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CURRENT-, FORCE-, AND VIBRATION-BASED TECHNIQUES FOR INDUCTION MOTOR CONDITION MONITORING

Doctoral Dissertation

Pedro Vicente Jover Rodríguez

Helsinki University of Technology
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Dissertation for the degree of Doctor of Science in Technology to be presented with due permission of the Department of Electrical and Communications Engineering for public examination and debate in Auditorium S4 at Helsinki University of Technology (Espoo, Finland) on the 14th of September, 2007, at 12 noon.

Helsinki University of Technology
Department of Electrical and Communications Engineering
Laboratory of Electromechanics

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ABSTRACT OF DOCTORAL DISSERTATION

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Laboratory Electromechanics
Field of research Electrical Machines
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Abstract
The aim of this research was to discover the best indicators of induction motor faults, as well as suitable techniques for monitoring the condition of induction motors. Numerical magnetic field analysis was used with the objective of generating reliable virtual data to be analysed with modern signal processing and soft-computing techniques. In the first part of the research, a fuzzy system, based on the amplitudes of the motor current, was implemented for online detection of stator faults. Later on, from the simulation studies and using support vector machine (SVM), the electromagnetic force was shown to be the most reliable indicator of motor faults. Discrete wavelet transform (DWT) was applied to the stator current during the start-up transient, showing how the evolution of some frequency components allows the identification and discrimination of induction motor faults. Predictive filtering was applied to separate the harmonic components from the main current signal.

The second part of the research was devoted to the development of a mechanical model to study the effects of electromagnetic force on the vibration pattern when the motor is working under fault conditions. The third part of this work, following the indications given by the second part, is concerned with a method that allows the prediction of the effect of the electromechanical faults in the force distribution and vibration pattern of the induction machines. The FEM computations show the existence of low-frequency and low-order force distributions acting on the stator of the electrical machine when it is working under an electrical fault. It is shown that these force components are able to produce forced vibration in the stator of the machine. This is corroborated by vibration measurements. These low-frequency components could constitute the primary indicator in a condition monitoring system.

During the research, extensive measurements of current, flux and vibration were carried out in order to supply data for the research group. Various intentional faults, such as broken rotor bars, broken end ring, inter-turn short circuit, bearing and eccentricity failures, were created. A real dynamic eccentricity was also created. Moreover, different supply sources were used. The measurements supported the analytical and numerical results.

Keywords fault diagnostics, indicator, induction motor, vibration, stress, finite element methods, fuzzy logic, DWT, predictive filtering

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Foreword

This work was carried out at the Laboratory of Electromechanics, Helsinki University of Technology (TKK). It was part of a project concerning the diagnosis of faults in electrical machines. Professor Antero Arkkio acted as my supervisor during the research period. I gratefully acknowledge his support and thank him for his guidance. I thank Dr. Anouar Belahcen for his valuable suggestions. I also thank all teachers and professors that have educated me since I was a child.

I thank Professor Tapani Jokinen and the whole SELA group for making it possible for me to study at TKK. Special thanks go to the Programme Manager of the International Masters Program in Electrical Engineering, Anita Bisi. I am very proud to have been associated with you all.

I thank my partners Marian Negrea, José Antonino-Daviu, Sanna Pöyhönen and Antti Laiho for their contribution to our results. Thanks must also be given to the entire research group at the Laboratory of Electromechanics. Together, they created a pleasant and peaceful working environment.

I thank the Fortum Foundation and TEKES for the financial support given during the research period. Finally, my warmest thanks go to my brother, parents, wife and daughters. They are the source of inspiration in my daily life. This work is dedicated to them.

Helsinki, May 2007

Sincerely,

Pedro Vicente Jover Rodríguez

List of publications

P1 Pöyhönen, S., Negrea, M., Jover, P., Arkkio, A., Hyötyniemi, H., 2003, "Numerical Magnetic Field Analysis and Signal Processing for Fault Diagnostics of Electrical Machines", *COMPEL, The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, Vol. 22, No. 4, pp. 969-981.

P2 Jover, P., Arkkio, A., 2007, "Detection of Stator Winding Fault in Induction Motor Using Fuzzy Logic", *Applied Softcomputing*, article in press, 23p.

P3 Jover, P., Negrea, M., Arkkio, A., 2005, "A General Scheme for Induction Motor Condition Monitoring ", *SDEMPED 2005*, *Proceedings of the 5th IEEE International Symposium on Diagnostic for Electrical Machines, Power Electronics and Drives,* Vienna, Austria, September, Conference Proceeding CD, 6p.

P4 Jover, P., Antonino-Daviu, J., Muñoz, E., Arkkio, A., 2006, "A simplified Online Technique for the Detection of Eccentricity in Induction Motors", *International Conference on Electrical Machines* (*ICEM 2006)*, Conference Proceeding CD, Paper No. 114, Crete Island, Greece, September, 6p.

P5 Antonino-Daviu, J., Jover, P., Riera, M., Arkkio A., Roger-Folch, J., 2007, "DWT Analysis of Numerical and Experimental Data for the Diagnosis of Dynamic Eccentricities in Induction Motors", *Mechanical System and Signal Processing,* Volume 21, Issue 6, August, pp. 2575-2589.

P6 Jover, P., Negrea, M., Arkkio, A., 2004, "Mechanical Model to Study Induction Motor under Fault Conditions", *International Conference on Electrical Machines* (*ICEM 2004)*, Conference Proceeding CD, Paper No. 100, Cracow, Poland, September, 6p.

P7 Jover, P., Belahcen, A., Arkkio, A., 2006, "Signatures of Electrical Faults in the Force Distribution and Vibration Pattern of Induction Motors", *IEE Proceedings Electric Power Applications,* Vol. 153, No. 4, July, pp. 523-529.

P8 Jover, P., Belahcen, A., Arkkio, A, Laiho, A., Antonino-Daviu, J., 2007, "Air-gap Force Distribution and Vibration Pattern of Induction Motor under Dynamic Eccentricity", *Electrical Engineering (Archiv fur Elektrotechnik),* article in press, 16p.

Contents

List of symbols and abbreviations

Symbols

A	Magnetic vector potential, state matrix
$A_{(S_k)}$	FFT of the measured vibration acceleration
a_n	Approximation signal
a,b,c,d	Integration coefficients
B	Magnetic flux density, input matrix
C	Output matrix
D	Feed forward matrix
d	Detail signal
e	Unit vector
F	Force
F_e	Electromagnetic force acting between the rotor and stator
f	Frequency
f_s	Supply frequency, sampling frequency
f_r	Rotation frequency
$F_{(S_k)}$	FFT of the calculated electromagnetic forces
$g[n]$	Half-band filter transfer function
$h[n]$	Low-pass filter transfer function
$H_{(S_k)}$	Accelerance
I	Current, moment of inertia
i, j	Indexes
K	Stiffness
l	Rotor and stator length
m	Mass, spatial harmonic order
N	Number of samples
n	Integer, time harmonic order, normal vector, decomposition level
p	Number of pole pairs
r	Radius
S	Section area

$S[n]$	Sampled signal
s	Slip, second, signal
t	Time
u	Voltage, displacement
W_c	Energy
x	Displacement, state vector
x, y, z	Nodal coordinates
y	Output vector

Greek symbols

α	Angular position of the rotor, scaling coefficients
β	Angular position of the stator, wavelet coefficients
φ	Angular position, scaling function
γ	Phase angle
λ	Coefficient defined by m, n
μ	Magnetic permeability
μ_0	Magnetic permeability of vacuum
σ	Conductivity, stress
ω	Angular frequency
ψ	Wavelet function
∇	Gradient operator (nabla)
$\nabla\times$	Curl operator

Abbreviations

AC	Alternating Current
AI	Artificial Intelligence
BEM	Boundary Element Method
D.C.	Direct Current
DCG	Direct Current Generator
DWT	Discrete Wavelet Transform

FE	Finite Element
FEM	Finite Element Method
FFT	Fast Fourier Transform
GA	Genetic Algorithm
IM	Induction Motor
MCSA	Motor Current Signature Analysis
mmf	Magnetomotive Force
NN	Neural Network
PDT	Power Decomposition Technique
PWM	Pulse Width Modulation
RMS	Root Mean Square
STFFT	Short Time Fast Fourier Transform
SVM	Support Vector Machine
UMP	Unbalanced Magnetic Pull
WT	Wavelet Transform

The quantities denoting vectors, tensors and matrices are represented by bold face.

The subscripts r and φ refer, respectively, to the radial and tangential components of a quantity.

The subscripts x and y refer, respectively, to the x- and y- components of a quantity in a Cartesian coordinate system.

The subscripts r and s refer, respectively, to the rotor and stator.

1 Introduction

The history of fault diagnosis and protection of electrical machines is as old as such machines themselves. However, nowadays, condition monitoring of electrical machines has become increasingly essential. It plays a very important role in their safe operation and helps to avoid heavy production losses in industry.

There are many published techniques to ensure a high degree of reliable uptime, and many available tools to monitor induction motors. Despite the availability of these tools, however, many companies are still faced with unexpected system failures and reduced motor lifetime. Many of the commercial products designed to monitor induction motors are not cost effective when used on typical low-to-medium-power induction motors. It is the advances in sensors, algorithms, and techniques that are worthwhile in providing the technology for effective incipient-failure detection.

The condition-monitoring schemes have concentrated on sensing specific failure modes in stator, rotor and bearing. All of the presently available techniques require the user to have some expertise in order to distinguish a normal operating condition from a potential failure state.

For a long time, different indicators, such as current, temperature, voltage, chemical debris and vibration, have been in use for monitoring electrical machines. The desired characteristics of the indicators are accessibility, reliability, sensitivity and the amount of information given. The indicator signal must be processed to find signatures that allow the motor condition to be known. The traditional technique for this purpose is based on the fast Fourier transform (FFT). This technique has some drawbacks, which are tackled in the present investigation by using wavelet transform and fuzzy logic.

The monitoring and fault-detection techniques of electrical machines have moved in recent years into artificial intelligence techniques. When an artificial intelligence technique is used, fault detection and evaluation can be accomplished without an expert. This research also includes the use of artificial intelligence techniques, which play a general role in the diagnostic field. The fuzzy logic is applied to make decisions about the condition of the motor. A fuzzy logic approach may help to diagnose motor faults because a fuzzy system is, in fact, reminiscent of human thinking processes and natural language, enabling decisions to be made on the basis of vague information.

Support vector machine (SVM) is applied to six different fault indicators, showing the electromagnetic forces between the rotor and stator as the best indicator of induction motor faults (Publication 1). From this primary study, it was decided to go into the basic understanding of the electromechanical interaction in the electrical machine, which generates vibrations. These vibrations constitute one of the possible indicators of motor health.

1.1 Aim of the study

This study, carried on the currents, electromagnetic force, vibration and techniques for induction motor condition monitoring, was based primarily on the generation of virtual data through a computer simulation program of magnetic field distribution, which allows the change in motor performance due to the changes of parameters as a consequence of the different faults to be foreseen. The diagnosis of a fault always commences with the basic physical understanding of the problem. In this phase, the knowledge of the well-tested models allowing the simulation of the different fault conditions is fundamental to obtaining the pattern characterisation of the fault.

One of the aims of this work is to study the indicators of induction motor faults and to choose the suitable ones for condition monitoring. Among the fault indicators, the motor current is the most desired one because of accessibility requirements. Thus, another aim of this work is to find appropriate techniques for processing this primary indicator signal to improve the reliability of the diagnostic systems.

Numerical magnetic field analysis shows that electromagnetic forces are good fault indicators. This research is also devoted to the implementation of mechanical models and methods that permit the acquisition of knowledge of the measurable effects produced by the electromagnetic forces in the vibration pattern. The goal is to predict measurable effects in the vibration pattern; whereas in monitoring, there is a vast amount of experience to be drawn upon.

1.2 Literature review

In the last ten years, much has been written about condition monitoring of electrical machines and numerous studies have been conducted in this field. In the following, a review of the most relevant papers is given from the point of view of the present study. This is divided into two main parts following the chronological order in which the research was carried out. The first topic concerns the condition monitoring of electrical machines and the second concerns the mechanical modelling and vibration monitoring of rotating electrical machines.

1.2.1 Fault and condition monitoring of induction machines

Many papers have been written concerning condition monitoring of induction motors. However, even though thermal and vibration monitoring have been utilised for decades, most of the recent research has been directed toward electrical monitoring of the motor with emphasis on inspecting the stator current. In fact, large machine systems are often equipped with mechanical sensors, i.e., with primarily vibration sensors based on proximity probes. Even if they are delicate and expensive devices, in many situations they are utilised to detect mainly incipient mechanical faults. However, it has been suggested that stator current monitoring can provide the same indications without requiring access to the motor.

Nandi et al. (2005) have a broad classification of the major faults in electrical machines:

- Stator faults resulting in the opening or shorting of one or more stator coils or phase windings,
- Abnormal connection of the stator winding,
- Broken rotor bars or cracked end rings,
- Static and/or dynamic air-gap eccentricities,
- Bent shaft,
- Shorted rotor field winding,
- Bearing and gearbox failures.

These faults produce one or more of the following symptoms:

- Unbalanced voltages and line currents,
- Increased torque pulsation,
- Decreased average torque,
- Increased losses and reduction in efficiency,
- Excessive heating,
- Vibrations.

The diagnostic methods of identifying the above faults may involve several fields of science and technology. Nandi et al. (2005) suggest that they can be described as:

- Electromagnetic field monitoring, search coils, coils wound around the motor shafts (axial-flux-related detection),
- Temperature measurements,
- Infrared recognition,
- Radio frequency emission monitoring,
- Noise and vibration monitoring,
- Chemical analysis,
- Acoustic noise measurements,
- Motor current signature analysis (MCSA),
- Model, artificial intelligence and neural network (NN) based techniques.

A review of bearing, stator, rotor and eccentricity-related faults and their diagnosis is presented in (Nandi et al. 2005). The paper concludes that MCSA is by far the most preferred technique to diagnose electrical machine faults. Since the earliest work in this field, the analysis of the current spectrum is the most popular because of the simple way of measuring the stator input current (Cameron et al. 1986 and Kliman et al. 1988). However, theoretical analysis and modelling of machine faults are indeed necessary to distinguish relevant components (signatures) from others that may be present due to time harmonics, machine saturation, etc. Moreover, these signatures do not appear in the current spectrum of any kind of machine. The appearance and magnitude of these signatures are highly dependent on the number of machine pole pairs, rotor and stator design and the winding factor as described for the case of eccentricity events by (Nandi et al. 2001).

Benbouzid (2000) made a review of MCSA as a medium for fault detection. This paper introduces in a concise manner the motor signature analysis for the detection and localisation of abnormal electrical and mechanical conditions that indicate, or may lead to, a failure of induction motors. The paper is focused on MCSA, which utilises the results of spectral analysis of the stator current. A résumé of the fault effects on the stator current is shown for the detection of air-gap eccentricity, broken rotor bars and bearing damage.

In MCSA, the monitoring method is based on the behaviour of the current at the side band associated with the fault. For that, intimate knowledge of the machine construction is required. It is explained that, when the load torque varies with rotor position, the current will contain spectral components, which coincide with those caused by the fault condition. The torque oscillation results in stator current harmonics that can obscure, and often overwhelm, those produced by the fault condition. Any stator current single-phase spectrum-based fault-detection scheme must rely on monitoring those spectral components that are not affected by load-torque oscillations.

Benbouzid (2000) also mentioned two techniques associated with MCSA: the Park's Vector Approach and the Finite Element Method (FEM). Cardoso et al. (1999) used the Park's Vector Approach, which evaluates space phasors calculated from two or three measured currents. This technique analyses the characteristic pattern of the locus diagram of the current phasor. The second mentioned technique (FEM) has been used extensively in our research into generating virtual data for fault detection. We also applied WT to tackle the shortcoming of the classical stationary approach signed by (Benbouzid 2000).

Benbouzid (2000) also reviewed the advanced data processing techniques that have been used in induction motor monitoring. Time-domain analysis using characteristic values to determine changes by trend setting, spectrum analysis to determine the trends of frequencies, amplitudes and phase relations, as well as cepstrum analysis to detect periodical components of spectra, are used as evaluation tools. The paper mentions some of the main stator current signature based techniques: the classical FFT, the instantaneous power FFT, bispectrum, high-resolution spectral analysis and wavelet analysis.

Benbouzid (2000) concluded that Fourier analysis is very useful for many applications where the signals are stationary. However, it is not appropriate for analysing a signal that has a transitory characteristic such as drifts, abrupt changes and frequency trends. To overcome this problem, Fourier analysis has been adapted to analyse small sections of the signal in time; this technique is known as the short time fast Fourier transform (STFFT). STFFT represents a sort of compromise between time- and frequency-based views of a signal and provides information about both. However, the precision is determined by the size of the window.

Benbouzid (2000) suggested that wavelet analysis could be applied for condition monitoring and fault diagnosis because this technique allows stator current analysis during transients. The Wavelet Transform (WT) was introduced with the idea of overcoming the difficulties mentioned above. WT analysis allows the use of long time intervals if we want more precise low-frequency information and shorter regions if we want high-frequency information.

Nowadays, the most promising tool for MCSA seems to be WT. Several authors have proposed the study of the transient processes of the machine as an alternative way to obtain information not directly visible in steady-state data (Watson 1999, Milimonfared et al. 1999, Zhang & Ren 2003 and Douglas et al. 2005). In particular, the start-up transient has drawn most attention. During this process, the machine is working under severe conditions (high stresses and currents). This fact may help to amplify the indicators of some faults that are present in the machine but at an early stage, providing more information about the fault than obtained in steady-state.

Eren & Devaney (2004) applied this technique successfully to detect bearing faults, which are one of the major causes of induction motor failures and, at the same time, one of the most difficult problems to figure out from the motor current spectrum. The proposed method in Eren & Devaney (2004) enables the analysis of frequency bands that can accommodate the rotational speed dependence of the bearing defect frequencies. Through WT, finer frequency resolution is achieved. By using this technique, a more efficient decomposition of signals containing both transient and stationary components is obtained. The authors concluded that the application of WT to the motor current provides a useful diagnostic tool for incipient bearing fault detection.

