of differences ') ; pause

DE2_minus_FF1_spec = DE2_col - FF1_col;
DE2_minus_DE1_spec = DE2_col - DE1_col;
DE2_minus_EB1_spec = DE2_col - EB1_col;
DE2_minus_RB1_spec = DE2_col - RB1_col;
\[ \text{var}_\text{DE2_minus_FF1} = \text{cov} (\text{DE2_minus_FF1}) \]
\[ \text{var}_\text{DE2_minus_DE1} = \text{cov} (\text{DE2_minus_DE1}) \]
\[ \text{var}_\text{DE2_minus_EB1} = \text{cov} (\text{DE2_minus_EB1}) \]
\[ \text{var}_\text{DE2_minus_RB1} = \text{cov} (\text{DE2_minus_RB1}) \]

Etc for remaining conditions

5.7 Coherence and Its’ Application

At each component frequency present in two signals, the coherence function measures the degree of linear relationship between the two signals. Similar to the correlation coefficient used above, the coherence \( \gamma^2(f) \) of two signals is a function on a scale from 0 to 1, where a coherence of 1 demonstrates a linearly identical signal frequency content and a coherence of 0 demonstrates no direct similarity in the two signals.

The matlab \( C_{xy} = \text{mscohere}(x,y) \) finds the magnitude squared coherence estimate \( C_{xy} \) of the input signals \( x \) and \( y \) using Welch's averaged, modified periodogram method. As stated above the magnitude squared coherence estimate is a function of frequency with values between 0 and 1 that indicates how well \( x \) corresponds to \( y \) at each frequency. The coherence is a function of the power spectral density (\( P_{xx} \) and \( P_{yy} \)) of \( x \) and \( y \) and the cross power spectral density (\( P_{xy} \)) of \( x \) and \( y \). \( x \) and \( y \) must be the same length. For real \( x \) and \( y \), \text{mscohere} returns a one-sided coherence estimate and for complex \( x \) or \( y \), it returns a two-sided estimate.

\[
C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)}
\]

The following m-code illustrates the main features of the code employed during this research to obtain the coherence based results. Unlike the above cases for the
correlation and variance based techniques, the coherence technique is applied to the
time based healthy-state and fault condition records only, since the matlab coherence
function involves the power spectral densities.

5.7.1 Coherence Results
The results are presented in the following tables 5.34 to 5.41, and as for the correlation
and variance based methods described above, a full discussion of the results obtained
from the use of applying a coherence based technique is included at the end of this
chapter.
**Highest Value ≡ Best Fit ; Green ≡ Diagnosis Correct ; Red ≡ Misdiagnosis**

**No Detection ≡ Healthy-State (Fault-Free) Highest Value Under Fault Condition**

### Coil A --- Motor Only --- Steady State

Cells Contain Mean of Coherence Between Row Data Set 2 and Column Data Set 1

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>0.8175</td>
<td>0.8141</td>
<td>0.1437</td>
<td>0.7953</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Dyn Eccen 2</td>
<td>0.7921</td>
<td>0.8374</td>
<td>0.1752</td>
<td>0.7670</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>End Brg 2</td>
<td>0.1282</td>
<td>0.0841</td>
<td>0.7021</td>
<td>0.0841</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Rot Bars 2</td>
<td>0.7778</td>
<td>0.7773</td>
<td>0.1168</td>
<td>0.8277</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5.34  Time Domain --- Mean of Coherences --- Set 1 versus Set 2

### Coil AplusB --- Motor Only --- Steady State

Cells Contain Mean of Coherence Between Row Data Set 2 and Column Data Set 1

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>0.8284</td>
<td>0.4764</td>
<td>0.0993</td>
<td>0.7472</td>
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<td>yes</td>
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<tr>
<td>Dyn Eccen 2</td>
<td>0.4098</td>
<td>0.7575</td>
<td>0.0945</td>
<td>0.4420</td>
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<td>End Brg 2</td>
<td>0.1234</td>
<td>0.1004</td>
<td>0.4158</td>
<td>0.1120</td>
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<tr>
<td>Rot Bars 2</td>
<td>0.6928</td>
<td>0.5466</td>
<td>0.0901</td>
<td>0.7433</td>
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</table>

Table 5.35  Time Domain --- Mean of Coherences --- Set 1 versus Set 2
Highest Value $\equiv$ Best Fit ;   Green $\equiv$ Diagnosis Correct ;   Red $\equiv$ Misdiagnosis

No Detection $\equiv$ Healthy-State (Fault-Free) Highest Value Under Fault Condition

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Misal 1 minus Rowx</th>
<th>UnBal 1 minus Rowx</th>
<th>Gear Flt 1 minus Rowx</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
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</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>0.8435</td>
<td>0.8323</td>
<td>0.8324</td>
<td>0.8346</td>
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<tr>
<td>Misal 2</td>
<td>0.8165</td>
<td>0.8248</td>
<td>0.8081</td>
<td>0.8048</td>
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<td>Unbal 2</td>
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<td>no</td>
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<td>0.8337</td>
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Table 5.36 Time Domain --- Mean of Coherences --- Set 1 versus Set 2

<table>
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<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Misal 1 minus Rowx</th>
<th>UnBal 1 minus Rowx</th>
<th>Gear Flt 1 minus Rowx</th>
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<th>Diagnosis Y/N</th>
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<td>Misal 2</td>
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<td>0.8312</td>
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<td>0.7731</td>
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Table 5.37 Time Domain --- Mean of Coherences --- Set 1 versus Set 2
Highest Value \equiv \text{Best Fit} ; \quad \text{Green} \equiv \text{Diagnosis Correct} ; \quad \text{Red} \equiv \text{Misdiagnosis}

No Detection \equiv \text{Healthy-State (Fault-Free) Highest Value Under Fault Condition}

Coil A \text{ --- Motor Only --- Accelerating Conditions}

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
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<td>Row 1-4</td>
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<td></td>
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<td></td>
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<td>Fault-Free 2</td>
<td>0.9336</td>
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<td>0.1738</td>
<td>0.1621</td>
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<tr>
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Table 5.38  Time Domain --- Mean of Coherences --- Set 1 versus Set 2

Coil AplusB \text{ --- Motor Only --- Accelerating Conditions}

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<th>Flt-Free 1 minus Rowx</th>
<th>Dyn Ecc 1 minus Rowx</th>
<th>End Brg 1 minus Rowx</th>
<th>Rot Bars 1 minus Rowx</th>
<th>Detection Y/N</th>
<th>Diagnosis Y/N</th>
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<td>Fault-Free 2</td>
<td>0.9414</td>
<td>0.3007</td>
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<td>Dyn Eccen 2</td>
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Table 5.39  Time Domain --- Mean of Coherences --- Set 1 versus Set 2
### Table 5.40  Time Domain --- Mean of Coherences  --- Set 1 versus Set 2