Some recent studies have successfully applied the Discrete Wavelet Transform (DWT) to the stator start-up current in order to detect the presence of broken rotor bars in induction machines (Antonino-Daviu et al. 2006a and Antonino-Daviu et al. 2006b). In these papers, DWT proved to be an ideal tool to study signals, the frequency of which varies in time, allowing a time-frequency decomposition of the signal to be studied. The objective of those works was to extract the evolution of certain frequency components associated with broken rotor bars, during the start-up transient. Our investigation extends those studies for the detection of the most common electromechanical faults during the start-up. Few studies have been carried out regarding the application of wavelet theory for the detection of other electromechanical faults and these are mainly focused on the variations that the fault causes on particular parameters of the wavelet transform, such as the wavelet packet coefficients, which does not always allow a clear understanding of the physical phenomenon that takes place (Ye et al. 2003 and Ye et al. 2006).

Direct research into MCSA to detect induction motor faults and, more specifically, broken rotor bars, shorted turns and abnormal air-gap eccentricity is reported in (Thomson & Fenger 2001). Broken rotor bars result in current components being induced in the stator winding, the so-called twice-slip frequency side bands. In this work, the different factors to be considered when monitoring broken rotor bars are analysed. The diagnostic strategy has to consider the following: different rotor designs, a wide range of power ratings, different load conditions, mechanical load characteristics and mechanical components in the drive train. In this paper, four case histories in industrial environments are reviewed, demonstrating that MCSA is a powerful technique for monitoring the health of induction motors. In the first two cases, MCSA is applied successfully to the detection of broken bars in large motors.

In the third case, the effect of complex drive trains on the motor current, which can produce current components that can be confused with the side bands produced by broken rotor bars, is analysed. On the other hand, in the fourth case, MCSA was applied to the detection of shorted turns. A very severe fault, where 30 % of the turns in a coil were short circuited, was analysed. Even with this very severe fault, it is difficult to detect via MCSA the presence of new harmonic components in the current spectrum, as is well explained in (Joksimovic & Penman 2000). Nevertheless, Thomson (2001) shows experimentally that it is possible to detect shorted turns in low-voltage induction motors. This paper also experimentally demonstrated that there is a lead time between the development of shorted turns and the total motor failure.

In addition to the current, broken rotor bars can be detected by monitoring the axial flux, torque, vibration and speed. However, there are various factors in a monitored system to be considered when selecting the most appropriated monitoring technique for application in industrial environments. These factors are as follows: sensors should be non-invasive, sensors and instrumentation systems must be reliable, diagnoses must be reliable, the severity of the problem should be quantified, ideally an estimation of remaining run-life should be given and a prediction of the fundamental cause of the problem should also be provided via online information.

Negrea et al. (2005), studied the ability of various electromagnetic fluxes to enhance the detection and location accuracy of the faults. Different winding designs were considered. The investigation was carried out with simulated and measured data, relying on 2-dimensional FEM to generate virtual data. The most common induction motor faults were considered in this paper. The authors arrived at the conclusion that the special configuration for the search coil $p \pm 1$ enhances the accuracy of detection of induction motor faults, especially in the case of eccentricity faults. Negrea et al. (2006) carried out a comparative investigation of different media for condition monitoring using simulated and measured data. According to this study, the best fault indicators are the axial flux and the electromagnetic forces acting between the stator and rotor.

In Negrea (2006), a detailed analysis of the electromagnetic flux patterns, which provide useful information about faults in induction motors, was made. For measuring such patterns, six search coils were located in various parts of the electrical machine and four search coils were used in FEM simulations. This work showed the usefulness of the search coils with special configurations according to the winding design.

From a number of surveys, it can be deduced that, for induction motors, the stator winding deficiencies account for approximately 30 % of all failures (IEEE, Motor Reliability Working Group 1985 and Thomson & Fenger 2001). These surveys also indicate that the majority of stator faults result from a breakdown of the turn-to-turn insulation. Although there is no experimental data to indicate the time delay between an inter-turn short circuit and a ground wall insulation fault, it is probable that the transition time is not instantaneous (Thomson 2001). Therefore, early detection of inter-turn short circuits would help to prevent subsequent damage to adjacent coils, reducing repair costs.

In Joksimovic & Penman (2000), the interaction between faulty stator winding and a healthy rotor cage is studied. The faulty asymmetric stator winding may produce spatial harmonics of any wave number into the air-gap field. However, all these harmonics vary at a single frequency, i.e., the supply frequency of the sinusoidal voltage source. The stator harmonics induce currents in the rotor cage and reflect back from the rotor as new air-gap field harmonics. Seen from the stator, the air-gap harmonics caused by the induced rotor currents vary at specific frequencies. The air-gap field harmonics induce electromotive forces in the stator winding and generate harmonic stator currents at these same frequencies. These are the same frequencies at which a healthy machine produces harmonic stator currents.

According to this analysis, a stator fault may generate only harmonic stator currents, which vary at the fundamental and rotor-slot harmonic frequencies. A fault in a stator winding may change the amplitudes of the stator-current harmonics, but it will not produce any new frequencies in the stator-current spectrum. This significant result implies that it may be difficult to detect a stator fault from a current spectrum using current signature analysis. Our work overcame this deficiency of MCSA in detecting shorted turns by applying fuzzy logic.

Another way of monitoring winding faults is analysing the axial flux (Penman et al. 1994 and Nandi et al. 2005). These theoretical studies have proved that there are components generated from short-circuited turns. Another approach applicable for detecting stator failures is related to detecting the negative sequence component generated by the inter-turn short circuit as in (Arkan et al. 2001). For detecting this fault, a simple external stray flux sensor is also applicable, as proved by (Henao et al. 2003).

Arkan et al. (2001) presented a non-invasive online method for the detection of stator winding faults in three-phase induction motors from the observation of the negative sequence supply current. A power decomposition technique (PDT) was used to derive positive and negative sequence components of measured voltages and currents. This paper carried out experimental studies, which showed that the negative sequence impedance could vary between 10 % and 50 % during an inter-turn short circuit. The problem is that an unbalanced supply voltage also carries negative sequence currents. This work tries to solve this problem when monitoring the effect of the supply voltage on the negative phase sequence components. This undesired effect is eliminated by using the value of negative sequence impedance for the motor when it is healthy. In this way, the negative sequence current can be separated into two parts: one due to the supply imbalance, the other to the motor degradation. The results of this paper showed that, under all operation conditions of load, the supply voltage imbalance, voltage variation and short-circuit faults can be seen clearly from the motor negative sequence fault current.

Another approach for detecting stator faults by monitoring the motor current was presented in Benbouzid & Nejari (2001), where a fuzzy logic system is implemented for monitoring online the stator condition. In this paper, the stator condition is described by using linguistic variables, fuzzy subsets and the corresponding membership functions describing the motor current amplitudes. A knowledge base comprising rules and database is built to support the fuzzy inference system; the induction motor condition is diagnosed using the inference system. The lack of proper processing of fuzzy input data and the construction of the membership functions are presented as the major difficulties in this research. We developed a similar system as the one showed by Benbouzid & Nejari (2001), tackling the shortcoming by applying FEM in order to generate reliable virtual data, which allows the construction of the membership functions in all fault and load conditions.

The monitoring and fault detection of electrical machines have moved in recent years from traditional to artificial intelligence (AI) techniques. Such techniques require minimum configuration intelligence since no detailed analysis of the fault mechanism is necessary. When AI is used, fault detection and evaluation can be accomplished without an expert. The main steps of the diagnostic procedure can be classified as follows: signature extraction, fault identification and fault severity evaluation. A résumé of the developments of induction motor drive fault diagnosis using AI techniques was given by (Fillipetti et al. 2000). It covers the application of expert systems, artificial neural networks and fuzzy logic systems that can be integrated into each other and also with more traditional techniques. This paper also describes the application of genetic algorithms (GA).

The essence of an expert system is the ability to manage knowledge-based production rules that model the physical system. The main feature of NNs is that they are non-linear approximators. However, the exact architecture of the neural network is not known in advance; it is usually obtained after a trial-error procedure. On the other hand, fuzzy logic systems are rule-based systems, but they can be also considered as non-linear approximators. In contrast with NNs, they give a very clear physical description of how the function approximation is performed. Finally, GAs are not linear function approximators but stochastic optimisation techniques. They can be used together with NN or fuzzy systems to obtain optimal efficiency in the detection system. Thus, they can be used in NN to obtain optimal weights or to obtain the membership functions in fuzzy systems. Our work applied fuzzy logic to detect stator faults. The developed system contains heuristic information that describes the faulty and healthy condition through semantic rules based on the understanding of the motor by the power engineer.

Recently, another modern signal processing technique known as support vector machine (SVM) has been applied to numerical and experimental data using different strategies (Pöyhönen et al. 2005). This technique is applied firstly to numerical data, aiming to distinguish a healthy spectrum from a faulty spectrum. Later on, it is applied to actual data. This technique has problems similar to all data-based identification methods; the performance of the classification can be only as good as the data it is based on. A huge amount of data that properly describes the whole operation of the process under study should exist for design and testing the classification structure. In fault classification, this may be a problem, because often there is not much reliable data available from all the faulty operations.

However, a new research presented by Su & Chong (2007) shows a successful monitoring system based on NN modelling. In this paper, an analytical redundancy method is created for induction motor vibrations. The STFT is used to process the quasi-steady vibration signals to continuous spectra for the NN model training. The faults are detected from the changes in the expectation of vibration modelling error. The system shows effectiveness with experimental data, but it has been tested with data from the same motor and similar conditions as were used for training the neural network. The key question is how to take into account the vast and random nature of vibration signal.

1.2.2 Vibration monitoring

Rotating electrical machines are designed to generate mechanical power from electrical power, or vice-versa. They are designed to work under variable loads, most commonly under periodic loads. Thus, all machines are prone to forced vibrations and hence dynamic stresses. In general, rotating machinery is subjected to dynamic loads. Therefore, any change in the mechanical condition of the machine affects its dynamic conditions and thus the vibration behaviour. There is also vast experience in detecting such conditions. Much has been written about vibration, particularly about the vibration of induction motors, in many books and papers over the years. In many applications, the overall vibration levels are sufficient to diagnose mechanical failures in the machine (Tavner & Penman 1987 and Rao 2000). In contrast, only a few papers have been written on the vibration caused by electrical faults.

To diagnose a vibration problem, one must first understand the root cause of the vibration. Where does the force come from? Is there a resonance that amplifies the response? How stiff is the motor structure? How does the motor react to transmit this force? This research is devoted to answer these and other questions related to electromechanical faults.

There are many mechanical and electrical forces present in electrical machines that can produce vibrations. Further, these forces interact, making the identification of the root cause elusive. Though, it is worth mentioning that our research into fault indicators using simulation data has identified the electromagnetic forces acting between the stator and rotor as the most reliable indicator of motor faults (Publication 1 and Negrea et al. 2006). However, poor accessibility gives rise to their main drawback. The air-gap of the machine is small and it is difficult to locate a sensor within it. Nevertheless, as vibrations are consequences of the interaction between forces and the machine structure, they might have identifiable signatures in their pattern. In the following, the most relevant approaches appearing in the literature are revised. They intend to explain the relationship between electromechanical faults and vibration monitoring.

Dorrell & Smith (1996) described an analytical model to study induction motors with a static eccentricity based on the air-gap permeance approach including the stator and rotor magnetomotive force (mmf). The model examines the interaction between the harmonics that produce unbalanced magnetic pull (UMP). This is verified by experimental investigation carried out in (Smith & Dorell 1996). They obtained a good agreement at low slip. They concluded that the effects of the higher order winding harmonics and rotor skew can influence the magnitude of the UMP.

Dorell et al. (1997) analysed the air-gap flux and vibration signals as a function of the air-gap eccentricity. This paper put forward a theoretical analysis of the interaction between harmonic field components due to eccentricity. The authors obtained an analytical expression for the magnetic stress during eccentric condition. It is illustrated how eccentricity faults can be identified from vibration analysis using condition monitoring techniques. The obtained analytical expression is in agreement with our results. However, the paper does not make clear the dependence of the vibration on the machine loading, an important factor to take into account in a monitoring system; also, the possible modal pattern of the stress waves is not calculated.

Finley et al. (2000) tried to explain the vibration pattern. To do so, they compile a résumé table with an impressive list of electrically and mechanically excited components in the vibration pattern. The main electromagnetic force component, which acts between the stator and rotor, is analysed first. This component is at a maximum when the magnetising current flowing in the stator is at a maximum, either negative or positive. As a result, there will be two peaks of force during each cycle of the power supply. This will result in a frequency of vibration equal to twice the frequency of the power source, widely known as twice the line-frequency vibration, which is sensitive to the motor support, frame and base stiffness and eccentricity problems.

Secondly, the change in the elliptical shape of the stator is analysed. In two-pole motors, the electromechanical force will attempt to deflect the stator into an elliptical shape. The primary resistance to the movement is the stiffness of the core. In motors with more than two poles, the deflection shape is a function of the number of poles. It is described later on, how the twice line frequency vibration can significantly increase when the air gap is not symmetric; when this occurs, the forces acting between the stator and rotor are bigger in the direction of the smaller air gap. Thus, an unbalanced magnetic pull will exist in the direction of the minimum air gap.

Finley et al. (2000) described the case of a broken bar or open brazes joint that, as result of the broken bar, has no field around the particular bar. Therefore, the force applied to that side of the rotor would be different from that on the other side of the rotor, creating an unbalanced magnetic force that rotates at the rotational speed and modulates at a frequency equal to the slip frequency times the number of poles. There is an analysis of secondary effects following the occurrence of broken bars; such effects might include heating around the rotor and consequently rotor bow, which causes basic rotor unbalance and a greater magnetic pull, thereby creating some minimal twice line frequency vibration. It should be noted that this condition could not be detected at no load. On the contrary, there is load-related magnetic vibration at or near the rotor slot passing frequency when current is induced into the rotor bars under load conditions. This source of vibration is at a frequency that is greater than the normally measured frequency spectrum (10 Hz to 1 kHz) in a normal vibration test.

Trutt et al. (2001) presented a theoretical review of the relationships that should exist between electrical winding deterioration and the mechanical vibration of AC synchronous machine elements under normal and faulty operation conditions. This research provides motivation for further studies in this respect. The result of this paper indicates a significant relationship between electrical deterioration and mechanical vibration and demonstrates that the relationship between electrical deterioration and mechanical vibration is measurable, and so could be used as a basis for monitoring applications of AC synchronous machines.

Trutt et al. (2001) showed on the basis of theoretical considerations that the changes in winding and coil currents due to electrical winding faults will be reflected in the spectrum of the forces acting on the stator and rotor of the rotating machine. The manner in which the mechanical structure will respond to these forces should be a critical factor in the use of vibration monitoring for the evaluation of winding deterioration. The dynamic response of the machine elements depends on a number of parameters including elasticity, geometry, natural frequencies, damping characteristics, and vibration modes. Although all of these characteristics are difficult to measure for a given machine, the forces acting at a frequency near a natural frequency will produce more dramatic motion responses than those that may act at more highly damped frequencies.

From experimental results, the authors were able to identify measurable differences in the spectrum components, proportionally with the fault current in the winding for winding faults. Similar results were obtained for a rotor winding fault. Based on the results, the authors recommend that the relationship between a winding fault and mechanical vibration shall be investigated in greater detail and that the potential application of such predictors in continuous monitoring systems be considered.

Trutt et al. (2002) described electrically excited vibrations as an alternative approach to the monitoring of internal deterioration currents. Results of these studies show that specific vibration frequencies might be monitored in order to provide an assessment of the stator winding integrity. The authors arrived at the conclusion that this type of information could be used as a supplement to other monitoring data with the goal of making more informed electrical and mechanical maintenance decisions, but further research is still needed. Trutt et al. (2002) intentioned to predict the excited vibration frequencies due to stator faults, by compiling some expected vibration frequencies predicted from the magnetic force components distributed spatially along the air-gap of the machine. The authors pointed out that the proximity of a particular magnetic force component, along with the damping characteristics associated with the natural frequencies, are important factors in the determination of the electrically excited vibration that will occur in response to that magnetic force component.

Trutt et al. (2002) explained that a measurable response should exist in the vibration spectrum if the frequency of one of the excitation forces due to the deterioration is not far from a natural frequency. Electrically excited vibrations are produced by the total air-gap magnetic field and not just the deterioration field acting alone. The total field is a combination of the field due to the deterioration current, the field due to the modified three-phase stator current, and the rotor reaction to these components. The fault should occur in such a way that the other air-gap fields in the machine do not significantly reduce the magnetic field due to the fault. In such a case, it is possible to observe new signs in the vibration spectrum. In this reference, experiments with an imitated short circuit in the stator are described and the results are confirmatory in that the predicted features appeared in the spectrum. Some new components also appeared in the spectrum that were not predicted from their theoretical studies. The new components seem to be forced vibrations. As a conclusion drawn from this work, it is stated that no accelerometer responses were observed at the lower force frequencies (0-64 Hz), while measurable responses were obtained at the higher frequencies (112-232 Hz). The authors could not properly explain the phenomena. They concluded that further research is needed in this area.

Verma & Balan (1998), from experimental results, and using distributed electromagnetic forces, made an attempt to validate the amount of damping present in the stators of electrical machines. Since vibration damping is not amenable to a mathematical formulation, one has to resort to experimental information for its determination. The authors presented a fundamental study using experimental modal analysis. Thus, modal testing is carried out to force the stator structure to vibrate predominantly at a selected resonance frequency. In order to achieve this, distributed electromagnetic forces were used.

The distributed excitation system used is designed to induce vibration of certain modes. By using such a distributed system, a sufficient amount of energy can be fed uniformly into the structure. This is especially required in laminated structures, where the energy supply through point excitation is rapidly dissipated within the structure, producing widely different vibration amplitudes at various locations. The excitation is so chosen that only the mode of interest is dominantly excited within the frequency range. Thus, the structure would then respond in that principal mode and the damping could be obtained.

In this paper, a smooth thick cylindrical shell made of mild steel is used, having the dimensions of a 120-hp induction motor. In the experimental setup, it was intended to predominantly induce circumferential vibration modes of 0, 1, 2, 3 and 4. The mode of vibration is characterised by the number of cycles of deformation around the circumference of the stator. The electromagnetic forces are produced using a 2-pole or 4-pole winding installed on a stationary rotor structure. Combining the two windings yields the force distribution necessary for every mode.