<table>
<thead>
<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Misal 1 minus Rowx</th>
<th>UnBal 1 minus Rowx</th>
<th>Gear Flt 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>0.8551</td>
<td>0.6356</td>
<td>0.6226</td>
<td>0.7693</td>
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<td>Misal 2</td>
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<td>0.9544</td>
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<td>0.6110</td>
<td>0.8406</td>
<td>0.9347</td>
<td>0.9135</td>
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</table>

### Table 5.41  Time Domain --- Means of Coherences  --- Set 1 versus Set 2

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<tr>
<th>Variance</th>
<th>Flt-Free 1 minus Rowx</th>
<th>Misal 1 minus Rowx</th>
<th>UnBal 1 minus Rowx</th>
<th>Gear Flt 1 minus Rowx</th>
<th>Detection</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault-Free 2</td>
<td>0.8900</td>
<td>0.1720</td>
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<td>Misal 2</td>
<td>0.1352</td>
<td>0.7872</td>
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<td>0.2574</td>
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<td>Gear Flt 2</td>
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<td>0.1833</td>
<td>0.8753</td>
<td>yes</td>
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</tr>
</tbody>
</table>
5.8 Coherence Based m-code

%%% Load records and filter as above cases %
load Coil_AplusB_Av_FF_nospec_SET1; %........ Etc

Coil_AplusB_Av_Dr_Brg_nospec_SET1_Fltrd =
filtfilt(b,a,Coil_AplusB_Av_Dr_Brg_nospec_SET1); %........ Etc

%%% LOOK FOR FF2 %
disp('Press any key for FF1 v FF2 cohere') ; pause

% FF1 v FF2
[cohere_FF_Set1_FF_Set2_Fltrd] =
mscohere(Coil_AplusB_Av_FF_nospec_SET1_Fltrd,Coil_AplusB_Av_FF_nospec_SET2_Fltrd,hamming(512),256,512,40000);
% Take mean of frequency dependant coherences
mean_FF1_FF2 = mean(cohere_FF_Set1_FF_Set2_Fltrd)
disp('Press any key for DE1 v FF2 cohere'); pause

% DE1 v FF2
[cohere_DE_Set1_FF_Set2_Fltrd] =
mscohere(Coil_AplusB_Av_Dyn_Ecc_nospec_SET1_Fltrd,Coil_AplusB_Av_FF_nospec_SET2_Fltrd,hamming(512),256,512,40000);
% Take mean of frequency dependant coherences

disp('Press any key for DE1 v FF2 cohere'); pause

Etc for remaining conditions

5.9 Tabular Summary of Results

The following tables 5.42 to 5.45 contain a summary of the results for both coilA and coilAplusB when the above three methods were employed during this research in order to provide a basis for the detection and possible diagnosis of the stated healthy-state and fault conditions.
### Table 5.42  Steady-State / Acceleration Time Domain Derived --- Detections / Diagnoses

Note: Fault-Free ≡ Healthy-State
<table>
<thead>
<tr>
<th>MOTOR ONLY</th>
<th>Coil A</th>
<th>Coil AplusB</th>
</tr>
</thead>
<tbody>
<tr>
<td>FREQUENCY</td>
<td>Flt-Free Set2</td>
<td>Flt-Free Set2</td>
</tr>
<tr>
<td>DOMAIN</td>
<td>Dyn Ecc Set2</td>
<td>Dyn Ecc Set2</td>
</tr>
<tr>
<td></td>
<td>End Brg Set2</td>
<td>End Brg Set2</td>
</tr>
<tr>
<td></td>
<td>Rot Bars Set2</td>
<td>Rot Bars Set2</td>
</tr>
</tbody>
</table>

Detection --- Steady-State --- Frequency Domain

| Autocorrelations | yes | yes | yes | yes | yes | yes | yes | yes |
| Variances        | yes | yes | yes | yes | yes | yes | yes | yes |

Diagnosis --- Steady-State --- Frequency Domain

| Autocorrelations | yes | yes | yes | yes | yes | yes | yes | yes |
| Variances        | yes | yes | yes | yes | yes | yes | yes | yes |

Detection --- Acceleration --- Frequency Domain

| Autocorrelations | yes | yes | yes | yes | yes | yes | yes | yes |
| Variances        | yes | yes | yes | yes | yes | yes | yes | yes |

Diagnosis --- Acceleration --- Frequency Domain

| Autocorrelations | yes | yes | yes | yes | yes | yes | yes | yes |
| Variances        | yes | yes | yes | yes | yes | yes | yes | yes |

Table 5.43  Steady-State /Acceleration Frequency Domain Derived --- Detections / Diagnoses

Note: Fault-Free ≡ Healthy-State
<table>
<thead>
<tr>
<th></th>
<th>Coil A</th>
<th>Coil AplusB</th>
</tr>
</thead>
<tbody>
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<td>MOTOR + RIG</td>
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<td></td>
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<tr>
<td>TIME DOMAIN</td>
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<tr>
<td></td>
<td>Fit-Free Set2</td>
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<tr>
<td></td>
<td>Misal Set2</td>
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<tr>
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<td>Unbal Set2</td>
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<td>Gear Tooth Set2</td>
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<td>Detection ---</td>
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<td>Steady-State ---</td>
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<td></td>
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<tr>
<td>Coherences</td>
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<td></td>
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<td></td>
<td>yes</td>
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</tbody>
</table>

Table 5.44  Steady-State / Acceleration Time Domain Derived --- Detections / Diagnoses

Note:  Fault-Free ≡ Healthy-State
<table>
<thead>
<tr>
<th>MOTOR + RIG FREQUENCY DOMAIN</th>
<th>Coil A</th>
<th></th>
<th></th>
<th></th>
<th>Coil AplusB</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Flt-Free Set2</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Misal Set2</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Unbal Set2</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Gear Tooth Set2</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

**Detection --- Steady-State --- Frequency Domain**

**Autocorrelations**
- yes
- yes
- yes
- yes
- yes
- yes
- yes
- yes

**Variances**
- yes
- yes
- no
- yes
- yes
- yes
- yes
- yes

**Diagnosis --- Steady-State --- Frequency Domain**

**Autocorrelations**
- yes
- yes
- no
- yes
- yes
- yes
- yes
- yes

**Variances**
- yes
- yes
- no
- yes
- yes
- yes
- yes
- yes

**Detection --- Acceleration --- Frequency Domain**

**Autocorrelations**
- yes
- yes
- yes
- yes
- yes
- yes
- yes
- yes

**Variances**
- yes
- yes
- yes
- yes
- yes
- yes
- yes
- yes

**Diagnosis --- Acceleration --- Frequency Domain**

**Autocorrelations**
- yes
- yes
- yes
- yes
- yes
- yes
- yes
- yes

**Variances**
- yes
- yes
- yes
- no
- yes
- yes
- yes
- yes

Table 5.45  Steady-State / Acceleration Frequency Domain Derived --- Detections / Diagnoses

Note: Fault-Free ≡ Healthy-State
5.10 Review of Results

5.10.1 Results From Coil Combinations --- Motor Only

With no rig connected, i.e. motor only, and for the three motor faults applied as required during the execution of this research the following points may be noted:

- All applied motor electro-mechanical faults are correctly detected and diagnosed.
- The results are the same for data obtained from both coilA, and the coil combination coilAplusB.
- The results are the same for both the time domain and the frequency domain.
- This success rate was achieved from both steady-state and acceleration period data. Although inspection of tables 5.2 to 5.17, tables 5.18 to 5.33 and tables 5.34 to 5.41 reveals that the acceleration derived data is more robust.

5.10.2 Results From Coil Combinations --- Motor + Rig

With the rig connected, and for the three load faults applied as required during the execution of this research the following points may be noted:

CoilA Derived Data --- Steady-State Time Domain:

- There is one undetected misalignment fault when variance is employed
- There is one undetected gear-tooth fault when coherence is employed
- There is one misdiagnosis when autocorrelation is employed
- There are two misdiagnoses when variance is employed
- There are two misdiagnoses when coherence is employed.
CoilA Derived Data  ---  Acceleration Period Time Domain:
- There are no undetected or misdiagnosed faults

CoilA Derived Data  ---  Acceleration Period Frequency Domain:
- There are no undetected or misdiagnosed faults

CoilA Derived Data  ---  Steady State Frequency Domain:
- There is one undetected load unbalance fault when variance is employed
- There is one misdiagnosed load unbalance fault when autocorrelation is employed
- There is one misdiagnosed load unbalance fault when variance is employed

CoilAplusB Derived Data  ---  Steady State Time Domain:
- There are no undetected or misdiagnosed faults.

CoilAplusB Derived Data  ---  Acceleration Period Time Domain:
- There are no undetected or misdiagnosed faults

CoilAplusB Derived Data  ---  Steady State Frequency Domain:
- There are no undetected or misdiagnosed faults

CoilAplusB Derived Data  ---  Acceleration Period Frequency Domain:
- There are no undetected or misdiagnosed faults

The results of the analytical techniques employed during this research strongly support the author’s proposition that using a combination of more than one coil will provide an improved and more robust database from which detection and diagnosis may be obtained. The results from coilAplusB is demonstrably superior for fault diagnosis purposes than the results from coilA. Tables 5.46 to 5.48 contain a final summary of the results presented in this chapter.
<table>
<thead>
<tr>
<th>TIME DOMAIN --- STEADY STATE --- Coil A</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>Undetected - Faults</td>
<td>Misdiagnosed - Faults</td>
</tr>
<tr>
<td>Correlation</td>
<td>No Faults Undetected</td>
<td>Load UnBalance</td>
</tr>
<tr>
<td>Variance</td>
<td>Load Misalignment</td>
<td>Load Unbalance, Misalignment</td>
</tr>
<tr>
<td>Coherence</td>
<td>Missing Gear Tooth</td>
<td>Load Unbalance, Gear Tooth</td>
</tr>
</tbody>
</table>

Table 5.46  Coil A --- Steady-State Time Domain Failed Results

<table>
<thead>
<tr>
<th>FREQUENCY DOMAIN --- STEADY STATE --- Coil A</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>Undetected - Faults</td>
<td>Misdiagnosed - Faults</td>
</tr>
<tr>
<td>Correlation</td>
<td>Load Unbalance</td>
<td>No Faults Undiagnosed</td>
</tr>
<tr>
<td>Variance</td>
<td>Load Unbalance</td>
<td>Load Unbalance</td>
</tr>
</tbody>
</table>

Table 5.47  Coil A --- Steady-State Frequency Domain Failed Results

<table>
<thead>
<tr>
<th>FREQUENCY DOMAIN --- Acceleration --- Coil A</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>Undetected - Faults</td>
<td>Misdiagnosed - Faults</td>
</tr>
<tr>
<td>Correlation</td>
<td>No Faults Undetected</td>
<td>No Faults Undiagnosed</td>
</tr>
<tr>
<td>Variance</td>
<td>No Faults Undetected</td>
<td>Missing Gear Tooth</td>
</tr>
</tbody>
</table>

Table 5.48  Coil A --- Acceleration Frequency Domain Failed Results
5.11 Final Conclusion of Chapter 5 Results

The results as presented demonstrate the following important points:

i. Stator to rotor magnetic flux monitoring provides a reliable basis for the detection and diagnosis of a range of fault conditions as described.

ii. Comparison of the results from coilA alone and from coilA connected in series with coilB (coilAplusB) demonstrates that using more than one coil significantly improves the efficacy of the method based upon magnetic field monitoring.

iii. Burnett and Watson [31] and Blaska and Sedlaceck [34] state that for fault detection obtaining readings of motor current during acceleration periods requires smaller currents than would be needed under steady-state speed, which means that condition monitoring can be effective at lower load levels. The data collected when accelerating, from start, did indeed provide more reliable results than those obtained under steady-state conditions. The frequency of vibration produced by unbalance is proportional to the square of the shaft speed, whilst the frequency of vibration produced by misalignment is proportional to shaft speed. Therefore as the shaft speed increases during the acceleration period, the frequency of vibration resulting from an unbalance fault and a misalignment fault will have a different shaft-speed dependency. This would enhance the ability of the data taken during acceleration periods to discriminate between these, and other, faults.
iv. Under steady-state conditions and for some results, refer to the results tables in this chapter, the differences between healthy-state and fault conditions are sometimes small, but prove to be repeatable and therefore it is proposed that they are reliable. In any event it is to be expected that for the fault levels applied there would not be any large frequency dependent differences in magnetic field magnitudes between fault conditions.
Chapter 6

Acceleration Period Time-Frequency-Distributions

6.1 Introduction

This chapter employs the Wigner-Ville [35] [36] technique to produce time-frequency representations of the motor acceleration period time records obtained with coilA and coilB (coilAplusB) connected in series. This combination is employed here, since it has already been proposed and subsequently demonstrated in chapter 4 and chapter 5 of this thesis that this combination is more successful at fault detection and diagnosis than that obtained by employing the time record obtained from a single coil.