The presented experimental setup in Verma & Balan (1998) permits the calculation of the damping ratio associated with each mode of vibration with accuracy and simplicity. The amount of damping present at a particular mode is derived from the amplitude response curve at a resonance, and is determined by the sharpness of the peak. It was shown that the actual damping presented in a laminated stator model will be much higher at higher frequencies. This implies that it is more relevant to check the low-frequency spectra for condition monitoring purposes, as was shown in our research. In Verma & Balan (1998), it is stated as a conclusion that, at any resonance, the amplitude of vibrations depends to a smaller extent on the type of force distribution. It was ascertained that the force frequency overrides the importance of the force distribution. As distinct from the prevalent rationale in the literature, it is stated that the stationary “standing-wave” deformation patterns of vibrations were produced at the resonance, even with rotating force distributions.

Chow & Fei (1995) introduced bispectrum for three-phase induction machine fault identification and condition monitoring. In this paper, the vibration signals operating at different rotating speeds and degrees of unbalance are thoroughly analysed. This paper shows that bispectrum can be successfully applied to machine asymmetric faults and stator winding fault analysis and identification. The bispectrum is capable of revealing both the amplitude and phase information of the signal; the identification of the machine fault is simply based on the analysis of the machine vibration signals.

In Chow & Fei (1995), the unbalance was obtained by adding a resistor to one phase, thereby altering the electromagnetic flux, the electromagnetic force acting upon the stator and rotor and, thus, the vibration pattern. The stator-winding fault was also studied in this paper; in this case, a broken phase was investigated. In both cases, the bispectrum of the vibration signal was quite different from the one of the healthy condition. As a conclusion, it may be stated that the bispectrum magnitude of the dominant component, caused by the machine rotation, increased with the increasing level of asymmetrical fault. This paper showed that there is a clear relationship between the asymmetrical fault and the vibration signals.

McCully & Landy (1997) explained the technique of monitoring the vibration spectrum and the effect of inter-bar currents, which produce informative components in the vibration spectrum. It is explained that an inter-bar current can flow in the laminated core, perpendicular to the bars. The interaction between the stator flux and the inter-bar current produces axial forces, which contain the fundamental and harmonic components. These forces produce an array of frequencies in the vibration spectrum. The axial vibration spectrum is measured in the stator end-shield. From the predicted axial vibration frequencies, specific frequencies can be analysed to determine the existence of a broken bar. This paper arrived at the conclusion that the axial vibration monitoring technique does not provide significant results when no inter-bar currents were present. However, when inter-bar currents are present, the axial vibration monitoring is very conclusive.

A theoretical and experimental detailed analysis of the effects of the broken rotor bars on the axial forces was presented by (Müller & Landy 2003). This paper presents a mathematical model showing that the inter-bar current interacts with the stator flux to produce forces in the axial direction. The experimental results verified the frequencies postulated in the mathematical model. It was also shown that the new frequency components are load dependent. The main limitation of this approach is given by the fact that it is applicable when there are inter-bar currents, just as in a few copper cage rotors.

Villada et al. (2003) studied the case of an induction motor fed from a Pulse Width Modulation (PWM) inverter. Measured vibration and current from a healthy machine and from a machine with stator faults are compared. This paper concluded that the vibration spectrum experiences measurable differences at many frequencies that can be used as signs for the early detection of incipient faults in the stator winding. A predictive program should correlate different types of data to form a complete picture, determine the beginning of the change and establish the cause of the problem. It is also stated that trending is crucial, which means it is impossible to determine the condition of any motor from only one set of data.

Similar research, to analyse the amount of vibration with different kinds of inverters was carried out by (Yacamini & Chang 1995). The paper concluded that a motor fed from a power converter suffers from increased vibrations. This paper showed that there is a significant difference between the vibration levels measured on machines that are working at full load and those measured on unloaded machines. This paper showed that, depending on the harmonic content, a motor would have a vibration spectrum that is very rich. It was also shown that, with a variable speed drive, a resonance frequency in the stator, found to be unimportant with a clean sinusoidal supply, became increasingly important if one of the exciting frequencies happened to coincide with it. In the wide range of frequencies present in a variable frequency supply, the chance of such excitation is greatly increased.

Li et al. (2000) carried out vibration monitoring for rolling bearing fault diagnoses. The final diagnoses are made with an artificial NN. The research was conducted with simulated vibration and real measurements. In both cases, the results indicate that a neural network can be an effective tool in the diagnosis of various motor bearing faults through the measurement and interpretation of bearing vibration signatures. In this paper, the vibration features are obtained from the frequency domain using the FFT technique. Five vibration signatures are constructed. They are created from the power spectrum of the vibration signal and consist of the corresponding basic frequencies, with varying amplitudes based on the defect present. Time-domain information, such as the maximum and mean value of the amplitude vibration waveform and the Kurtosis factor of the vibration waveform, are also considered. Thus, the complete neural network has six input measurements.

Li et al. (2000) showed how the neural network can be used effectively in the diagnosis of various motor bearing faults through appropriate measurement and interpretation of motor bearing vibration signals. In Jack & Nandi (2000), there is an approach that brings better results. In this, the artificial neural network is helped by a genetic algorithm. In this paper, statistical estimates of the vibration signal are considered as input features. The paper examines the use of a genetic algorithm to select the most significant input features in the machine condition monitoring contexts. By doing this, a subset of six input features from a large set of possible features is selected, giving a very high classification accuracy of 99.8 %. Li et al. (2000) and Jack & Nandi (2000) are devoted to detecting mechanical faults; a similar approach could be extended to analyse the vibration pattern when an electrical machine is working with an electrical fault.

Wu & Chow (2004) developed a radial-basis-function neural-network-based fault detection technique for performing induction machine fault detection and analysis. The inputs of the system are four-feature vectors, which are extracted from the power spectra of machine vibration signals. The proposed system is not only able to detect electrical and mechanical faults, but the system is able to detect the extension of the mechanical faults. The four-feature vectors used are the total power, average frequency, normalised second-order central moment and normalised third-order central moment of the vibration measurements. The authors of this research obtained good results in the detection rate at frequencies varying from 40 to 60 Hz. The studied electrical fault was an imitated inter-turn short circuit in the stator. This is made by adding a resistor in one phase, thus altering the magnetic force and consequently the electromagnetic force acting upon the stator core. Such a fault could cause some changes in the vibration pattern. However, it is far from the real vibrations produced by an inter-turn short circuit in the stator winding.

The research carried out in Wu & Chow (2004) also included the detection of mechanical faults in induction motors. A very simple mechanical fault, consisting of the mechanical looseness of a screw used for fixing the machine, was investigated. Even if the simulated faults are very simple, this paper shows how it is possible, using appropriately featured extraction, to detect with a high degree of accuracy the motor condition. In this case, the proposed neural network diagnostic system performs remarkably well in machine fault identification at different rotation speeds. The above mentioned papers showed that vibration monitoring has potential application in monitoring induction motors. But neural networks still do not show a clear understanding of the vibration problem. The first step in understanding vibration is to identify the root cause of the vibration, i.e., the force. Nowadays, the most suitable technique to analyze the acting force is FEM.

The advantage of FEM over traditional analytical techniques is given by the fact that complex structures such as rotating machines can be modelled accurately, representing the material properties and non-linearity. FEM for force calculation, vibration and noise analysis has been widely used in electrical machines (Belahcen et al. 1999, Neves et al. 1999, Vandevelde & Melkebeek 2001, Ishisbashi et al. 2003, Jang & Park 2003 and Mori & Ishiskawa 2005).

Belahcen et al. (1999) presented a numerical method to solve the magnetic field in the air-gap and iron core of a synchronous generator. The distribution of the forces acting on the inner surface of the stator was calculated using the Maxwell stress tensor, which in turn is developed in two dimensional Fourier series in space and time. The obtained agreement between the simulations and measurements of noise and vibrations was rather good. This method is applied in our research work to investigate the effects of the radial forces on the stator when the induction motor is working under fault conditions.

Neves et al. (1999) developed a FEM model, which allows the calculation of the winding and bar currents, the magnetic forces and induction motor structure dynamic response. The local radial magnetic forces were calculated by means of the Maxwell stress tensor and validated by measurements. The authors obtained a good agreement between the calculations and measurements.

Vandevelde & Melkebeek (2001) developed a method for numerical analysis of induction motor vibrations based on magnetic equivalent circuits and structural finite element models. From the combined electromechanical analysis, the vibration and noise are predicted. This investigation overcomes the drawbacks from the analytical models and develops the calculation of the radial forces in the (frequency, spatial order)-domain; but in this work, the effects of the low-order forces due to electromechanical faults were not analysed. This approach could be also applied to study the effects of the electromechanical faults in the vibration pattern.

In Ishibashi et al. (2003), the electromagnetic noise is calculated by the boundary element method (BEM) using the electromagnetic force of the Maxwell stress tensor calculated in 2-dimensional FEM. The natural frequency and behaviour of the stator are calculated by mechanical FEM. The authors introduced in the calculation spring elements between the stator frame and the stacked core and calculated the vibrations by mechanical FEM. The calculated noise was compared with experimental results obtaining a good accuracy. In this paper, the mechanical contact condition between the core and frame was considered for the first time.

Jang & Park (2003) made simulations of electromechanical faults in a single-phase induction motor. This work investigated broken rotor bars and rotor eccentricities. Numerical analysis is performed by solving the non-linear time-stepping finite-element equations coupled with magnetic field equations, circuit equations and mechanical equations of motion. The characteristic frequencies of the magnetic forces and rotor vibrations generated by the fault under study were presented. This paper showed that each source of the studied faults can be distinctively identified. The results of this work are close to our results for the case of broken bars. However, the authors took into account neither the spatial harmonics of the forces, nor the behaviour with the loading condition of the motor.

Mori & Ishiskawa (2005) analyse the radial electromagnetic force of induction motors by using 2-dimensional non-linear FEM considering the rotor coupled with voltage equations. The authors analysed the steady-state characteristic and clarified the influence of the slip and the stator winding on the radial force at the teeth and slots.

Throughout all the literature review, a method that clearly explains the forced vibrations during electromechanical fault events, their relationship with the stress waves frequency and spatial distribution for every electromechanical fault was not found. For this reason, part of this thesis is devoted to find such a method. The solution is a cornerstone when we are willing to choose vibrations as the primary fault indicator.

1.3 Scientific contribution of this study

The main contributions of this work are as follows:

- ♦ It is indicated from the comparison of various indicators of motor faults generated by FEM simulations that the electromagnetic forces acting between the rotor and stator are a good indicator of motor faults. The electromagnetic forces seem to be the most sensitive parameter.

- ♦ It is shown from simulations and measurements that the circulating currents in parallel branches are better indicators of faults than the phase currents.

- ♦ An online monitoring fuzzy system was developed for stator winding faults. It showed a better accuracy detection rate than other methods found in the literature. The system is able to work in variable frequency and it does not need load information.

- ♦ Predictive filtering is used to separate the fundamental component from the harmonic components of the motor current. A method to detect online dynamic eccentricity from the motor current is developed. The method avoids the spectral analysis.

- DWT is applied for the first time to the stator current during the start-up transient in order to detect eccentricity faults. The approach shows up frequency components dependent on the slip, which evolve in a particular way during the transient. This fact enhances the diagnosis of the eccentricity faults and the discrimination between different faults, showing advantages over the traditional stationary method. The technique allows discrimination between broken bars, torque oscillations and eccentricity faults, which is not always possible in the traditional stationary method.

- A mechanical model showed the effects of electrical faults in the vibration pattern. The model is simulated in Matlab/Simulink® and the electromagnetic forces are calculated in FEM.

- The existence of low-frequency and low-order force distributions acting on the stator of the electrical machine is shown when the motor is working under fault conditions. These forces are able to produce forced vibrations in the stator.

- A method for determining the signatures of electrical faults in the air-gap force distribution and vibration pattern of induction machines and their relations with their spatial harmonics is implemented. By applying the method, a concise table for induction motor monitoring through vibration is deduced. The method is validated by vibration measurements. It is demonstrated that the low-frequency vibration has potential application in fault condition monitoring of induction motors.

- The comparative table (Table II, page 63) contains new features that allow discrimination between the faults. These are the spatial harmonics and the behaviour with loading.

- When the above-mentioned method is applied to the study of dynamic eccentricity, new findings are encountered. The no-load test is the most informative one and a non-linear relationship between loading, stress waves and vibration exists during dynamic eccentricity events.

The first and second items related to electromagnetic force and circulating current were reached by the whole work team. Each of the items listed above is discussed in the following summary of the publications.

1.4 Summary of articles

Publication P1

In this paper, a numerical magnetic field calculation was used to provide virtual measurement data from healthy and faulty operation. Data were generated for eight different faults. A relatively new classification method called support vector machine (SVM) was applied to fault diagnostics relating to a cage induction motor and a slip-ring generator. In this research, different indicators of faults obtained from simulation and measurements were compared as media for fault detection.

The main contribution of this paper is to provide a comparative investigation between different fault indicators, showing the electromagnetic forces and the circulating currents as natural indicators of motor faults. The electromagnetic force acting between the stator and rotor is presented as the most reliable indicator of induction motor faults.

The first author made the SVM analysis and wrote the core of the paper. The contribution of the author of this thesis to this paper was to carry out the measurements of phase and circulating currents and pre-processing the real data for the experimental verification. Moreover, together with the second author, he provided the simulated data. A minor contribution took the form of giving the idea of pre-filtering the noise signal through an adaptive predictive filter when the stator current was used as fault indicator.

Publication P2

In this paper, the author of this thesis developed a non-invasive fuzzy monitoring system for detecting the stator condition online based on monitoring the stator current amplitudes. The system was tested with simulated and measured data, showing a high degree of accuracy in the detection rate. The major contribution of this paper is the introduction of a new rule in the inference system, providing better results than former investigations. The virtual data is generated by FEM motor simulation program, permitting a better approximation in building the membership functions. Thus, the fuzzy system is enhanced. The system is also able to work in variable speed drives and it is remarkable that it does not need load information.

This work showed an application of fusion between soft computing and hard computing techniques. The author of this thesis developed the method and is the main writer and contributor to this paper. The second author supplied the simulated data.

Publication P3

This work proposes a general scheme to detect induction motor faults by monitoring the motor current. The scheme is based on signal processing (predictive filters), soft computing techniques (fuzzy logic), the analytical studies of induction motor under fault conditions and the analysis of data generated by FEM. The predictive filter is used in order to separate the fundamental component from the harmonic components. Fuzzy logic is used to identify the motor state and FEM is utilised to generate virtual data. The layout has been proved in Matlab/Simulink®, with both data from the FEM motor simulation program and real measurements. The proposed method has the ability to work with variable speed drives.

This work, on the one hand, shows the feasibility of spotting broken bars and inter-turn short circuit by monitoring the stator current. On the other hand, it shows that the detection of static eccentricity and bearing faults are quite difficult tasks by monitoring the stator current.

The author of this thesis wrote the full paper. The second author assisted the first in generating the simulated and measured data. The third author provided the method for generating the virtual data.

Publication P4

This paper presents a simplified method for detecting eccentricity in induction motors. It is based on predictive filtering of the stator current. The motor condition is analyzed from the root mean square (RMS) of the harmonic current components, which are obtained by subtracting the original and filtered current. A detailed spectral analysis of the motor current is avoided. The system is able to work in variable frequency and precise motor data are not needed. The technique has been implemented in Matlab/Simulink®, and tested with data from FEM and real measurements, showing the ability to discriminate between the faulty and healthy condition.

The main contribution of the paper is an online method for detecting eccentricity in induction motors, where the spectral analysis is not needed. The writer of this thesis developed the method and wrote the paper. The second and third authors assisted in the measurements. The fourth author gave valuable comments.

Publication P5

In this paper, a time frequency analysis of the stator start-up current is carried out in order to detect the presence of dynamic eccentricity in an induction motor. For this purpose, discrete wavelet transform (DWT) is applied and wavelet signals at different levels are studied. Data are obtained from simulations, using a FEM model that allows forcing eccentricity at different levels and from a real machine with forced eccentricity. The results show the validity of the approach for detecting the fault and distinguishing it with respect to other failures, presenting some advantages over traditional stationary analysis.

The main contribution of this paper is the application of DWT for detecting eccentricity problems during the start-up transient. The approach shows up frequency components dependent on the slip, which evolve in a particular way during the transient. This fact allows the diagnosis of the corresponding fault and the discrimination between different faults.

The first author and the writer of this thesis carried out the investigation and wrote the paper together. They shared the core of the paper 50-50. The introduction was written by both authors. In the method of analysis (Chapter 2, Method), Sections 2.1 and 2.3 were written by the writer of this thesis, Section 2.2 was written by the first author. Chapters 3 (Results) and 4 (Analysis) were written by both the authors, as were the conclusions. Chapter 5 was written by the first author. The other authors contributed valuable discussions and important comments.

Publication P6

This paper develops two mechanical models for the study of induction motors working under fault conditions. Firstly, a mechanical model is implemented in Matlab/Simulink®. It is fed by forces calculated by FEM, showing components to be excited when the motor has an electrical fault. Secondly, a hybrid model obtained from vibration measurement and FEM calculated forces showed the vibration components to be monitored.

By comparing the healthy vibration pattern to the faulty one, an increase in vibration amplitude can be observed when the motor is working with an electrical fault. This increment of amplitude can be interpreted as a signature that allows an understanding of the motor condition, as was predicted from the analytical and simulation studies. Both models are able to predict the frequency components to be monitored.

The author of this thesis is the main writer of this paper. Nevertheless, the two other authors shared their knowledge of the subject and gave important guidance.

Publication P7

This paper presents a method for determining the signatures of electrical faults in the air-gap force distribution and vibration pattern of induction machines. The monitoring of faults is achieved through measurement of the vibrations of the stator frame. The radial electromagnetic force distribution along the air gap, which is the main source of vibration, is calculated and developed into a double Fourier series in space and time. Finite element simulations of faulty and healthy machines are performed; they show that the electromagnetic force distribution is a sensible parameter to the changes in the machine condition. The computations show the existence of low-frequency and low-order force distributions acting on the stator of the electrical machine when it is working under fault conditions.

The simulation results are corroborated by vibration measurements on an induction motor with implemented broken bars and inter-turn short circuit. The measurements and simulations show that low-frequency components of the vibrations can be used as identifiable signatures for condition monitoring of induction motors. The determination of the vibration frequency corresponding to a given electric fault in a given machine can be achieved through numerical simulations of the magnetic field and electromagnetic forces in the cross section of the machine, without need for complex structural analysis.

The author of this thesis is the main writer and contributor to this paper. The second and third authors gave very important guidance.