Under steady-state operating conditions when employing the well tried and documented current monitoring technique to the problem of fault detection and diagnosis of faults in induction motors, it is necessary, for successful detection [31] [32], to operate the motor under heavily loaded conditions. This may not always be appropriate, for example, the motor has been taken offline or removed to a workshop environment. To overcome the problems associated with large supply currents Burnett and Watson [31] [32] investigated the possibility of utilising the supply current record obtained during the initial acceleration period of the motor at start-up. During these acceleration periods, between standstill and operational speed, it is observed that the supply current to the motor is typically 5 – 8 times the full load steady state current. These starting currents, present as the motor accelerates, can flow for up to 10s for large machines. Burnett and Watson [31] found that obtaining stator current time records during the acceleration period allowed successful detection to take place without the need for applying a large load to the machine.
For the purpose of this research it was also considered that mechanical faults such as load unbalance and shaft misalignment would also have a greater effect upon supply energy requirements during acceleration periods than during steady-state operating conditions. As claimed in chapter 5, the time records obtained from the coils under accelerating conditions, for any equivalent connection pattern, did indeed result in an improvement in the detection and diagnosis rate for the fault conditions applied under steady-state conditions during the research. This improvement in the detection and diagnosis rate was particularly apparent when considering those faults applied to the motor load shaft. This fact is perhaps not entirely surprising since the detection of these particular faults will rely heavily on the modulation of the energy supplied, rather than having an additional significant direct effect such as that obtained for motor shaft dynamic imbalance or broken rotor bars. In any case whether motor electro-mechanical or mechanical load faults, the modulation effect during the acceleration period appeared to have a greater measurable direct and modulating effect upon energy supplied and therefore upon the magnetic field and subsequent coil induced voltages.

The recording of coils’ output voltages was triggered to commence at the instant of start-up as the supply is applied to the motor, and the record duration was, by trial and error set at 0.1 seconds duration. A visual inspection of the coil voltages showed that steady-state conditions were obtained at the end of the 0.1 second period, it was however later decided to use the acceleration period in which it was apparent that most activity was taking place. Visual inspection again showed that this occurred during the earlier part of the acceleration coil derived voltage waveform and both chapter 5 and this chapter present those results obtained by employing matlab code to enable the first 0.05 seconds of the acceleration time record to be employed for the purposes of data analysis.
6.2 Signal Processing -- Time Frequency Distribution Techniques

In chapter 4, the signal processing techniques employed were based upon the FFT technique. Although the coil voltage time record would constitute a non-stationary signal during the acceleration period of the motor, as stated, it was decided during this research, and presented in chapter 4 and chapter 5, that since the motor accelerates relatively slowly, there would be sufficient intervals of time where the motor can be assumed to operate in a sufficiently stationary manner. This was tested and as reported in chapters 4 and 5 resulted in fault related data that did result in, using the data collected for this research, successful data detection and diagnosis.

However, in addition, for the purpose of this research it was decided to investigate the effect of the evolution in time of both the frequency and amplitude components of the recorded coil voltage waveform obtained during the motor acceleration period. This waveform is non-stationary by definition since for a deterministic signal, whether real or complex, stationarity requires the signal to have constant instantaneous amplitudes and frequencies. Neither is true for the acceleration signal, which is therefore non-stationary.

The technique employed gives a time-frequency representation (TFR) in which the frequency content present in the waveform at any time can be determined. This allows an alternative set of results to those obtained in chapter 4 and chapter 5, which employed the standard FFT technique. Although not directly employed during this research, the short time Fourier transform (STFT) is used here to introduce the concept of producing a TFR, since it has a largely intuitive interpretation and serves to provide sufficient basic understanding to enable other techniques to be usefully employed as described below.
6.2.1 Time-Frequency Representation --- Basic Methods

For signal processing purposes Auger et al [36] reported that a version of the Fourier transform technique known as the STFT can be usefully employed for the detection and diagnosis of induction motor faults when operating in varying operating conditions. The resulting short-time Fourier transform [37] is a windowed version of the well known Fourier transform and is given by:

$$\text{STFT}\{x(t)\} = F_{x}(\tau,f; w) = \int_{-\infty}^{+\infty} x(t)w(t-\tau)e^{j2\pi ft} \, dt$$

where \(x(t)\) is the non-stationary signal, \(f\) is the frequency and \(w(t - \tau)\) is a short time analysis window. Multiplication by the relatively short window \(w(t - \tau)\) suppresses the signal outside a neighbourhood around the analysis time point \(t = \tau\). The window is typically a Hann or Gaussian window and \(F_{x}(\tau,f; w)\) is essentially the Fourier transform of \(x(t)w(t - \tau)\), a function giving the phase and magnitude of the signal over time and frequency. The STFT is therefore a localised spectrum of the signal \(x(t)\) around \(\tau\). The STFT produces information which allows the mathematical and graphical representation of a non-stationary signal as a function of both signal amplitude w.r.t. time, and localised frequency w.r.t. time. This is important since, unlike the relatively simple amplitude versus frequency spectrum produced from the FFT technique, the STFT gives information regarding the localised frequency content at different time instances in the signal. In other words, for the normal FFT we can merely state that a frequency has a particular frequency content, but we are unable to state (for a non-stationary signal) where in the signal (w.r.t.) this frequency is present. A STFT however allows us to determine where in signal time a particular frequency component is present. This is often presented as a 3-axis amplitude-time-frequency
three dimensional plot, similar to those presented later in this chapter. The ability to determine particular amplitudes and frequencies in time can be expressed in terms of the resolution of the STFT. The time resolution of the STFT is proportional to the effective duration of the analysis window $w(t - \tau)$, a narrow window giving good time resolution. Similarly, the frequency resolution of the STFT is proportional to the effective width of the analysis window $w(t - \tau)$, and since frequency and time are inversely related a wide window gives a narrow bandwidth and therefore good frequency resolution. Therefore, for the STFT, there is a trade-off between time and frequency resolutions since a good time resolution requires a short window $w(t - \tau)$ which results in a poor frequency resolution and a good frequency resolution requires a long window $w(t - \tau)$. This conflict in required window widths to obtain both a good time and a good frequency resolution is the main drawback of the STFT, since the moving window results in a fixed resolution.

The matlab suite includes a Wavelet Toolbox in which wavelet decomposition techniques are installed that allow a non-stationary signal to be decomposed into a time-frequency form. The continuous wavelet transform (CWT) projects the signal $x(t)$ onto a family of zero-mean functions (the wavelets) deduced from an elementary function, the mother wavelet. The basic difference between the wavelet transform and the STFT is that the duration and bandwidth of the wavelet can be changed, and unlike the STFT which uses a single analysis window, the CWT uses short windows at high frequencies and long windows at low frequencies, which partially overcomes the resolution limitation of the STFT.

$$\text{CWT} \{x(t)\} = C_x(t,a; w) = \int_{-\infty}^{+\infty} x(t) w \left[ \frac{t - b}{a} \right] dt$$
The mother wavelet is given by \( w(t) \), and is, for example, a Gaussian window, \( e^{-t^2/2} \), which is effectively zero outside the interval \(-3 < t < 3\). The value of \( a \) is a scaling value which can stretch the window, whilst \( b \) shifts the window from time \( t \). The CWT uses the scaling variable \( a \) to employ short windows at high frequencies and long windows at low frequencies, which partially overcomes the resolution limitation of the STFT by giving good frequency resolution at low frequencies and good time resolution at high frequencies. Since the matlab toolbox was unavailable when required, the wavelet decomposition method was not employed during this research. It is considered by the author to be appropriate to include a description of CWT as above in order to inform the reader of the improved time and frequency resolution when compared to the STFT method and that there is an available tool for the job. If required, the reader is able to refer to “Wavelet Toolbox User’s Guide For Use With Matlab” and the considerable amount of available literature.

6.2.2 Time-Frequency Representation --- Wigner-Ville Method

Since the matlab wavelet toolbox was not available to the author, it was necessary to look for an appropriate alternative means of deriving the TFR representation. The author’s research showed that as an alternative to employing matlab based wavelets a method based upon the Wigner-Ville [33] [35] [36] time-frequency analysis method proved to be an appropriate alternative. The matlab based software required to obtain Wigner-Ville TFRs [36] has been produced by the French CNRS (Centre National de la Recherche Scientifique) and the Rice University USA. This software can be downloaded from the internet free of charge, permission to do so being granted under the terms of the “GNU Free Documentation License”.

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An improved method to the basic Wigner-Ville (WVD) method is the “Smoothed Pseudo Wigner-Ville Distribution” (SPWVD), which has an improved time and frequency resolution when compared to the basic WV method. The author utilised the improved method downloaded m-code files to produce the resulting plots as presented later in this chapter which can be displayed as 2-D plots of e.g. frequency-v-time or of amplitude-v-time or even of a 3-D plots amplitude-v-time-v-frequency.

The Wigner-Ville method will require to utilise the “analytic signal”, which is a complex valued signal, $x_a(t)$ which is derived from the real valued signal $x(t)$. Unlike the real signal which contains both positive and negative component frequencies the analytic signal will contain no negative frequencies and consequently will allow the instantaneous amplitudes and frequencies to be determined by the SPWVD. If the real signal is used, the WVD will produce [35] [36] both a positive and a negative part to the resulting spectrum. This will produce cross terms between the negative and positive frequencies which may mask the fault dependant frequencies and make it more difficult to detect fault conditions. Use of the analytic signal removes the negative frequency terms and therefore removes the problems associated with the unwanted cross terms. For a real valued signal $x(t)$, we associate a complex valued signal $x_a(t)$ defined as:

$$x_a(t) = x(t) + jx_H(t)$$

where $x_H(t)$ is the Hilbert transform of $x(t)$ [34][35][36] which is obtained using the m-file hilbert.m as illustrated in the attached m-file used in this research. The use of the Hilbert function removes the negative frequency components present in the real signal, whilst maintaining the equivalent positive signals which contain the information required when applied to real-world practical systems. When the analytic signal is
employed, rather than the real signal, the results obtained with the use of FFT based methods such as SPWVD can be employed without altering the resulting information content [35] [36].

A hypothetical test signal approximating the stator current due to a rotor fault was used by S. Rajagoplan et al. [35] to enable a comparison to be made between STFT, WVD and SPWVD. The results showed that the SPWVD of the Hilbert transformed signal offered complete suppression of cross-terms while still offering better frequency resolution than the STFT and eliminates the “ghosting” in the frequency-time plot.

The basic Wigner-Ville distribution of an analytic signal $x_a(t)$ is given by:

$$
WV \{x(t)\} = W_x(t,f) = \int_{-\infty}^{+\infty} x_a(t + \tau/2) x_a^*(t - \tau/2) e^{j2\pi ft} d\tau
$$

The pseudo Wigner-Ville distribution (PWVD) is a windowed version of the Wigner-Ville distribution. It is also known as the Windowed-Wigner distribution, and the PWVD further suppresses cross-terms present in the original WVD and also has much better resolution than the STFT.

$$
PWV \{x(t)\} = PW_x(t,f) = \int_{-\infty}^{+\infty} w(\tau)x_a(t + \tau/2) x_a^*(t - \tau/2) e^{j2\pi ft} d\tau
$$

Where $w(\tau)$ is a regular window.
The smoothed-pseudo Wigner-Ville improves the smoothing function performed by the previous window \( w(\tau) \). It does this by adding another degree of freedom in the form of a separate smoothing window, illustrated as follows.

\[
\text{SPWV} \{x(t)\} = \text{SPW}_{x}(t,f) = \int_{-\infty}^{+\infty} h(\tau) \int_{-\infty}^{+\infty} w(t - \tau) x_a(t + \tau/2) x^*_a(t - \tau/2) dt e^{-j2\pi ft} d\tau
\]

### 6.3 TRF Plots Obtained For CoilAplusB

As previously stated, the CNRS and Rice University matlab based software was employed to obtain the following time-frequency representation (TFR) 3-D plots of frequency, time, and amplitude. The essential features of the matlab code, calling the m-code functions provided by CNRS/Rice University is presented later in this chapter.

The following figure 6.1., illustrates the results obtained when considering a test signal in which the generated sine wave increases in frequency as time elapses. This allows a comparatively easy interpretation and evaluation of results to be quickly undertaken. The 3-D plot demonstrates that the lower frequency range is initially high but tails off as time progresses, conversely, it can be seen that the higher frequencies are initially low in value but increase in amplitude as time progresses. This is what would be expected, and provides an acceptable level of confidence in the ability of the software to produce sufficiently accurate results.

In addition to a 3-D plot, figure 6.1 also presents a 10 Hz wide “slice” through the TRF plot. This allows the amplitude of a limited range of frequencies to be plotted as amplitude against time in the form of a 2-D plot as shown. This was considered of importance since different frequency ranges would have different profiles. Although
not the subject of this research, the frequency ranges that provide most information could be investigated and established for a particular fault and load condition. The frequency slice of width 10 Hz was chosen here since, as described earlier in this thesis, when recording data the time record duration was chosen to allow a resolution of 10 Hz to be achieved in the spectrum, and the chosen TFR slice would result in at least an equivalent TFR resolution.

![Figure 6.1. – Test Signal – Time-Frequency 3-D Plot and 10 Hz Slice](image)

For the purposes of the processing and presentation of results in this chapter, the first 50 mS of the available 100 mS time record was employed in order to obtain the Wigner-Ville time-frequency-representations as presented below. The purpose of the following section of this thesis is to demonstrate that the processing of acceleration period time records as non-stationary waves can effectively be employed to provide an
alternative, effective, and information rich source of data which can form the basis of effective fault detection and diagnosis strategies.