Publication P8

This paper applies the method presented in Publication 7 for determining the signatures of dynamic eccentricity in the air-gap force distribution and vibration pattern of induction motors. The computations show the existence of low-frequency and low-order force distributions, which can be used as identifiable signatures of the motor condition by measuring the corresponding low-order vibration components. These findings are supported by vibration measurements and modal testing. The low-frequency components offer an alternative way to the monitoring of slot passing frequencies, bringing new components that allow discrimination between dynamic eccentricity and rotor mechanical unbalance.

The main contribution of this paper is to extend the method presented in Publication 7 to cover dynamic eccentricity. It revealed the no-load test as the most informative for detecting the dynamic eccentricity through vibration monitoring. It also revealed a non-linear relationship between loading, stress waves and vibration during dynamic eccentricity.

The author of this thesis wrote the paper. The second and third authors gave valuable comments. The fourth author, assisted by the writer of this thesis, carried out the modal testing. The fifth author assisted the first author in the vibration measurements.

1.5 Contribution per paper

Table I shows the percentage contribution of the author per paper.

Table I. Contribution per publication.

Publications	Author's contribution [%]
[P1] Numerical Magnetic Field Analysis…	20
[P2] Induction Motor Stator Fault…	90
[P3] A General Scheme for Induction Motor…	90
[P4] A simplified online technique for…	80
[P5] DWT analysis of numerical…	50
[P6] Mechanical Model to Study…	80
[P7] Signatures of Electrical Faults in…	80
[P8] Air-**gap force distribution and…**	80

2 Methods and simulation tools

The main difficulty in monitoring induction machines is the lack of an analytical model that can describe a faulty machine at all operation points and with different supply sources. In this research work, a FEM motor simulation program, fuzzy system, DWT, Matlab/Simulink® and measurements have been used.

2.1 Numerical electromagnetic field analysis

FEM is applied in order to solve electromagnetic problems described by the Maxwell equations. The aim of FEM here is to foresee the changes of motor performance due to the changes in the internal parameters when the motor is working under fault conditions. Numerical simulations generate useful data, which are used to test different diagnostic techniques. The FEM program also allows the verification of former analytical results, permitting the evaluation of the influence of different motor faults in an inexpensive and accurate manner.

The advantage of FEM over traditional analytical techniques is given by the fact that complex structures such as rotating machines can be modelled accurately, representing the material properties and non-linearity. By using FEM, a complex problem represented by differential equations is transformed into a series of algebraic problems, which are easier to solve. Thus, FEM divides the problem domain into a large number of small elements. For the solution, the material properties, excitations on the problem regions and the boundaries conditions are also needed.

The used model solved the Maxwell equation in two dimensions, having the main drawback that some three-dimensional effects are not taken into account. The three-dimensional end region fields are modelled approximately by constant end winding impedances in the circuit equations of the windings (Arkkio 1987). The calculation is made under the following assumptions: the magnetic field in the core is two-dimensional, the current density in the stator conductor is constant, neglecting the skin effect in the stator and the laminated iron core is treated as a non-conducting, magnetically non-linear medium, and the non-linearity is modelled by a single-value magnetisation curve. The details of the calculation method are presented in Publication 1.

The FEM model is used in this research to generate virtual data for, firstly, the analysis of the parameter behaviour and, secondly, for testing online the implemented monitoring system, and also to allow the verification of analytical studies and well-known formulas given in the literature. A diagram of the FEM modelling is given in Figure 1. The parameters used in this work are currents, circulating currents and forces.

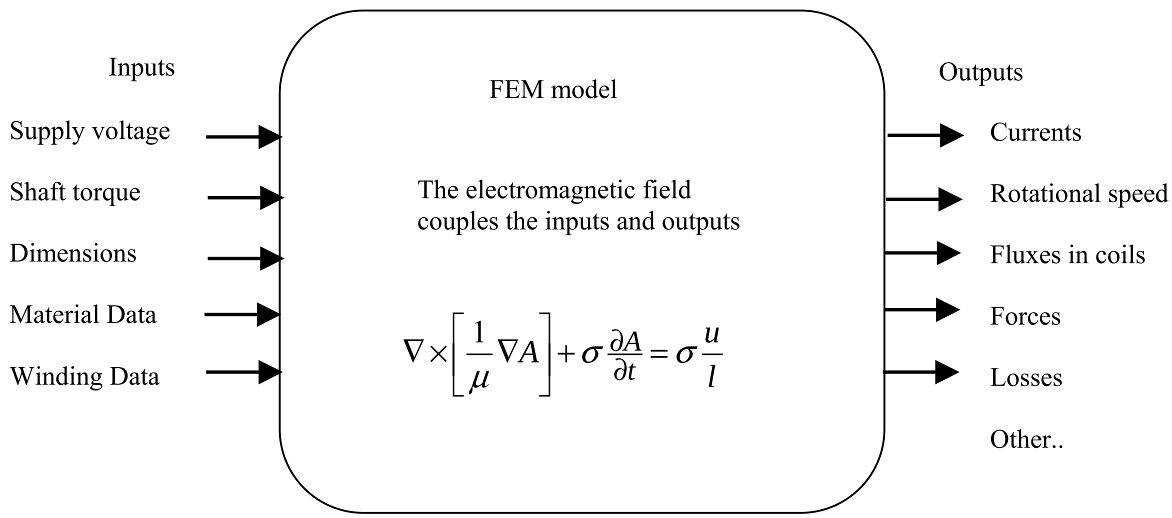

Figure 1. Electrical machine modelling by FEM.

2.1.1 Force calculation

There are two basic methods of calculating the forces acting between the stator and rotor, the Maxwell's stress tensor and a method based on the principle of virtual work. Both methods are used in our research. They are theoretically closely related and equivalent (Coulomb 1983).

In Maxwell's stress tensor the electromagnetic force is calculated as a surface integral

$$\mathbf{F} = \oint_S \boldsymbol{\sigma} \cdot d\mathbf{S} \tag{1}$$

$$\mathbf{F} = \oint_S \left[\frac{1}{\mu_0} (\mathbf{B}_r \cdot \mathbf{n})\mathbf{B} - \frac{1}{2\mu_0} B^2 \mathbf{n} \right] d\mathbf{S} \tag{2}$$

where $\boldsymbol{\sigma}$ is the Maxwell stress tensor, $\mathbf{n}$ is the unit normal vector of the integration surface $\mathbf{S}$ and $\mathbf{B}$ is the magnetic flux density. For a two-dimensional model, the surface integral is reduced to a line integral along the air gap. If a circle of radius r is taken as the integration path, the force is obtained as

$$\mathbf{F} = \int_0^{2\pi} [\ \frac{1}{\mu_0} B_r B_\varphi \mathbf{e}_j + \frac{1}{2\mu_0}(B_r^2 - B_\varphi^2)\mathbf{e}_r\ ] r d\varphi \tag{3}$$

where B_r, B_φ are the radial and tangential components of the flux density. The calculated force depends greatly on the integration radius.

In the method based on the principle of virtual work, the force is calculated as the partial derivative of the coenergy functional with respect to the virtual movement u (Coulomb 1983).

$$\mathbf{F} = \frac{\partial W_\mathrm{c}}{\partial \mathbf{u}} = \left[\frac{\partial W_\mathrm{c}}{\partial x} \frac{\partial W_\mathrm{c}}{\partial y} \right]^\mathrm{T} \tag{4}$$

where W_c is the coenergy functional and $\mathbf{F}$ is the force vector.

2.1.2 Magnetic field and magnetic forces

From the solution of the magnetic field, the force distribution in the air gap of the machine is calculated by using the Maxwell stress tensor averaged over the air-gap area (Belahcen et al. 1999). The Maxwell stress tensor in the Cartesian coordinate system can be presented

$$\boldsymbol{\sigma} = \frac{1}{\mu_0} \begin{bmatrix} B_x^2 - \frac{1}{2}\mathbf{B}^2 & B_x B_y & B_x B_z \\ B_y B_x & B_y^2 - \frac{1}{2}\mathbf{B}^2 & B_y B_z \\ B_z B_x & B_z B_y & B_z^2 - \frac{1}{2}\mathbf{B}^2 \end{bmatrix} \tag{5}$$

In two dimensions and polar co-ordinates, it reduces to a radial stress component or normal stress

$$\sigma_r = \frac{1}{2\mu_0}(B_r^{\ 2} - B_\varphi^{\ 2}) \tag{6}$$

and a circumferential stress component or shear,

$$\sigma_\varphi = \frac{1}{\mu_0} B_r B_\varphi \tag{7}$$

with B_r and B_φ respectively the radial and circumferential components of the magnetic flux density in the air gap.

Due to the high permeability of the iron, the radial component of the flux density vector B_r is much higher than its circumferential counterpart B_φ. This fact results in a very high value of the normal stress compared to the shear. The latter is responsible for the torque production, whereas the former is responsible for the vibrations of the stator of the machine. The radial component of the stress tensor can be written as double Fourier series in terms of the position φ and time t, space and time harmonic decomposition (Belahcen et al. 1999),

$$\sigma_r = \sum_{m=0}^{\infty}\sum_{n=0}^{\infty}\lambda_{mn}\begin{Bmatrix} \mathrm{a}_{mn}\cos(mp\varphi)\cos(n\omega t) + \mathrm{b}_{mn}\cos(mp\varphi)\sin(n\omega t) + \\ \mathrm{c}_{mn}\sin(mp\varphi)\cos(n\omega t) + \mathrm{d}_{mn}\sin(mp\varphi)\sin(n\omega t) \end{Bmatrix} \tag{8}$$

where the coefficients

$$\mathrm{a}_{mn} = \frac{p\omega}{\pi^2}\int_0^{\frac{2\pi}{p}}\int_0^{\frac{2\pi}{\omega}} \sigma_r \cos(mp\varphi)\cos(n\omega t)\mathrm{d}\varphi\mathrm{d}t\,,\ \mathrm{b}_{mn} = \frac{p\omega}{\pi^2}\int_0^{\frac{2\pi}{p}}\int_0^{\frac{2\pi}{\omega}} \sigma_r \cos(mp\varphi)\sin(n\omega t)\mathrm{d}\varphi\mathrm{d}t$$

$$\mathrm{c}_{mn} = \frac{p\omega}{\pi^2}\int_0^{\frac{2\pi}{p}}\int_0^{\frac{2\pi}{\omega}} \sigma_r \sin(mp\varphi)\cos(n\omega t)\mathrm{d}\varphi\mathrm{d}t\,,\ \mathrm{d}_{mn} = \frac{p\omega}{\pi^2}\int_0^{\frac{2\pi}{p}}\int_0^{\frac{2\pi}{\omega}} \sigma_r \sin(mp\varphi)\sin(n\omega t)\mathrm{d}\varphi\mathrm{d}t \tag{9}$$

are integrated from step to step and λ_{mn} is given by

$$\lambda_{mn} = \begin{cases} \dfrac{1}{4} & \text{for } m = n = 0 \\ \dfrac{1}{2} & \text{for } m = 0,\ \text{n} > 0 \ \text{ or } \ m > 0, n = 0 \\ 1 & \text{for } \ m > 0,\ n > 0 \end{cases} \tag{10}$$

ω is the fundamental frequency and p the number of pole pairs in the machine. The integer n and m are respectively the order of time and space harmonics of the stress waves.

Equation (8) can be written as

$$\begin{aligned} \sigma_r = \sum_{m=0}^{\infty}\sum_{n=0}^{\infty}\{ \ & \frac{1}{2}\lambda_{mn}\left\{(\mathrm{a}_{mn} + \mathrm{d}_{mn})^2 + (\mathrm{b}_{mn} - \mathrm{c}_{mn})^2\right\}^{\frac{1}{2}} \cdot \cos(-mp\varphi + n\omega t + \gamma_+) + \\ & \frac{1}{2}\lambda_{mn}\left\{(\mathrm{a}_{mn} - \mathrm{d}_{mn})^2 + (\mathrm{b}_{mn} + \mathrm{c}_{mn})^2\right\}^{\frac{1}{2}} \cdot \cos(mp\varphi + n\omega t + \gamma_-) \ \} \end{aligned} \tag{11}$$

so that it can be interpreted as stress waves of different wave lengths rotating in either the same direction as the rotor (forward) or opposite direction (backward) with different speeds or frequencies. The spatial order m of these waves defines the spatial harmonic of the stress wave, whereas the time order n determines the corresponding frequency. In order to compare the healthy and faulty condition, the normalised stress difference is defined for every spatial harmonic,

$$\textit{Normalised stress difference} = \frac{\textit{Stress in faulty condition} - \textit{Stress in healthy condition}}{\textit{Maximum value of stress per spatial harmonic}} \tag{12}$$

This normalised value allows the comparison between the healthy and faulty condition for each spatial harmonic. It shows the dominant frequency components of the stress for a given spatial harmonic when the motor is operating under fault.

The presented FEM analysis and decomposition of electromagnetic stress into rotating waves showed the existence of remarkable changes in the amplitudes of the individual spatial harmonic during electric fault events. Hence, the following hypothesis was stated: these stress waves acting on the stator core will cause it to vibrate at their own frequencies. Therefore, the vibration pattern will contain frequency components characteristic of every fault.

2.2 Matlab/Simulink® analysis and simulation tool

Throughout all the research, Matlab/Simulink® environment has been the fundamental tool for analysing the simulated and measured data. This software provides a flexible way of introducing the data to be analysed. It also provides a set of powerful functions that allow the analysis of the signal in the time and frequency domain in an easy way. In this research work, it has been extensively used for analysing the signals and for creating models able to simulate online condition-monitoring systems.

2.3 Fuzzy logic

In a classical mathematical set, one thing must be either asserted or denied. This means that everything falls into one group or the other. Meanwhile, in fuzzy logic, the truth of any statement becomes a matter of degree; any statement can be fuzzy. In fact, fuzzy logic is reminiscent of human thinking processes and natural language, enabling decisions to be made based on vague information.

The fuzzy logic approach may help to diagnose induction motor faults because experienced engineers are usually required to interpret inconclusive data. The concept of fuzzy logic was introduced by Professor Lofti A. Zadeh to present vagueness in linguistic terms and express human knowledge in a natural way (Zadeh 1965). The first work in the industrial application of fuzzy logic was carried out for Mandani (Gao 1999).

In general, fuzzy systems are suitable for uncertain or approximate reasoning, especially for those systems that are non-linear and for which a mathematical model is difficult to derive. Fuzzy logic bases its decisions on inputs in the form of linguistic variables derived from membership functions, which are formulated to determine the fuzzy set on which a value belongs and the degree of membership in that set. Then, the variables are matched with the pre-conditions of linguistic IF-THEN rules and the response of each rule is obtained through fuzzy implication. The membership functions and rules are defined by studying the human-operated system and then testing the design for proper output.

During fault diagnosis, there are several situations in which an object is not obviously “good” or “bad” but may fall into some intermediate range. From the point of view that sees induction motor condition as a fuzzy concept, there have been some fuzzy logic approaches for diagnosis (Mishra et al. 1998, Fillippeti et al. 2000 and Benbouzid & Nejari 2001). The major inconvenience is the lack of a good processing of fuzzy input data. Even if the linguistic rules are more suitable than the crisp ones for describing the inexact nature of a real machine, it is important that the type and number of membership functions be initially selected using a large database of experimental data or simulated data.

Fuzzy logic has been chosen because it has proven to have the ability of mimicking human decisions. The design of fuzzy controllers is based on the operator’s understanding of the behaviour of the process instead of detailed mathematical models. One main advantage of this approach is that it is easy to implement on the basis of experiences and heuristics. The drawback comes from the fact that it is difficult to automate the design process. Nevertheless, there are a few guidelines for deriving the control rules (Mishra et al. 1998). Rules can be derived from several bases, including the following:

- The expert’s experience and experimental data for the system under consideration,
- The fuzzy model of the process,
- Observation of the operator’s control actions,
- Learning algorithms.

In this research work, fuzzy logic has been used to make decisions about the stator condition and the first method has been adopted. The fuzzy system compares the RMS of the phase current online and it is based on a set of rules that decides the stator condition. The set of rules compiles certain machine knowledge, allowing decisions to be made without direct load information. The fuzzy system behaves like a technician with an ammeter, who is able to gauge to some degree the condition of the motor.

2.4 Discrete Wavelet Transform

For many years, FFT has been used for signal processing of the stator current, as it is suitable for the study of a wide range of signals. Nevertheless, it only allows the extraction of the frequency content of a signal, eliminating the information concerning time-localization of the frequency components. STFFT is better in this aspect, but implies some constraints regarding the selection of the optimum window size for data analysis. To overcome the previous shortcomings, the wavelet theory was introduced as a tool for analysing signals with frequency spectrum varying in time. It allows a time-localization of the frequency components occurring within the signal, being able to extract their time evolution. This property makes possible the detection of characteristic patterns within the evolution of those components, which can be related to the occurrence of certain phenomena.

The DWT performs the decomposition of a sampled signal $s(t)$ $(s_1, s_2, s_3 ... s_n)$ onto an approximation signal at a certain decomposition level n ($a_n(t)$) and n detail signals (d_j (t) with j varying from 1 to n). Each signal is the product of the corresponding coefficients (approximation coefficients for a_n and wavelet coefficients for d_j) and the scaling function or the wavelet function at each level, respectively. The signal then can be approximated (Burrus et al. 1998)

$$s(t) = \sum_{i=1}^{n} \alpha_i^n \cdot \varphi_i^n + \sum_{j=1}^{n} \sum_{i=1}^{n} \beta_i^j \cdot \psi_i^j(t) = a_n + d_n + ... + d_1 \tag{13}$$

where α_i^n, β_i^j are the scaling and wavelet coefficients, respectively, $\varphi^n(t)$, $\psi^j(t)$ are the scaling function at level n and wavelet function at level j, respectively, and n is the decomposition level. a_n is the approximation signal at level n and d_j is the detail signal at level j (Burrus et al. 1998).

The practical procedure for the application of DWT is known as Mallat's algorithm or Subband coding algorithm; the approximation signal behaves as a low-pass filter whereas each wavelet signal behaves as a pass-band filter, extracting the time evolution of the components of the original signal included within its corresponding frequency band (Burrus et al. 1998). Figure 2 shows the subband coding algorithm regarding the coefficients of the transform at the different levels according to the description by (Polikar et al. 1998). Beside the length of those coefficients, frequency content at each level is shown, considering an original signal with n=512 samples and sampling frequency of f_s. It is shown how the original sampled signal $S[n]$ is passed firstly through a half-band high-pass filter $g[n]$ and a low-pass filter $h[n]$.