The plot presented in figure 6.2 below illustrates both the first 50 mS of the averaged time record and the resulting 3-D TFR plot obtained when employing the SPWVD as described above. As can be seen by inspection of the 3-D plot, presented in figure 6.2 below, the lower frequency components increase in amplitude as time elapses whilst the higher frequency components noticeably reduce in amplitude as time elapses. This is evident by simple visual inspection of the 50 mS duration acceleration time record, where it can readily be seen that the time record plot contains high frequency components in the early stages, which noticeably diminish in amplitude from about the 30 mS point, until the latter part of the record. The TFR plots allow a more quantitative estimate of the presence of time dependant signal frequency components to be carried out and to subsequently form an additional source of fault dependent data which can be employed to reinforce the robustness of any decisions that are made regarding the condition of this or any other induction motor driven system.

Figure 6.2. – Example – Time-Frequency 3-D Amplitude v Frequency v Time Plot
Unlike the 3-D TRF plot illustrated in figure 6.2 above, the remaining plots presented in this chapter limit the result to a frequency slice of 10 Hz width centred around the 125 Hz plain of the 3-D frequency representations of the time records taken under the motor accelerating conditions. The resulting plot, as presented, shows how the amplitude of the 125 Hz frequency component varies with time over the first 50 mS of the acceleration time record. The 125 Hz centred slice was chosen to demonstrate the 2-D results obtained, but it is not claimed here that this particular frequency is the optimum frequency to yield sufficient information for the purposes of fault detection and diagnosis.

The following figure 6.3, presents the 10 Hz slice centred around 125 Hz for the healthy-state condition of the induction motor with load rig attached. As was the case reported in earlier chapters of this thesis, two sets of data are presented. Each of the two sets were taken under identical load and fault conditions, the recording of each set of data being interspersed with sets of data taken under different conditions. Inspection of figure 6.3. reveals that the two sets of data are extremely similar, and can indeed be taken to consistently represent the fault-dependent time record for the motor plus rig healthy-state condition. Later figures in this chapter represent the time records and resulting TFR plots for a range of fault and healthy-state conditions as previously described. For any particular fault or healthy-state condition, the remaining plots in this chapter illustrate only the results from set1. This is because it has already been demonstrated that the acceleration records taken as sets one to three for any particular condition have a high correlation, whilst correlations between the records taken under between differing fault conditions will have comparatively lower values.
The remaining records, as presented in figures 6.4 to 6.10, are also those obtained from applying the smoothed pseudo Wigner-Ville technique to the healthy-state and fault conditions listed. As for the above case, all of these plots present a 10 Hz slice centred around 125 Hz, for the first 50 mS of the acceleration time record. Inspection of the plots reveals that they do indeed have a different frequency content, which it can be demonstrated is dependent upon the fault condition applied. In addition figure 6.10. again demonstrates the consistency of results obtained at different times but under an identical fault condition.

Figure 6.3. – Motor + Rig --- Healthy-State – TFR 125 Hz Slice --- SET1 and SET2
Figure 6.4. – Motor + Rig --- Load Unbalance Fault – TFR 125 Hz Slice

Figure 6.5. – Motor + Rig --- Load Misalignment Fault – TFR 125 Hz Slice

Figure 6.6. – Motor + Rig --- Gear Tooth Fault – TFR 125 Hz Slice
Figure 6.7. – Motor Only --- Healthy-State – TFR 125 Hz Slice

Figure 6.8. – Motor Only --- Rotor Bars Fault – TFR 125 Hz Slice

Figure 6.9. – Motor Only --- End Bearing Fault – TFR 125 Hz Slice
The Wigner-Ville Matlab Functions

The following matlab m-file presents the essential coding features employed to run the Wigner-Ville software. All of the Wigner-Ville functions required to produce the TFR plots were downloaded from the internet and saved in a matlab working folder for use by the listed code. In particular the Smoothed Pseudo Wigner-Ville time-frequency distribution was employed by calling the m-code function “tfrspwv”[36], which as previously stated can be freely downloaded from the internet.

Figure 6.10. – Motor Only -- Dynamic Eccentricity Fault – TFR 125 Hz Slice SET1 and SET2
The Code:

% %%%% Using Coils A and B in series %%%%%

load AplusB_Av_FF_accn_nospec_to_2001_set1
load AplusB_Av_FF_accn_nospec_to_2001_set2
load AplusB_Av_RotBars_accn_nospec_to_2001_set1
load AplusB_Av_RotBars_accn_nospec_to_2001_set2

load AplusB_Av_FF_accn_with_spec_to_2001_set1
load AplusB_Av_FF_accn_with_spec_to_2001_set2
load AplusB_Av_Misal_accn_with_spec_to_2001_set1
load AplusB_Av_Misal_accn_with_spec_to_2001_set2

%%% etc for remaining records

%%% create analytic signals

sig1   =  hilbert(AplusB_Av_FF_accn_nospec_to_2001_set1) ;
sig2   =  hilbert(AplusB_Av_FF_accn_nospec_to_2001_set2) ;
sig5   =  hilbert(AplusB_Av_RotBars_accn_nospec_to_2001_set1) ;
sig6   =  hilbert(AplusB_Av_RotBars_accn_nospec_to_2001_set2) ;
sig9   =  hilbert(AplusB_Av_FF_accn_with_spec_to_2001_set1) ;
sig10  =  hilbert(AplusB_Av_FF_accn_with_spec_to_2001_set2) ;
sig15  =  hilbert(AplusB_Av_Misal_accn_with_spec_to_2001_set1) ;
sig16  =  hilbert(AplusB_Av_Misal_accn_with_spec_to_2001_set2) ;

%%% etc for remaining records

%%% Coil_A+B Motor Only Healthy-State %%%

disp('Press any KEY for Coil_AplusB Motor Only Healthy-state SET1 TFR');
disp('') ; pause

g=tftb_window(31,'Kaiser'); h=tftb_window(63,'Kaiser');
tfrspwv(sig1,1:length(sig1),64,g,h,1);

disp('Press any KEY for Coil_AplusB Motor Only Healthy-state SET2 TFR');
disp('') ; pause

g=tftb_window(15,'Kaiser'); h=tftb_window(63,'Kaiser');
tfrspwv(sig2,1:length(sig2),64,g,h,1);
%%%
Coil_A+B  Rotor Bars Fault
%

disp('Press any KEY for Coil_AplusB Motor Only Rot Bars Fault SET1 TFR');
disp(''); pause

g=tftb_window(15,'Kaiser'); h=tftb_window(63,'Kaiser');
tfrspwv(sig5,1:length(sig5),64,g,h,1);

disp('Press any KEY for Coil_AplusB Motor Only Rot Bars Fault SET2 TFR');
disp(''); pause

g=tftb_window(15,'Kaiser'); h=tftb_window(63,'Kaiser');
tfrspwv(sig6,1:length(sig6),64,g,h,1);

%%%                              Coil_A+B  MOTOR + RIG  Healthy-State    %%%

disp('Press any KEY for Coil_AplusB Motor and Rig FF SET1 TFR ');
disp(''); pause

g=tftb_window(15,'Kaiser'); h=tftb_window(63,'Kaiser');
tfrspwv(sig9,1:length(sig9),64,g,h,1);

disp('Press any KEY for Coil_AplusB Motor and Rig FF SET2 TFR ');
disp(''); pause

g=tftb_window(15,'Kaiser'); h=tftb_window(63,'Kaiser');
tfrspwv(sig10,1:length(sig10),64,g,h,1);

%%%                            Coil_A+B  Misalignment Fault                                   %%%

disp('Press any KEY for Coil_AplusB Motor and Rig Misal SET1');
disp(''); pause

g=tftb_window(15,'Kaiser'); h=tftb_window(63,'Kaiser');
tfrspwv(sig15,1:length(sig15),64,g,h,1);

disp('Press any KEY for Coil_AplusB Motor and Rig Misal SET2');
disp(''); pause

g=tftb_window(15,'Kaiser'); h=tftb_window(63,'Kaiser');
tfrspwv(sig16,1:length(sig16),64,g,h,1);

%%%                  Coil_A+B Motor Only Rot Bars Fault SET1 TFR                   %%%
6.5 Chapter Conclusions

As a final note on the plots presented in this chapter, it has been demonstrated that they do provide a valuable source of additional information that can be used to reliably determine the health condition of the machine. As was the case in chapters 4 and 5 there are measurable differences between the TFR plots produced from the acceleration period time records taken under the stated healthy-state and applied fault conditions. The TFR processing and the resulting 3-D plots increases the extent of system health related data that can be employed for fault detection purposes. As demonstrated above it is also possible to establish the behaviour with respect to amplitude versus time of a frequency-slice which can then be employed for fault diagnosis purposes.
Chapter 7

Conclusions and Suggestions for Further Work

7.1 Introduction

This chapter presents and summarises the conclusions that can be made as a result of the work carried out as part of this research and as described in this thesis. In addition, and supplementary to the conclusions, suggestions are made describing some further work and investigations that are either necessary, or at least desirable, in order to further explore the application of magnetic field monitoring in order to provide a data base that may be effectively employed for fault detection purposes.

7.2 Research Conclusions

The time records obtained under the applied fault and running conditions as described in earlier chapters of this thesis do indeed provide a source of fault dependant data. It has been demonstrated that the fault conditions applied to the induction motor itself, i.e. rotor eccentricity, broken rotor bars, and damaged end bearing, do result in a fault related modification of the search coil voltage time record. In addition it has also been demonstrated that the fault conditions applied to the load test rig, i.e. shaft misalignment, unbalanced load, and faulty gearbox, result in a fault dependant modulation of the coil voltage time record.

The time domain records obtained for each healthy-state and fault condition were processed, using the matlab FFT function, to produce a frequency domain spectral plot for each. The time domain records were processed as described in chapter five of this
thesis using correlation, variance and coherence matlab functions. The equivalent spectra were processed, again as described in chapter five, but by employing only the correlation and variance based techniques. These techniques were employed in order to obtain a quantitative numerical value which could be used to indicate that a particular healthy-state or faulty condition is present. A summary of the numerical fault indicators obtained are presented in tables 5.42 to 5.45, and an inspection of the tables reveals that with a few exceptions, which will be discussed later in this chapter, the numerical indicators can be readily employed to determine machine health condition.

The tables also reveal that, in terms of fault discrimination, the health condition data obtained as the motor was accelerated from the rest condition, resulted in greater differences in the numerical indicators obtained with the system operated under the listed applied fault conditions. This would suggest that wherever possible data collected when the motor is started from rest will provide a more discriminative fault data base. However for motors running continuously for long periods, or started only infrequently, then the data collected under steady state running conditions, may also be usefully employed since an appropriate set of time records for time synchronous averaging can be readily obtained whilst the drive is operating under suitable load levels.

Of even greater significance to this research, the author proposes that it has been reliably demonstrated that using more than one coil does improve the fault detection and diagnostic capability of the search coil method. In this thesis the comparison is made between the results obtained when employing a single coil and when employing two coils positioned 120º apart. Inspection of the tables in chapter five reveals that when processing the data collected from coilA alone there are no misdiagnoses when
processing the acceleration period data but there are some misdiagnoses when
processing the steady state data. This, although not entirely unexpected, is
disappointing since the time records are most conveniently collected with the motor
operating at steady state speed. However inspection of the same tables reveals that
when the fault related time records collected from the two coils connected in series
was processed, there were no misdetections or misdiagnoses under both steady state
and accelerating running conditions. This is very promising since it demonstrates that
using more than one coil does indeed improve the sensitivity and ability of the search
coil method to accurately discriminate between drive healthy-state and faulty
conditions.

The results referred to in the above paragraphs were obtained from fault related data
collected under accelerating conditions and processed using the FFT algorithm.
Strictly the FFT algorithm is employed for stationary waveforms, but as stated, since
the frequency change whilst accelerating is reasonably slow then it was decided to
employ the FFT, the results of which are reported on in chapter five and summarised
above. In addition, however, the non-stationary nature of the acceleration data
waveforms was considered and the Wigner-Ville technique employed to determine the
time frequency distribution. The results presented in chapter six of this thesis are in the
form of typical three dimensional amplitude versus time versus frequency plots. Also
presented in this chapter are the amplitude versus time of a narrow band or slice of 10
Hz centred around 125 Hz. Inspection of these plots readily demonstrates that the
particular shape of the waveform slice does depend upon the healthy-state or faulty
condition applied to the system. These TFR waveforms were obtained from the data
obtained from two coils connected in series, since it has been demonstrated that this is
the more robust and reliable data.
A final note regarding the above results summary is to remind the reader that all the results were obtained from more than one set of readings. Each data set was collected, non-contiguously, with the same applied fault condition. The results, in the form of both visual and numerical indicators, proved reliably and robustly consistent between equivalent sets. This is important, since it is essential that fault related differences are reliably recognisable and repeatable for the same faults and load levels.