According to Nyquist criterion for sampling, a downsampling by two can be performed, obtaining, for successive levels, half the number of samples of the previous level. These coefficients, multiplied by the scaling function or the wavelet function at each level (which depends on the selected mother wavelet) give the approximation and detail signals at the different levels. The analysis of these signals is the basis of the proposed method.

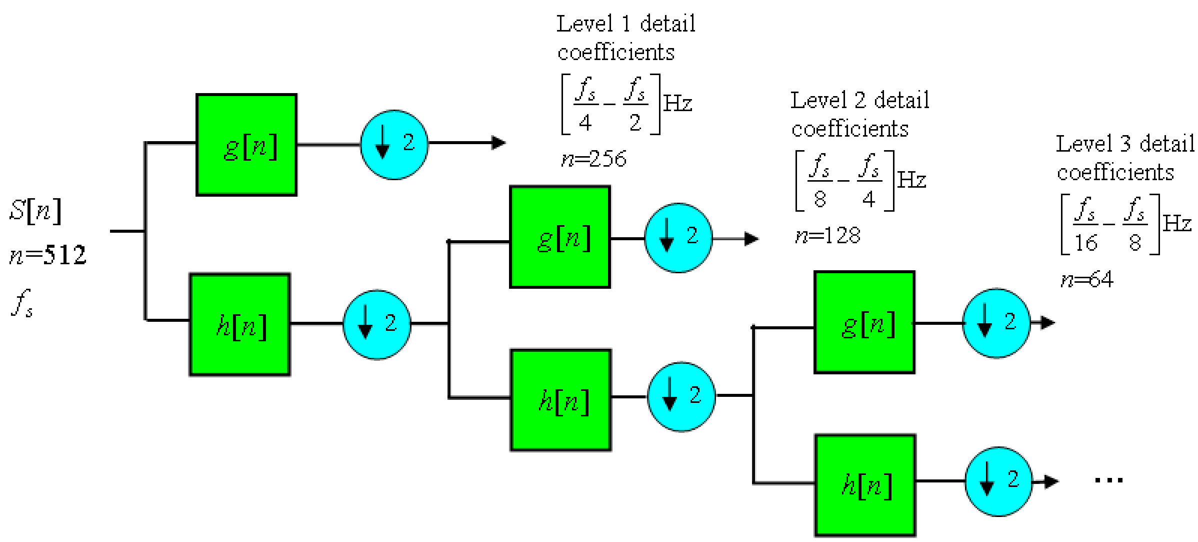

Figure 2. The subband coding algorithm.

If f_s is the sampling rate used for capturing *s(t)*, the detail d_j contains the information concerning the signal components whose frequencies are included in the interval $[2^{-(j+1)} f_s,\ 2^{-j} f_s]$. The approximation signal a_n includes the low-frequency components of the signal, belonging to the interval $[0,\ 2^{-(n+1)} f_s]$.

This filtering process performed in the DWT is shown in Figure 3. Nevertheless, as can be seen in that figure, there is a certain overlap between bands due to the non-ideal characteristic of the wavelet filters, raising the problem of aliasing between bands as was stated by (Tarasiuk 2004). That is, when DWT subbands are subsampled by a factor of two, according to the Mallat algorithm, the Nyquist criterion is violated and frequency components above or below the cut-off frequency of the filter are aliased into the wrong subband. This phenomenon causes what is known as shift-variance, as was explained by (Bradley & Willson 2004).

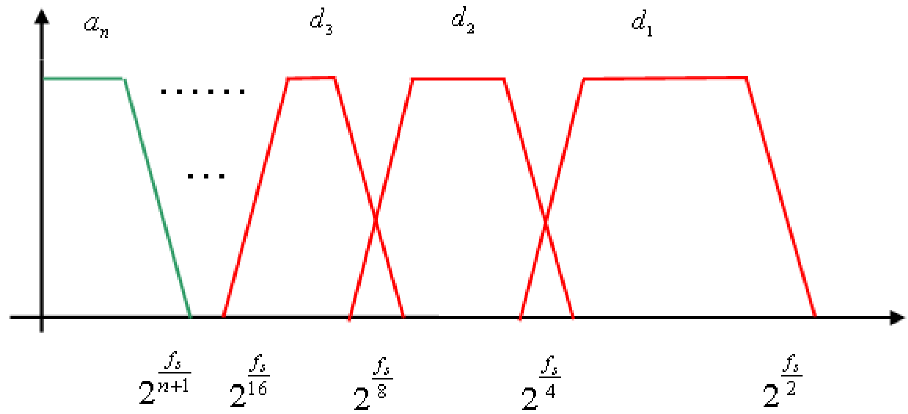

Figure 3. Filtering performed with Mallat algorithm (DWT).

For the approach presented in this research, the application of the DWT to the start-up stator current is proposed. Resulting from the DWT decomposition, a set of wavelet signals (approximation and details) is obtained. Each one of those signals contains the time evolution of the components within the original current signal that are included within its corresponding frequency band, according to the band expressions shown above. The analysis of those signals can allow the detection of some patterns caused by the evolution of the components associated with the fault. For the analyses performed, Daubechies 44 has been employed, although other types of wavelet families also provide satisfactory results. The use of such a high-order wavelet is justified by the decrease in the overlap between bands (Antonino-Daviu 2006b).

2.5 Mechanical model

The mechanical model was developed on the basis of the following assumptions. The rotor is supported with flexible bearings, and the stator is connected through a certain stiffness to the foundation. Moreover, there is a certain stiffness between the rotor and foundation, as can be seen in Figure 4. The rotor and stator are considered rigid bodies. The electromagnetic forces are acting between the centres of the bodies and both bodies are allowed to rotate around an imaginary pivot point.

From the vibration point of view, the stator of an electrical machine can be modelled as a system consisting of a number of masses interconnected by springs. However, the distribution of masses and stiffness, which is essential for the calculation of resonance, is somewhat difficult to derive from a realistic point of view. In this model, neither the damping factors present in the real motor nor the torque that produces rotor rotation are considered.

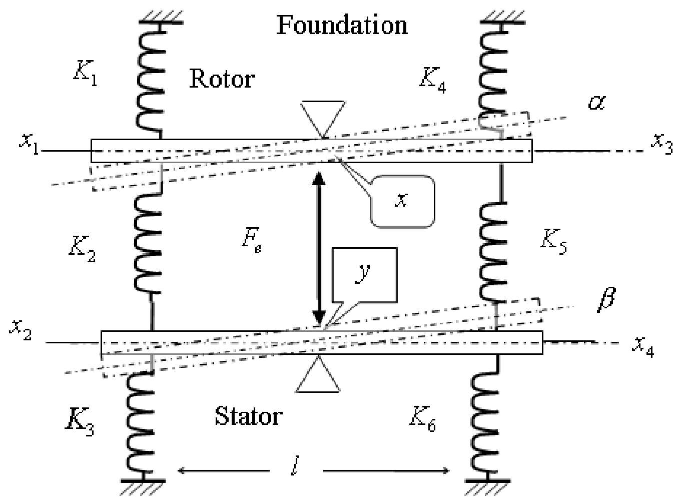

Figure 4. Mechanical model.

Applying Newton's second law from the equilibrium of forces acting in the system we have

$$-K_1x_1 + K_2(x_2 - x_1) - K_4x_3 + K_5(x_4 - x_3) - F_e = m_r \ddot{x} \tag{14}$$

$$K_2(x_1 - x_2) - K_3x_2 + K_5(x_3 - x_4) - K_6x_4 + F_e = m_s \ddot{y} \tag{15}$$

$$-[-K_1x + K_2(x_2 - x_1)]\frac{l}{2} + [-K_4x_3 + K_5(x_4 - x_3)]\frac{l}{2} = I_r \ddot{\alpha} \tag{16}$$

$$-[K_2(x_1 - x_2) - K_3x_2]\frac{l}{2} + [K_5(x_3 - x_4) - K_6x_4]\frac{l}{2} = I_s \ddot{\beta} \tag{17}$$

Where, $K_1, K_2, K_3, K_4, K_5, K_6$ are stiffnesses, m_r, m_s the rotor and stator masses, F_e the electromagnetic force and I_s, I_r the stator and rotor moments of inertia, respectively. For small displacements and angles, the following approximations hold

$$x_3 - x_1 = l\sin\alpha \approx l\alpha \tag{18}$$

$$x_4 - x_2 = l\sin\beta \approx l\beta \tag{19}$$

$$x = \frac{1}{2}(x_1 + x_2) \tag{20}$$

$$y = \frac{1}{2}(x_2 + x_4) \tag{21}$$

Thus, the system of differential equation is rewritten as follows

$$\frac{2}{m_{\mathrm{r}}}[x_1(-K_1-K_2)+K_2x_2+x_3(-K_4-K_5)+x_4K_5-F_e]-\ddot{x}_2=\ddot{x}_1 \tag{22}$$

$$\frac{2}{m_{\mathrm{s}}}[x_1K_2+x_2(-K_2-K_3)+x_3(K_5)+x_4(-K_5-K_6)+F_e]-\ddot{x}_4=\ddot{x}_2 \tag{23}$$

$$\frac{l^2}{2I_{\mathrm{r}}}[x_1(-K_1+K_2)+x_2(-K_2)+x_3(-K_4-K_5)+x_4K_5]+\ddot{x}_1=\ddot{x}_3 \tag{24}$$

$$\frac{l^2}{2I_{\mathrm{s}}}[-K_2x_1+x_2(K_2+K_3)+x_3K_5-x_4(-K_5-K_6)]+\ddot{x}_2=\ddot{x}_4 \tag{25}$$

A Matlab/Simulink® model is built to represent the system of differential equations. The flow chart of the simulation system is shown in Figure 5.

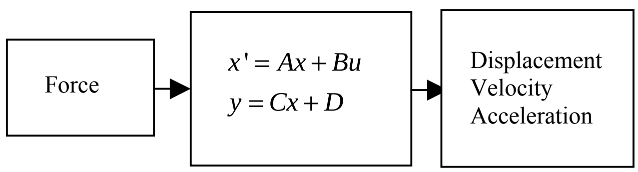

Figure 5. Block diagram of the simulation setup.

2.6 Hybrid model

The hybrid model consists of the calculation of the transfer function of the system (accelerance) by the division between the measured acceleration and the calculated electromagnetic forces in FEM. The model is called hybrid due to the use of two types of data: measured and calculated. In this case, in order to obtain a good match between simulated forces and measured vibrations, the voltage measured in the inverter output is fed to the FEM program. From the fact that vibrations are periodic movement because periodic electromagnetic forces originate them, the frequency response function accelerance of the system can be computed from (Ewins 2000).

$$H(s_k)=\frac{A(s_k)}{F(s_k)} \tag{26}$$

where:

$A(s_k)$ is the discrete FFT of the measured vibration acceleration,

$F(s_k)$ is the discrete FFT of the calculated electromagnetic forces.

Both the time-domain-measured acceleration and the calculated force from FEM were sampled with equal sampling time (25 μs) and the data set with the same number of samples (20 000), keeping for both sets of data the same frequency resolution. The electromagnetic forces are calculated for the cases of broken rotor bars and inter-turn short circuits.

2.7 Measurements

During the research work, the author and his team-mates carried out several measurements of a 35 kW cage induction motor. Various faults were generated in an artificial way, broken rotor bars, broken end ring, inter-turn short circuit, static, dynamic and mixed eccentricity and bearing faults. Different search coils were also constructed and located in different parts of the motor in order to discover, in an experimental way, the search coil most satisfactory to monitor faults. Thus, great amounts of valuable data were collected.

A frequency converter Vacon 90CX4A00 was used to feed the motor. The converter technical data are shown in Appendix II. Voltages, current and vibration measurements were carried out. The registration of measurements was made with a Kontron Transient Recorder WW700. This device is a transient recorder based on an MS DOS AT computer. It is able to store the measured data in its hard disk. The amplitude resolution is 12 bits. The sampling frequency and size of the data file can be chosen. Figure 6 shows a block diagram of the measurement setup.

The motor currents were measured through Hall sensors (LEM) and the values read in the transient recorder. A Norma Wide Band Power Analyzer D 6110 was used in order to monitor the current, voltage, power and frequency during the measuring process. The voltage was measured in the transient recorder through a Sony Tectronik A 6907 isolator. Five piezoelectric acceleration sensors took the vibration measurements; they were located in different parts of the motor. Charge amplifiers amplified the signals from the sensors and the transient recorder registered the amplified outputs. A modal testing was also carried out; details can be seen in Publication 8. The magnetising current in the D.C. generator was controlled using an autotransformer, controlling the induction motor load. The measurements were carried out at different frequencies and under three different load conditions. Figure 7 shows a photograph of the induction motor and D.C. generator under study. Figure 8 shows the measurement devices.

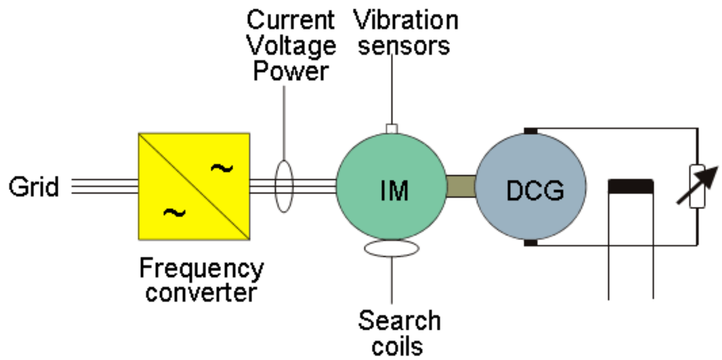

Figure 6. Block diagram of the measurement setup.

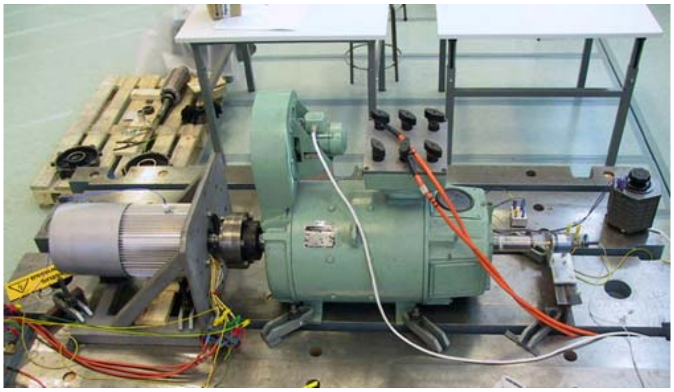

Figure 7. Induction motor and D.C. generator.

Figure 8. Measurement devices.

3 Results

In this chapter, the most relevant results are presented.

3.1 Detection of stator winding fault using fuzzy logic

The developed model was implemented in Matlab/Simulink® and tuned with the simulated data. This section presents the results with real measured data. The Matlab/Simulink® model works online with the data, for details see Publication P2. In the measurements as well as in Matlab/Simulink® simulations a sampling frequency of 40 kHz was used. The experimental tests were carried out with the motor in healthy condition and with a real inter-turn short circuit. Data of current were collected at four different frequencies. The test results are shown in Table II, the faulty condition refers to the real inter-turn short circuit. Measurements at full load were not carried out because of some concern whether or not the motor could withstand the short-circuit conditions. The most difficult case to identify might be when there is only one inter-turn short circuit, see Figure 9 and compare with Figure 10. These figures shows measured data.

Table II. Percentage of correct detections. Measured data with inverter supply for the 35 kW motor.

Frequency [Hz]	Load	Detection accuracy [%]	
		Healthy	Faulty
25	No-load	94.7	100
	Half load	97.2	94.4
	Full load	96.3	--
50	No-load	94.7	100
	Half load	96	100
	Full load	97.3	--
75	No-load	100	100
	Half load	100	100
	Full load	100	--
100	No-load	100	100
	Half load	100	100
	Full load	100	--

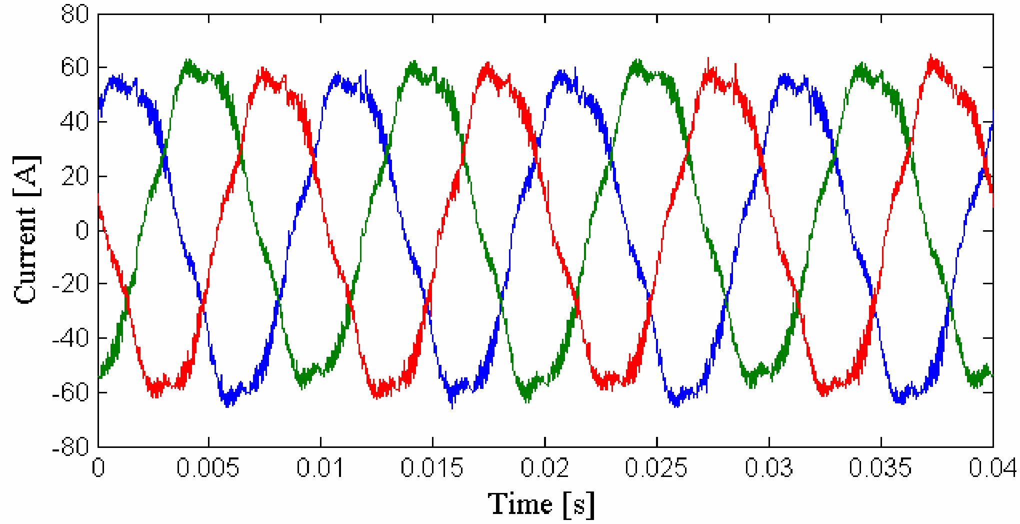

Fig. 9. Terminal phase currents in a healthy motor. Inverter-fed motor at 100 Hz.