7.3 Suggestions for Further Work

There are a number of suggestions that can be made for extending the work already successfully carried out as part of this research. The particular and specific details comprising each general suggestion are presented as follows:

7.3.1 Optimise Loading Levels

The system health related time records obtained during this research, and presented in this thesis, have been collected with the motor lightly loaded. Investigations need to be carried out to determine whether varying the load level applied to the drive can result in an improvement or increase in the level of health related information contained within the collected time records. It is known that for Induction motor current signature monitoring, better results are obtained when the motor is heavily loaded [31]. As stated, for this research however, it was decided to lightly load the motor to avoid any magnetic saturation of the search coils. It is therefore suggested to carry out further investigation in order to determine an optimum level of load which would contain the most health related information.
7.3.2 Fault Types and Levels and Fault Combinations

Extend both the range of fault types and the level of faults which are applied to the system. For example the fault types could be extended to include faults such as worn ball bearings, damaged drive belt, bent shaft, damaged load shaft pillar bearings, worn gear teeth etc. In addition to including extra fault types, it would also be useful to investigate the transition of the fault through a level range from small and incipient faults through to unacceptably high levels of fault severity. This would enable the ability of the technique to be able to provide an early warning of fault development to be evaluated. This is an important factor since, it is essential that any form of condition monitoring is capable of providing a sufficiently early warning of fault development so that some corrective action can be planned before an unacceptable level of performance is reached.

In order to obtain fault related data this research applied one of a list of possible faults at any one time. This proved satisfactory in order to allow an evaluation of the fault detection capabilities of the search coil method. In practice, however, it is likely that more than one fault will be present at any given time. It is suggested here that the effects of combinations of two or more faults simultaneously applied should be investigated. This is especially relevant to the effects of multiple faults upon the diagnostic capability of the methods employed for data collection and data processing.

7.3.3 Number, Construction and Position of Search Coils

The search coil pitch used for data acquisition in this research spanned a single stator pole pitch. In addition, a coil pitch amounting to 120° of stator arc was employed, but it was subsequently found that this reduced the amount of fault information contained in the time record data collected. As a result it was decided early on that a narrower
pitch gave better resolution with respect to fault data. However it is now suggested that further research would usefully be employed to investigate the effect of a search coil pitch varying between a single stator tooth pole pitch and a 120º coil pitch, both shaving been employed during this research. Further research work should also be carried out to consider the type, number, and mounting position of the stator to rotor magnetic field detectors. As stated in chapter 2 [21], search coils were employed since the literature survey revealed that they have a wider frequency response than Hall-effect devices. However this research reveals that for the faults applied during this research a frequency range from approximately 50 Hz to 1500 Hz is sufficient for fault detection purposes. It is now suggested that Hall-effect devices are employed in place of the search coils, since they would be physically small and could be relatively easily attached to the face of the stator pole piece.

It is also suggested that the number and position of magnetic detectors is investigated. As reported, the results presented in this thesis are obtained from two detectors placed 120º apart. Also, as reported in this thesis, the fault detection and diagnostic capability of the stator to rotor magnetic field detectors, is noticeably improved when the two detectors are employed when compared to employing only one. It is suggested here that it would be useful to investigate the effect of employing two or more detectors and in addition to the 120º placed them at 90º and 180º intervals. This would enable the optimum number and position of detectors could be investigated.

7.3.4 TFR and Pattern Recognition

When employing a time frequency distribution technique which can be applied to non-stationary waveforms, such as Wigner-Ville or matlab’s wavelet toolbox Wavelet Decomposition technique, to provide amplitude versus time versus frequency 3-D
distributions, it is suggested that further investigation be carried out to establish the behaviour of amplitude versus time of a particular component frequency, and to determine whether there is an optimum frequency or group of frequencies capable of providing maximum fault information.

This research employs the techniques as reported in chapter five to obtain a numerical indicator of the health condition of the system under test. The numerical indicator for every healthy-state and faulty condition can be stored in a fault dictionary. This fault dictionary can then be employed by comparing the processed data obtained from the monitored system, to each of the condition dependant indicators held in the fault dictionary, and to look for the nearest match in order to determine the most probable matching condition. In addition to the methods employed during this research it is suggested that some form of pattern recognition technique such as the use of the ‘nearest neighbour’ rule or the use of a neural network based strategy [16] [39][40] be employed. In looking for motor drive bearing faults, Da-Ming Yang and James Penman [16] employed a multilayer perceptron (MLP) neural network to recognise and classify fault patterns obtained by the use of motor current and vibration sensing. The neural network when trained using back-propagation, resulted in a reported 100% success rate when vibration data was employed and a very creditable 97.5% and above success rate when the motor supply current signature was employed.

7.3.5 Combining Methods

It would prove useful to make a comparison of the ability of the system employing a number of strategically magnetic field sensors, as described in this thesis, to other methods of fault data collection and analysis. In particular the methods employed during this thesis could be compared to current, vibration, heat distribution, acoustic
emission etc, in order to make an effective evaluation of the proposed methodology, as described in this thesis.

To produce the most robust system, it may be necessary to combine the results obtained from two or more sources of fault related data, e.g. current and vibration monitoring or magnetic field and vibration. This would improve the diagnostic success rate for the maximum number and range of system faults. Ideally the monitoring system would operate in real time and provide continuous access to a health condition report.

### 7.3.6 Employing Phase Related Information

This research has employed the differences in spectral peak position and amplitudes in order to evaluate the effectiveness of the search coil method. Further work may be carried out to take into account the phase difference between signal components. The phase versus frequency information can be obtained as a result of employing the FFT algorithm in matlab since a complex form of the FFT is available. Boulahbal et al [38] and Parikh et al [40] all refer to the use of phase differences in radial and axial vibration frequencies.

### 7.3.7 Size and Type of Drive Motors

Since the principle of operation of all electric motors is based upon the presence of a magnetic field, it is suggested here that the search coil method applied to other types of electric motor should be investigated. Other types of motor would include alternating current synchronous and direct current brush and brushless motors.
Motors are employed in a wide variety of applications ranging from relatively low power domestic uses to low medium and high power industrial applications. It is therefore suggested that the feasibility of applying the techniques described in this research is investigated over a range of motor power ratings.
References

[1] Thomson W. T., “Condition Monitoring of Induction Motor Drives” – A One Day Seminar @ Aberdeen Marriott Hotel ; December 2002


Also Published as condensed version ( less case histories ), W.T.Thomson and Mark Fenger, IEEE Industry Applications Magazine Vol 7, No 4, July/August 2001.


[30] “Methods Of Vibration Analysis”, IRD Mechanalysis Technical Paper, IRD Mechanalysis Inc, 6150 Huntley Road, Columbus, Ohio, USA.


[37] “Signal Processing Toolbox”, User’s Guide For Use With Matlab,


[39] “Neural Network Toolbox”, User’s Guide For Use With Matlab,

Bibliography