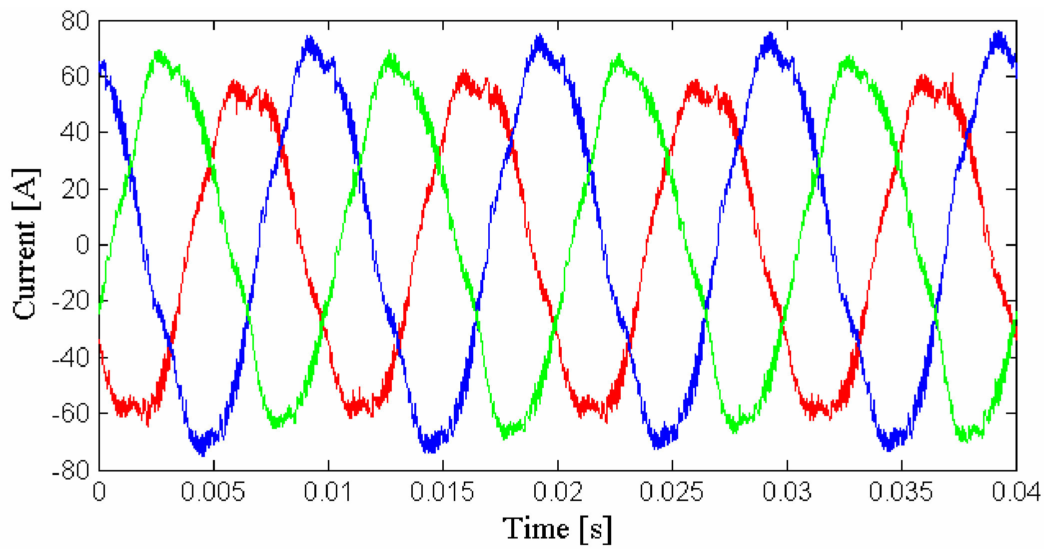

Fig. 10. Terminal phase currents in a faulty motor during an inter-turn short circuit. Inverter-fed motor at 100 Hz.

3.2 Online technique for the detection of eccentricity

A Matlab/Simulink® model was implemented to test the developed system. The details are presented in Publication 4. The model was tested with both data from FEM motor simulation program and real measurements. The sampling frequency in both data was 40 kHz. The model is working online with the data. The RMS value of the difference current is calculated every 50 ms.

The results of the simulations can be seen in Figure 11 for the case of simulated data and Figure 12 for the case of measured data. The RMS value allows one to know the eccentric condition.

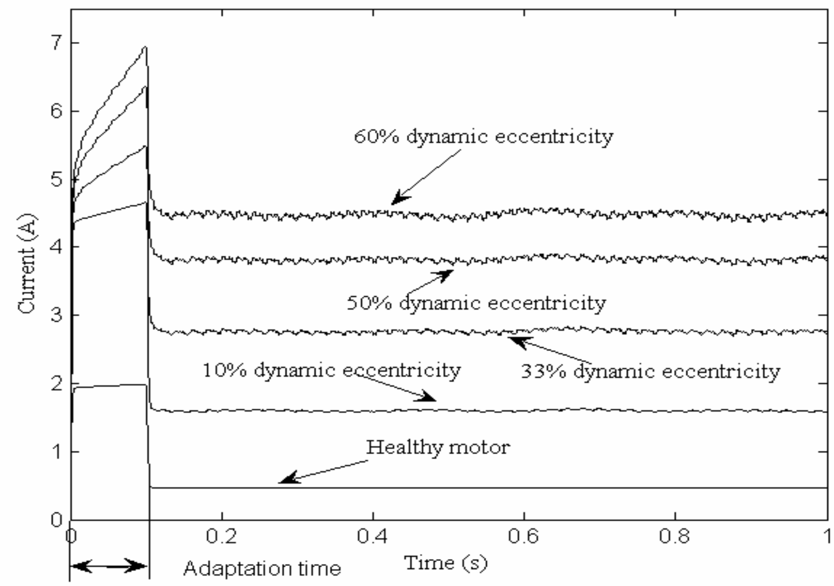

Figure 11. RMS of the difference current. Simulated data at full-load condition. Sinusoidal supply at 100 Hz.

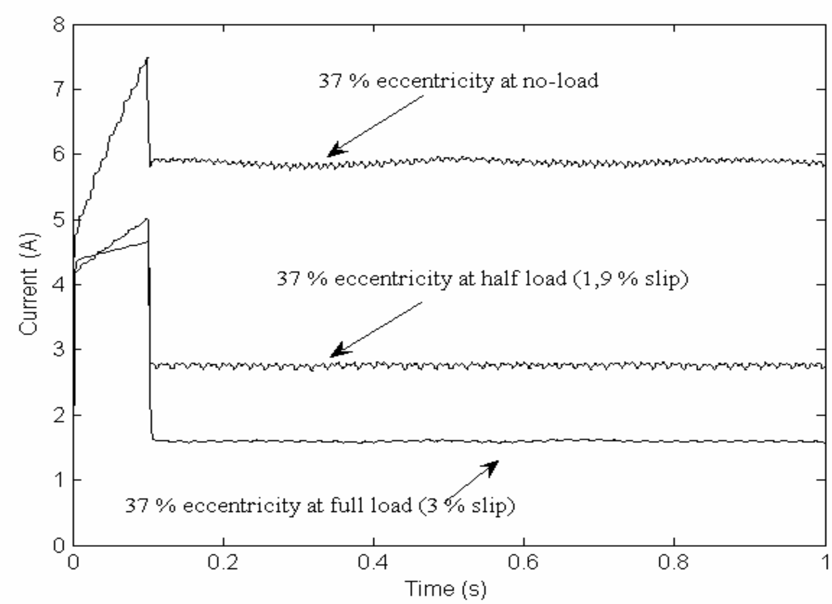

Figure 12. RMS of the difference current. Measured data for the motor working with 37% dynamic eccentricity. Sinusoidal supply at 100 Hz.

3.3 Detection of faults during start-up transient by DWT

Figures 13 to 16 show the ability of the DWT to discriminate between healthy, broken bars and eccentric conditions, for more details see Publication 5. They show the decomposition of the stator start-up current for each considered case. At the top of each figure, the start-up current is plotted. Beneath, the approximation signal a_n at the corresponding decomposition level is displayed. Below, the high-level detail signals d_j are shown. The frequency bands associated with each wavelet signal resulting from the decomposition are displayed right beside each signal.

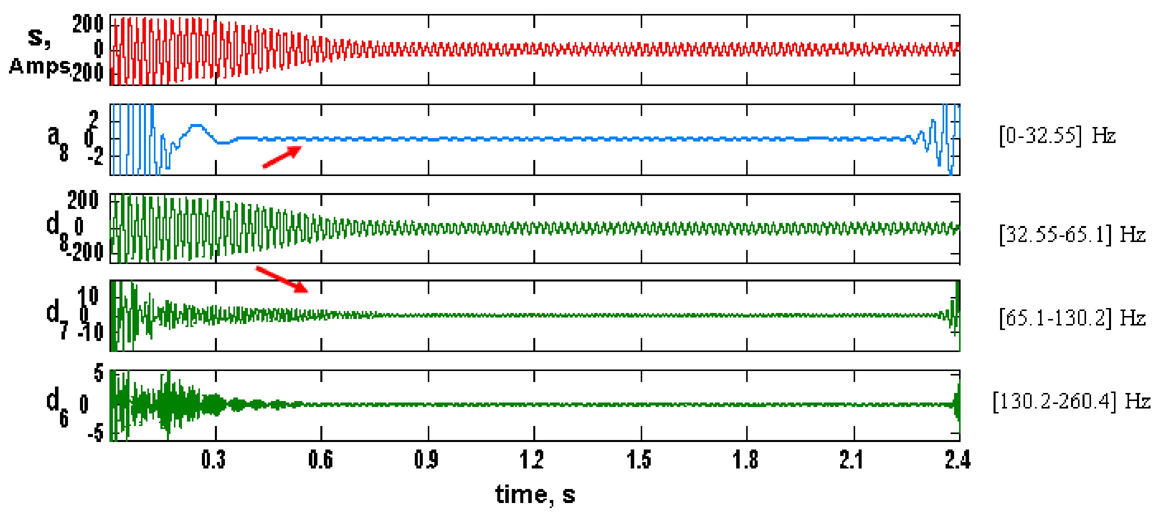

Figure 13. DWT of the simulated start-up current for the healthy machine in unloaded condition (inertia=1 kgm², 200 V, 50 Hz).

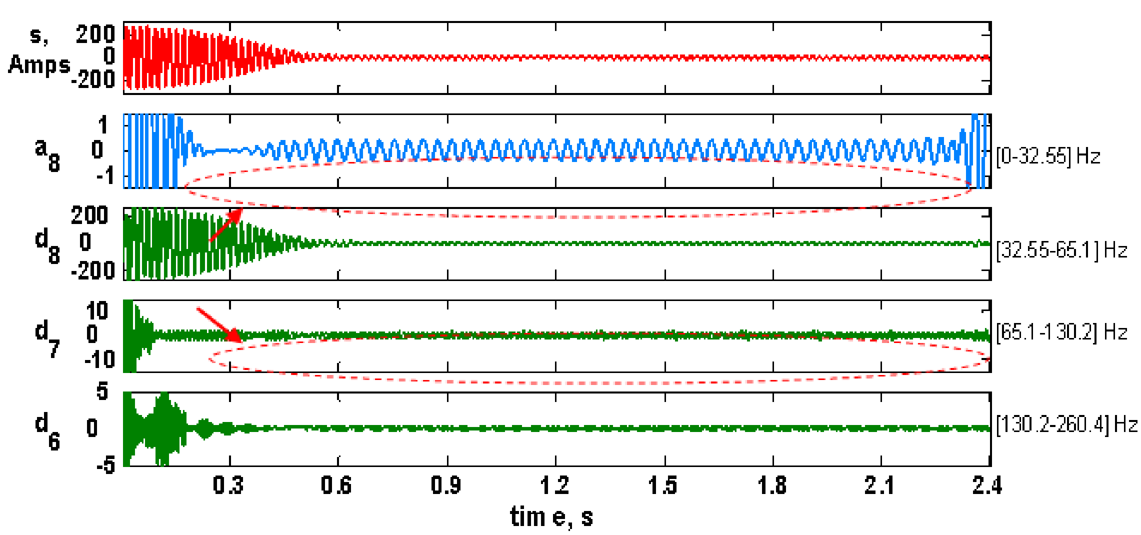

Figure 14. DWT of the simulated start-up current for the machine in unloaded condition with 10% eccentricity (inertia=1 kgm², 200 V, 50 Hz).

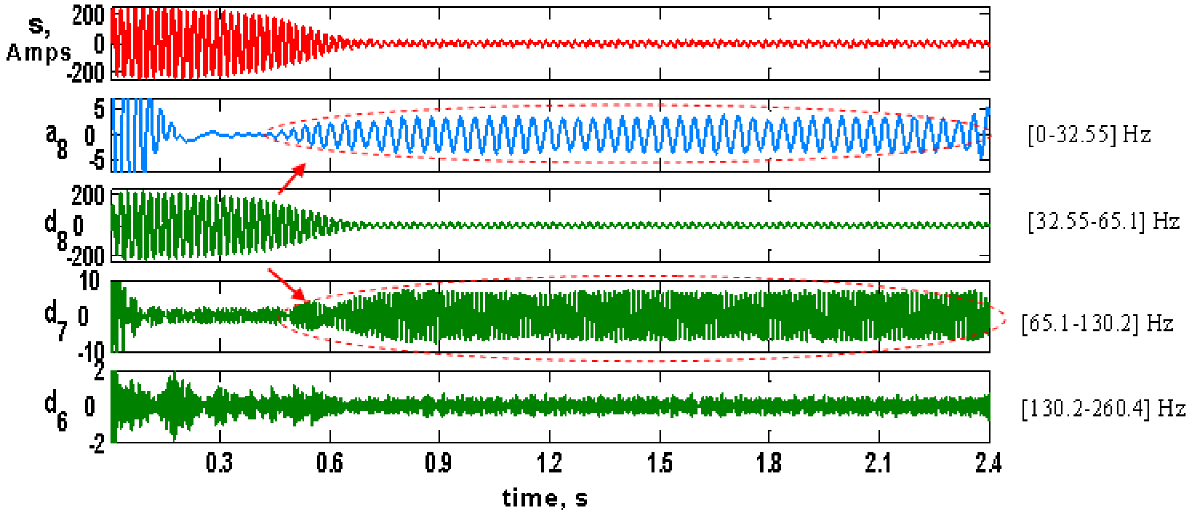

Figure 15. DWT of the experimental start-up current for the unloaded machine with 37% of dynamic eccentricity (200 V, 50Hz).

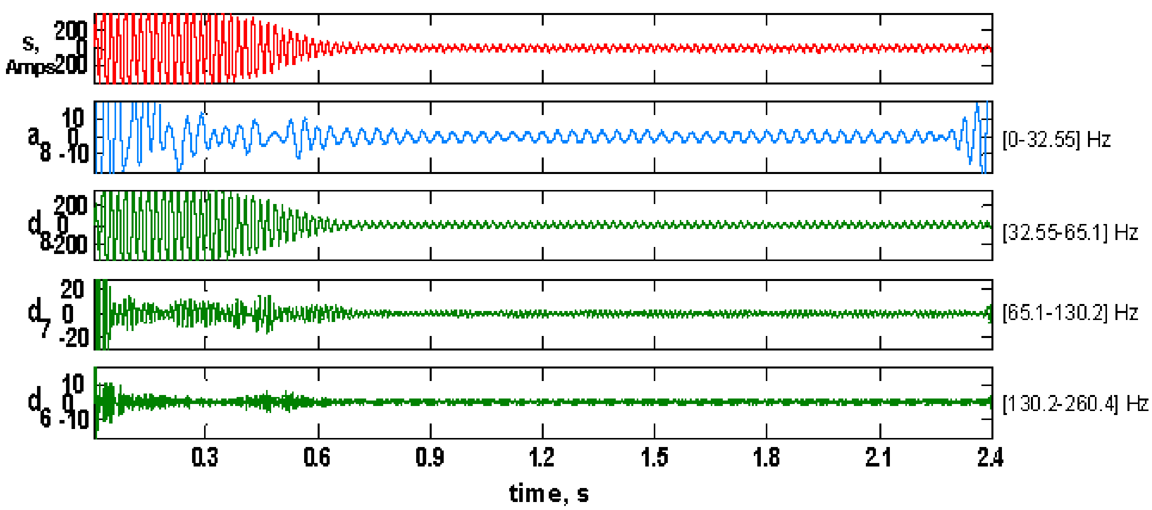

Figure. 16. DWT of the experimental start-up current for the unloaded machine with one broken rotor bar (200 V, 50Hz).

3.4 Calculated radial force

Publication 1 shows the radial forces acting between the rotor and stator as a good indicator of motor faults. These forces are natural indicator of induction motor faults. They are ideally zero in a healthy machine. Figure 17 shows the y-component of the calculated force, following the principle of the virtual work (Equation 4), for different motor conditions. These forces are calculated by evaluating the integral surrounding the rotor at every time step. In Publication 6, these forces are used as input for the mechanical model.

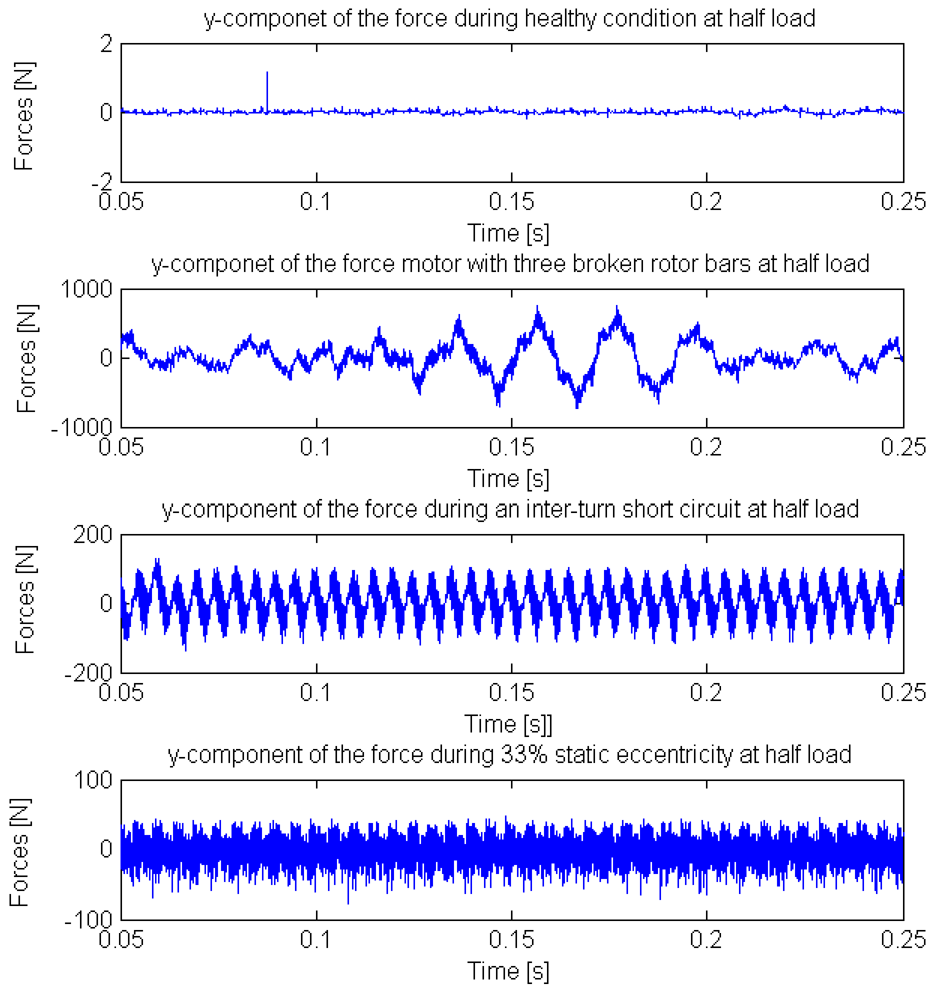

Figure 17. y-component of the radial force for different motor conditions.

3.5 Calculated radial stress and vibration measurements

The simulations are carried out with a fixed time step of 25 μs and the total number of 40 000 steps. The frequency spectra of the stress waves were calculated for every spatial harmonic with a frequency resolution of 1 Hz. Two different motors were analyzed in FEM. Motor I is a four-pole machine and Motor II is a two-pole machine. The FFTs of the vibration measurements were also calculated with a frequency resolution of 1 Hz. For more details see Publication 7 and Publication 8. Figure 18 shows the calculated radial stress for the first spatial harmonic in healthy condition and for a motor working with three broken bars. In the healthy conditions, the first spatial harmonic has no appreciable stress waves.

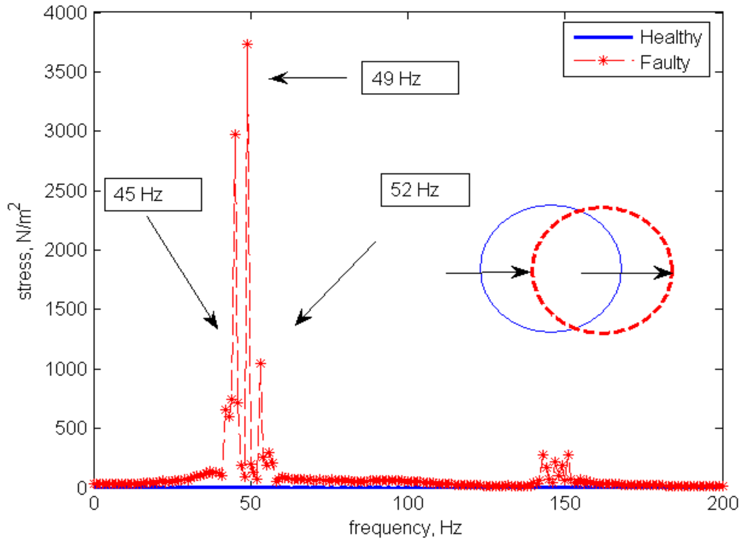

Figure 18. Spectra of the calculated stress for the first spatial harmonic. Motor I, at half load (1,9 % slip). Continuous line denotes healthy operation and discontinuous line three broken bars.

The normalised stress difference (Equation 12) allows the comparison between the healthy and faulty condition for each spatial harmonic. It shows the new prominent frequency components of the stress when the motor is operating under a fault. Figure 19 shows the calculated normalised stress difference for the spatial harmonics 1, 2, 3, 5 and 6 for the case of Motor I working with 33% dynamic eccentricity, at rated slip and voltage supply of 200 V at 50 Hz.

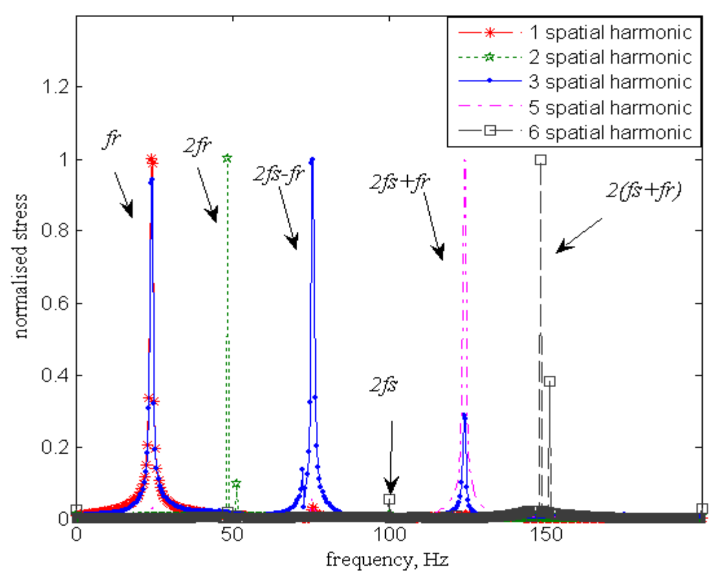

Figure 19. Calculated normalised stress in case of 33 % dynamic eccentricity. Motor I is working at rated slip (3 %), supply at 50 Hz.

Figure 20 and Figure 21 present the behaviour of the stress waves with loading for the cases of broken bars and dynamic eccentricity, respectively. Both cases are for Motor II at 50 Hz supply.

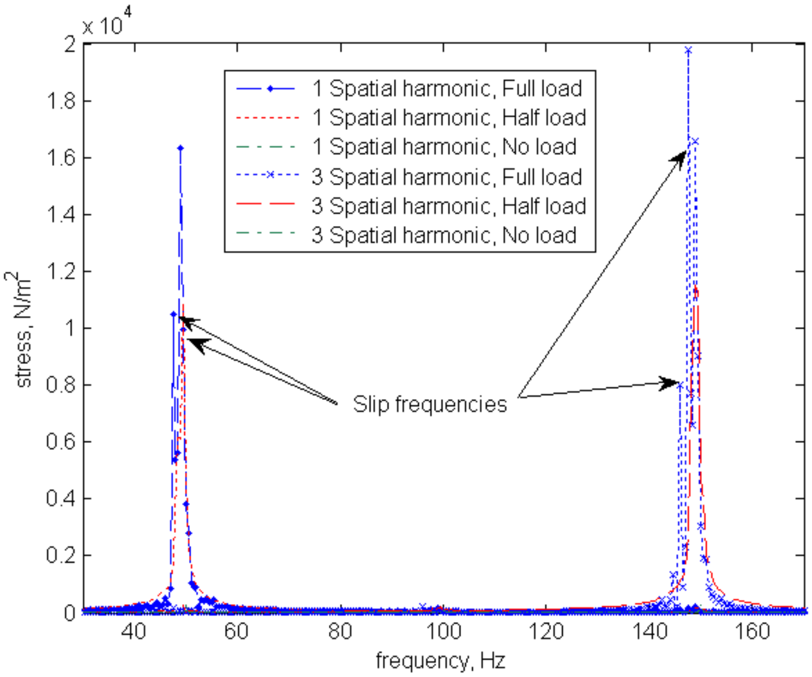

Figure 20. Stress calculated at different load conditions for spatial harmonic 1 and 3. Full load (1,6 % slip), half load (0,8 % slip), no load (0,01 % slip). Motor II with three broken bars.

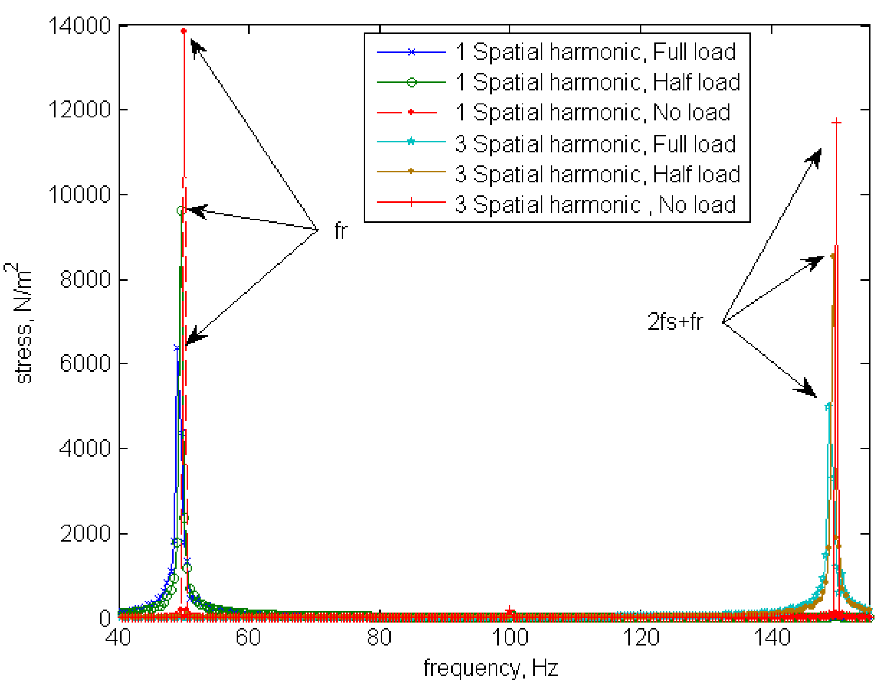

Figure 21. Stress calculated at different load conditions for mode 1 and mode 3. Full load (1,6 % slip), half load (0,9 % slip), no load (0,001 % slip). Motor II with 33 % dynamic eccentricity.

Figure 22 shows the FFT vibration acceleration in the healthy condition and with three broken bars at half load for Motor I. Figure 23 shows the low-frequency spectrum of the same case.

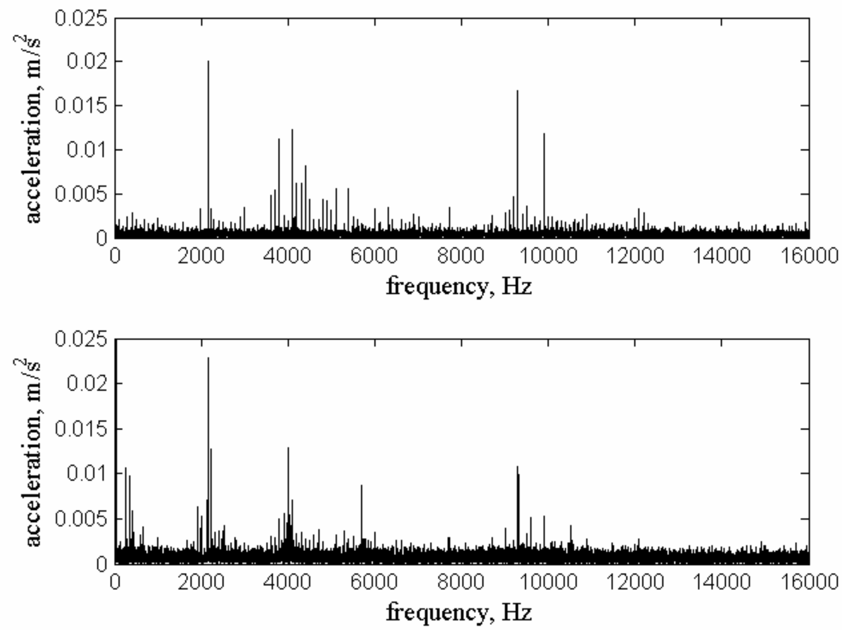

Figure 22. Spectra of the measured vibration acceleration of the motor at half-load operation (1,5 % slip). Healthy motor on the top and motor with three broken rotor bars on the bottom.

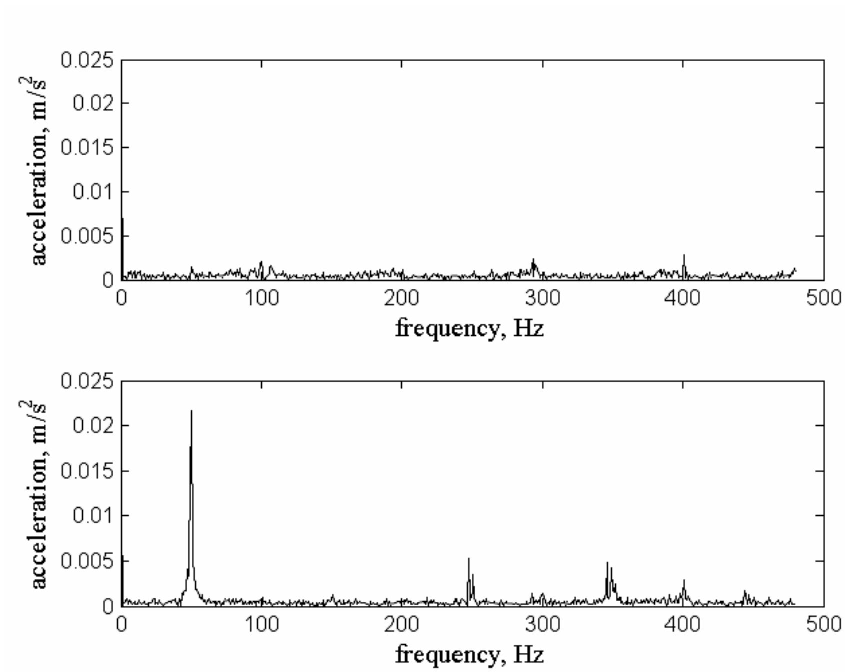

Figure 23. Low-frequency spectra of the measured vibration acceleration of the motor at half-load operation (1,5 % slip). Healthy motor on the top and motor with three broken rotor bars on the bottom.

Figure 24 shows the calculated stress spectra for the relevant mode shapes for Motor I with 37 % dynamic eccentricity. Figure 25 shows the measured vibration acceleration for the same eccentric condition at two loading points.

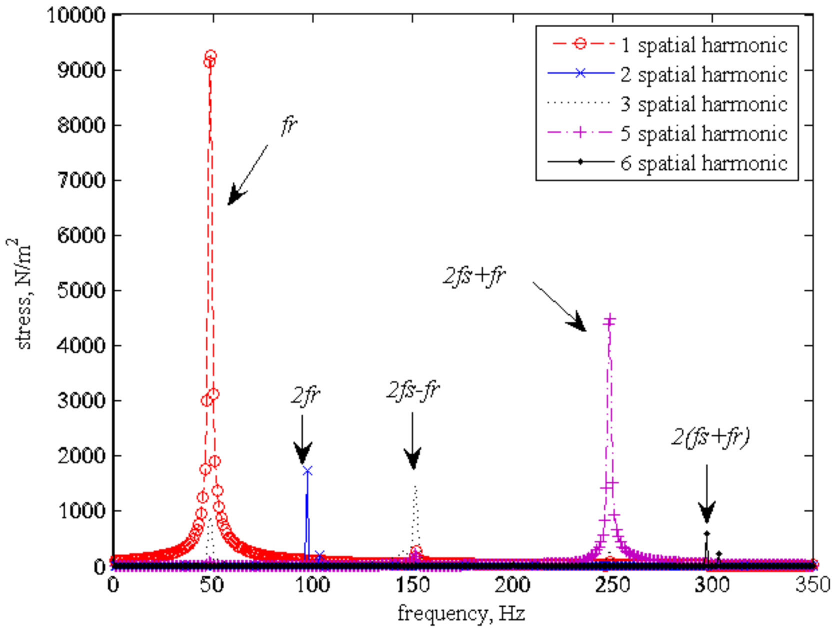

Figure 24. Calculated stress waves amplitudes for the relevant spatial harmonics. Motor I with a 37 % dynamic eccentricity working at half load (1,9 % slip) and supply at 100 Hz.

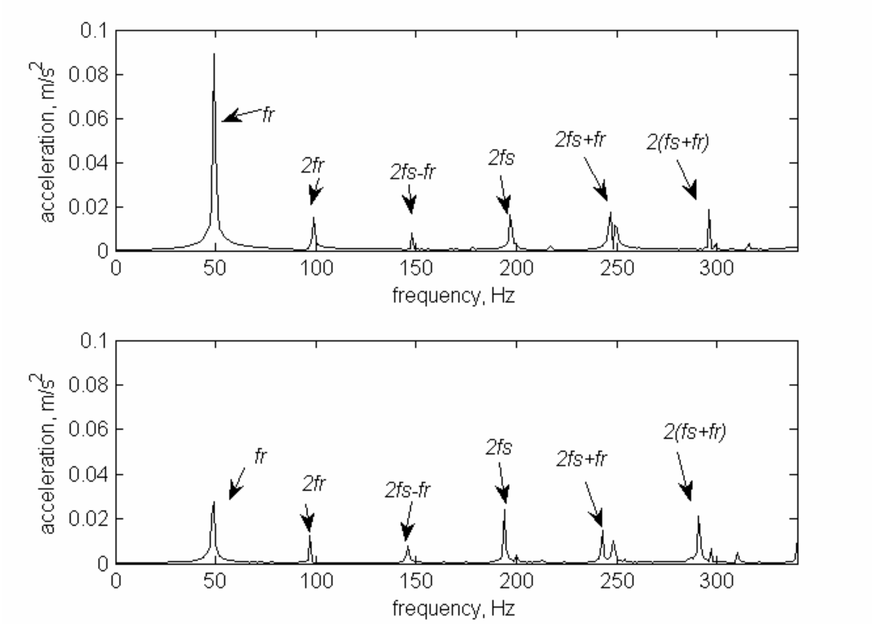

Figure 25. Measured acceleration vibration pattern at two load conditions, Motor I with a 37 % dynamic eccentricity, supply at 100Hz. Upper figure at half load (1,9 % slip), bottom figure at full load (3 % slip).

Based on the results of this study and compiling the results from publications P7 and P8, Table III is proposed for condition monitoring of induction machines. According to Table III, it is possible to discriminate between the most common faults in induction motor through vibration monitoring. New factors are added, which help to discriminate between the faults: the behaviour of the stress waves and vibration with the loading and the prominent spatial harmonic of the stress waves.

Table III. Major changes in the electromagnetic harmonics stress under different electric faults and their proportionality to loading.

Fault Frequency and wave number	Broken bars	Dynamic Eccentricity	Static Eccentricity	Inter-turn Short circuit	Inter-coil Short circuit
Rotational frequency (f_r) Wave number 1	xxx	xxx	---	xx	xx
Odd multiples of the rotational speed and sidebands, odd wave numbers	xxx	---	---	---	---
Twice the supply frequency ($2f_s$). Wave numbers $(2p+1),(2p-1)$.	---	---	xxx	---	---
Frequencies ($2nf_s$), Even wave number	---	---	---	xxx	xxx
$2f_r$, Wave number 2 $2f_s - f_r$, $(2p-1)$ $2f_s + f_r$, $(2p+1)$ $2(f_s - f_r)$, $(2p-1)$ $2(f_s + f_r)$, $2(p+1)$	--	xxx	--	--	---
Stress amplitude with loading	Proportionally	Inversely	Hardly change	Proportionally	Hardly change

"xxx" Large change
"xx" Moderate change
"x" Small change
"--" No change

4 Discussion

4.1 Fuzzy logic

Firstly, it was intended to overcome the shortcomings of the traditional MCSA, which is not powerful enough to detect stator faults. Instead of using this kind of analysis, a simple fuzzy system monitoring the amplitude of the motor current was developed and tested. This application for the detection of the stator condition was extended and tested with real data in variable frequency, showing a good accurate detection rate, as can be seen in Table II. It is important to emphasize that, in the case of stator faults in induction machines, the most important fault to be detected is a primary inter-turn short circuit (the fault at an early stage, as it is shown Figure 10). Detecting this at an early stage would avoid the total destruction of the stator winding. Table II refers to detection of this relevant fault.

Such a fuzzy system corresponds to a well-known knowledge-based system where certain knowledge of the machine is described by linguistic terms. In this application, the fuzzy system was enhanced by the use of FEM while building the membership functions. By the use of FEM, reliable motor data was generated while the motor was working under healthy and faulty conditions. Such a data saves time and money in comparison with repeated experiments. This work showed a perfect fusion between a hard computing and a soft computing technique, allowing the building of a system with high reliability.

The fuzzy system showed a better detection rate than another encountered in the literature. It is remarkable that it is able to work in variable frequency and does not need load information. A possible drawback of the method is associated with the fact that a current unbalance originating from the supply source may be identified as a fault condition of the motor. Nevertheless, the system can be extended to cover also the voltage measurements, being able to detect from where the root cause of the unbalance is coming.

Fuzzy logic was used to analyse the data and make decisions in Publication 2 and Publication 3. It proved to be a good option because there is no general and accurate analytical model that describes successfully the induction motor under fault conditions. The system showed in Publication 2 could be implemented in the software of the inverter to monitor the stator condition on line. It is able to work with motors connected in star and delta. Further, it has a short delay time between fault and response. A forward application is in variable speed drives.

4.2 Predictive filtering

A second attempt to improve the traditional technique of MCSA by applying predictive filtering was made (Publication 3 and Publication 4). The predictive filter shows some interesting features that allow to separate out the fundamental component from the harmonics components, allowing the detection of dynamic eccentricity without spectral analysis of the stator current. By removing the main component, we obtain as output the harmonic components, which constitute the useful information for detecting the motor condition. Once we do not have the main component, we just have to calculate the root mean square of the difference current and a simple algorithm detects the motor condition. If the RMS value is bigger than a preset level, the motor is considered damaged, if not, it is considered healthy.

Figure 11 and Figure 12 show the performance of the system with simulated and measured data, respectively. From these figures can be seen how after the adaptation time (0,1 s), the RMS values of the harmonic components are different for every condition, allowing to discriminate and quantify the eccentric condition. Obaid et al. (2000) presented a similar system to detect mechanical faults using a 60 Hz notch filter. However, by introducing the predictive filter, the system is able to work in variable frequency, following automatically the frequency variation in the power supply (Vainio & Ovaska 1997).

4.3 Discrete wavelet transform

A third promising technique applied during this investigation is the DWT, which shows to be a powerful tool in condition monitoring. The DWT is an ideal tool to study signals, whose frequency spectrum varies in time, allowing a time-frequency decomposition of the signal to be studied. The application of this tool allowed some of the drawbacks of the traditional steady-state analysis to be avoided. For the case of dynamic eccentricity, a characteristic pattern can be detected during the start-up, see Figure 14 and compare with Figure 13.

The pattern shown in Figure 14 is provoked by the evolution of two components associated with the eccentricity within the wavelet signals adjacent to that containing the fundamental frequency. This pattern brings a qualitative way for detecting the presence of the fault, since it is completely different from that caused by other faults such as broken bars (see Figure 16) or by other phenomena. In addition, the relative increment in the energy of the wavelet signals through which the two components evolve can be used as a quantitative indicator of the degree of severity of the fault. A prominent distinctive pattern is shown in Figure 15 for the case of measured data with a real 37% dynamic eccentricity.

The method provides some advantages with respect to the classical approach: it allows the discrimination between the eccentricity fault and the bar breakages due to the different patterns produced by these two faults on the high-level wavelet signals. This discrimination is not always possible with the classical Fourier approach as can be seen in Publication 5, Figure 11b and Figure 12. This shortcoming is also described by (Benbouzid 2000).

Moreover, the introduction in the Fourier spectrum of frequencies similar to those caused by the eccentricity when there are load torque oscillations, may lead to a wrong diagnosis of the fault as is observable in Publication 5, Figure 11b and Figure 13. This phenomenon is also mentioned by (Obaid et al. 2000). Similarly, it could also happen during voltage fluctuations (Benbouzid, 2000). With the DWT method, this is avoided since the oscillations arising in the wavelet signals due to the above mentioned phenomena, do not follow the pattern associated with the eccentricity fault.

The results show the usefulness of the DWT for detecting some of the most common faults that could appear in induction machines, which can constitute the basis for the implementation of reliable condition monitoring systems. The strength of DWT is given by the fact that it provides a time-frequency decomposition, being possible to locate not only the frequencies which occur (as FFT does) but when they take place and how evolve. Its usefulness in detecting inter-turn short circuit during start-up is shown in (Antonino-Daviu et al. 2006c). DWT could also be applied when the machine is working in steady state in order to detect any unexpectedly transient that might occur. This is an interesting topic to investigate, which is recommended for future work.

4.4 Fault indicators

During this research work, intensive studies of different fault indicators were carried out, arriving at the conclusion that the electromagnetic forces and the circulating currents in parallel windings are good indicators of motor faults (Publication 1). The circulating currents can be used as fault indicators in those machines with parallel branches. It was also demonstrated with the application of SVM, from both simulated and measured data that the circulating current are more sensitive to fault conditions than the total stator current. This result can be seen by comparing Tables II, III, and IV of Publication 1. From these tables is also visible how the forces are the top indicator of motor faults.

The main drawback of the circulating currents is given by the fact that they are not reachable in standard machines. Thus, accessibility is a severe limitation of this indicator. Moreover, relying on this indicator appears difficult to discriminate between different faults (Negrea 2006).

In an ideal symmetric machine, the total radial force is zero. However, when there is a fault event these forces increase appreciably as can be seen in Figure 17. From this figure a distinctive pattern for every fault is observable, which in turn should produce a distinctive vibration pattern. As the electromagnetic forces acting between the rotor and the stator are difficult to measure, a mechanical model in the Matlab/Simulink® environment was built to study induction motor vibration behaviour (Publication 6). This model could be the foundation for a more complex model that takes into account the rotor rotation, damping factor and the gyroscopic phenomena. This model shows that the radial forces during faults events are able to produce forced vibration in the stator and rotor of the machine, see Publication 6, Figure 6. An achievement with this model is the possibility of coupling the calculated forces in FEM with a simple analytical model.

In addition, a hybrid model was implemented, from which it is possible to predict the frequencies to be excited during a fault condition. The hybrid model is a new idea and, possibly, it might provide a way of calculating the transfer functions of the complex rotating electrical machines. It allows insight into the remarkable effects of the forces in the vibration pattern. The hybrid model seems to be a better option than a simple analytical mechanical model. Such a hybrid model is able to predict the frequency components to be monitored with higher accuracy.

4.5 Signatures of faults in the stress distribution

By comparing the healthy stress pattern and the faulty one, an increase in the amplitude of some specific components of the stress can be observed when the motor is working under an electrical fault, see Figure 18. The effects in the vibration pattern of these low-frequency components can be used as signatures for the detection of faults in induction motors, which are clearly easier to identify than the twice supply frequency component presented in some literature as a signature for the detection of electrical fault (Finley et al. 2000). In Figure 18 can be seen the stress components, whose frequencies depend on the rotor slip for the case of broken bars. This result is in agreement with a FEM calculation carried out by (Jang & Park 2003). However, they did not consider the spatial harmonics of the stress.

The increment of the amplitude of low-order vibrations could be interpreted as an identifiable signature that allows knowing the motor condition, see Figure 22. The motor condition is clearly easier to identify in the low-frequency spectrum because this region is cleaner and far from the natural frequencies of the motor, compare Figure 22 and Figure 23. The first important conclusion is the existence of low-order vibration components, which allow the identification of the motor condition, instead of monitoring slot passing frequencies as is described for the case of eccentricity events by (Cameron et al. 1986 and Nandi et al. 2005).

The presented FE analysis and decomposition of electromagnetic stress into rotating waves showed up the existence of remarkable changes in the amplitudes of the individual stress waves modes during electric fault events. These stress waves acting on the stator core will cause it to vibrate at their same frequencies. Therefore, the stator vibration will contain frequency components characteristics for every fault. This is supported by the fact that neither the natural frequencies of the stator nor those of the whole mechanical system coincide with the predicted frequencies from the simulations and supported by the measurements.

The natural frequencies of the motor stator and mechanical system are obtained throughout modal testing in Publication 8, the first natural frequency of the stator is at 936 Hz and it is associated with circumferential vibration mode “2”. The results of the presented method are verified by measurements on a machine with artificially created faults for the cases of broken rotor bars, inter-turn short circuit (Publication 7) and dynamic eccentricity (Publication 8).

The radial electromagnetic stress calculation showed that the changes in stress occur for the lower spatial harmonics when the motor is operating under electrical faults. The fact that the originated vibration due to the stress are forced, together with the fact that the cylindrical structure of the stator is less stiff to the lower order spatial harmonics allow us to predict the way in which the stator will vibrate in faulty conditions. This is demonstrated by observing Figure 24 (calculated stress) and Figure 25 (measured vibration); a clear relationship can be seen. Thus, the stress calculation allows the prediction of the relevant components to be monitored. The component of twice supply frequency $2f_s$, which appears in Figure 25 is due to inherent static eccentricity in the real motor. In practice it is quite difficult to isolate both types of eccentricity.

The case of static eccentricity is predicted from Figure 12 in Publication 7. This figure corresponds to the normalized stress (Equation 12), which shows up the prominent frequency components during the fault. As a second example, Figure 19 shows the case of the dynamic eccentricity. The observed peaks correspond with the predicted forced vibration, in this case, for Motor I supply at 50 Hz. Figure 25 shows how the loading decreases the amplitude of some vibration components (for the case of dynamic eccentricity); this is also predicted from the FEM calculation, as can be seen in (Figure 9, Publication 8) and in Figure 21 for a different motor.

The results of the vibration measurements show that the presented method is valid and the hypothesis made on the forced vibrations are correct. A good agreement between the measurements and the simulations is also achieved for the cases of broken bars and inter-turn short circuit as can be seen in Publication 7. The vibrations at frequencies corresponding to the rotational speed are clearly present for the case of broken bars and dynamic eccentricity, as has been suggested in the literature. However, it has not before been numerically demonstrated why they do occur nor how they relate to the spatial harmonics.

No direct measurements have been made for the case of static eccentricity, but the cases studied in the literature showed that the main vibration under this fault is at twice the supply frequency (Dorrel et al. 1997, Finley et al. 2000 and Jang & Park 2003). The calculated stress during static eccentricity events is in agreement with those reported results.

From the application of the method to the most common faults, a concise table (Table III) for induction motor condition monitoring is deduced. Such a table has not been found in the literature. This table includes two new characteristics: the loading behaviour and the prominent spatial harmonics. These characteristics may also help to discriminate between the faults. For example, even if broken rotor bar and dynamic eccentricity produce appreciable stress components at the rotation frequency, these faults could be discriminated with a loading test. On the one hand, the radial stress at the rotation speed increases with loading when there are broken bars, see Figure 20. On the other hand, this stress component decreases with loading during dynamic eccentricity events, see Figure 21. This is also observable with measured vibration data in Figure 25 and (Figure 17, Publication 7).

Dorrell et al. (1997) mentioned the unpredictable behaviour of the vibration with loading for the case of dynamic eccentricity. This is now explained by applying our method. A non-linear relationship was found between loading stress waves and vibrations. This is explained in Publication 8. Nandi et al. (2005) presented an equation for the detection of mixed eccentricity through vibration monitoring, which, according to our method and experimental results, is erroneous and lacks foundation.

This method is applicable to all rotating electrical machines. A possible drawback could show up in very large machines if the resonance frequencies are close to the monitoring frequencies. In such a case, the situation is very dangerous for dynamic stability. The method could also help the designers to avoid certain operational points. In general, the application of the method shed some light on the complex phenomena of vibration and the relationship with fault diagnosis. However, to obtain a better description of these phenomena, a 3-dimensional model that takes into account all the geometry, elasticity, gyroscopic effect, resonance frequencies, damping in the machine and foundation and the acting forces is needed.

It is important to note that our calculation is 2-D, thus some 3-D effects like the homopolar flux are not taken into account. This is recommended for future work. It is also strongly recommended for experimental investigation. As a continuation of this work, it is suggested to measure the running modes of the vibrations under electrical faults. This will help to clarify the effects of the force distribution in the vibration pattern and probably will help to discriminate between faults.

5 Conclusion

This work shows the suitability of monitoring the motor condition by accessing different indicators of motor faults. It also demonstrates the ability of different techniques to monitor electrical machines.

It has been found that:

1. FEM is a useful tool in the analysis of induction motor under fault conditions. It allows the generation of virtual data in an accurate and inexpensive way.

2. The fuzzy logic can be extensively applied in fault diagnosis. The synergy of this technique with MCSA will overcome some of the shortcomings of the traditional technique.

3. Predictive filtering is a useful tool to separate out the harmonic components from the fundamental component. It has potential applications in fault diagnosis and other fields.

4. DWT is a powerful and promising tool for electrical machine monitoring. It adds a new comparative factor, the evolution of frequency components related with the fault.

5. The electromagnetic force is a sensitive parameter to any internal malfunction in the machine. During electromechanical fault events they are able to produce forced vibrations.

6. Continuous vibration monitoring has a potential application in electrical fault detection. This makes it possible to detect both mechanical and electrical faults from the same fault indicator, making vibration a universal indicator.

7. The proposed method for detecting vibration signatures has a potential application in the study of induction motors and other electrical machines such as synchronous generators.

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Appendix I Publications [P1]-[P8]

Appendix II Power converter technical data

Power converter technical data

Vacon, type: 90CX4A00

Mains connections: Input voltage U_{in}: 380–440 V; -15%– +10%

Input frequency: 45–66 Hz

Motor connection: Output voltage: 0-U_{in}

Continuous output current: I_{CT} Ambient max: +50 ºC

Overload 1.5 I_{CT} (1 min/10 min)

I_{VT} : ambient max +40 ºC, no overloading

Starting torque: 200 %

Starting current: 2.5 I_{CT}: 2 s every 20 s if output frequency <30 Hz and if the heat sink temperature <+60 ºC

Output frequency: 0–500 Hz

Frequency resolution: 0.01 Hz

Control features: Control method: Frequency control (U/f)

Open loop sensor less vector control

Closed loop vector control

Switching frequency: 1–16 KHz (up to 90 kW, 400/500 V)

1–6 KHz (110–1500 kW, 600 V)

Frequency reference: Analog I/P: resolution 12 bits

Panel reference: resolution 0.01 Hz

Field weakening point. 30–500 Hz

Acceleration time: 0.1–3000 s

Deceleration time: 0.1–3000 s

Braking torque: DC Brake: 30% T_N

Environmental- : -limits Operating temperature: -10(no frost)–+50 ºC at $I_{CT,}$ (1.5 I_{CT} max)

-10(no frost)–+40ºC at $I_{VT\,,}$ no overloading

Storage temperature: -40–+60 ºC

Relative humidity: < 95 ºC, no condensation allowed

Vibration (EC 721-3-3): Operation, max displacement amplitude 3mm at 2–9 Hz

Max acceleration amplitude: 0.5 G at 9–200 Hz

An example of voltage output of the power converter is shown bellow. This case corresponds to the frequency of 100 Hz.

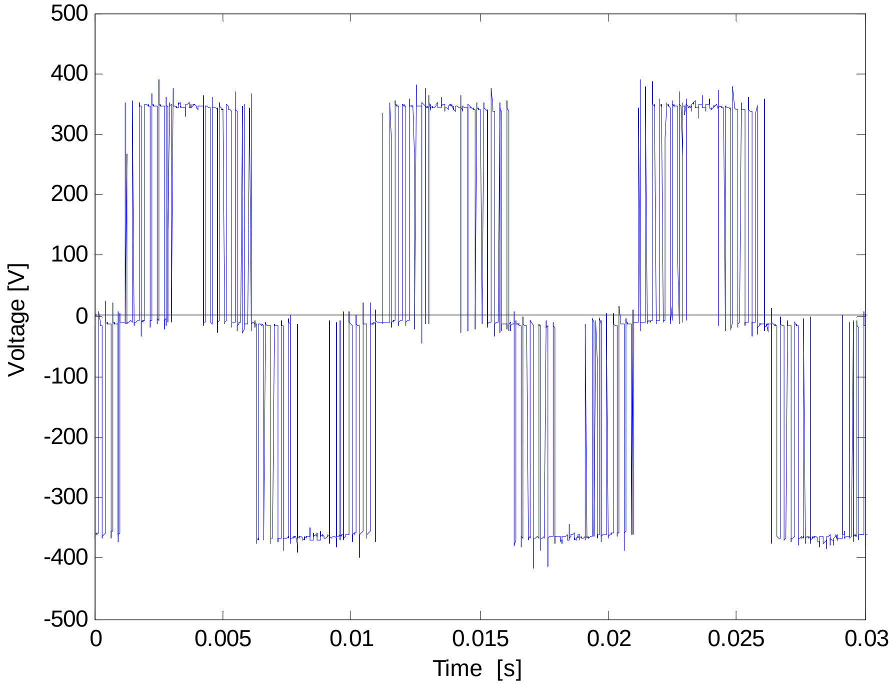

Figure 1. One phase of the measured voltage in the inverter output.

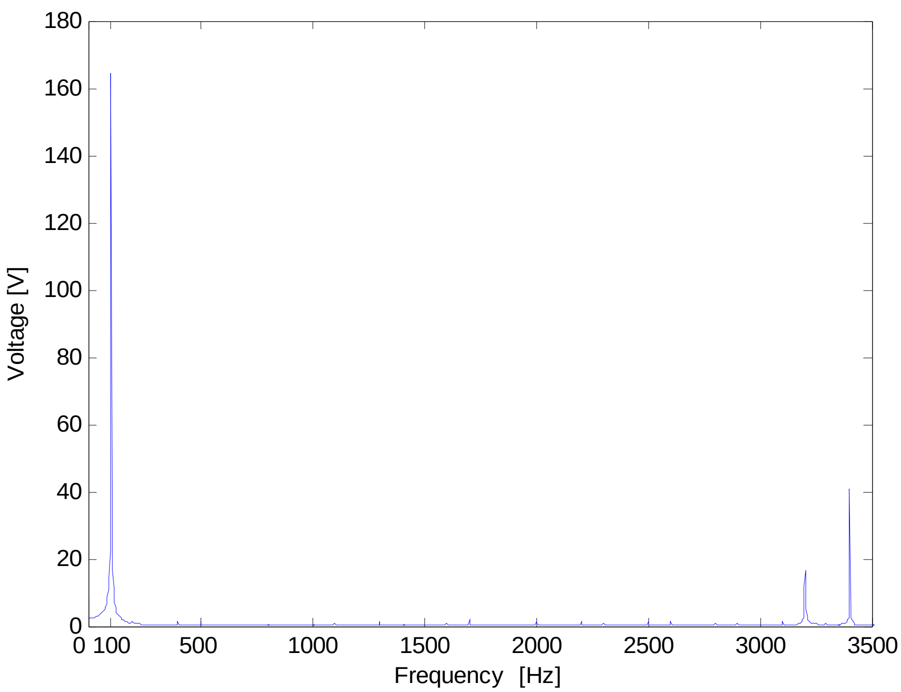

Figure 2. FFT of the measured voltage in the inverter output.

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