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Date April 21, 1995

FAULT MONITORING AND RESIDUAL LIFE ESTIMATION OF ELECTRIC MOTORS

A Thesis

Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Baishali Raychaudhuri

May 1995

Dedicated to

My Teachers

(especially Bapi, Ma and Subhomoy)

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ABSTRACT

Techniques for predictive maintenance of plant components primarily focus on fault monitoring and diagnostics of rotating machinery. Consequently, the analysis systems used by plant personnel perform the function of vibration monitoring and trending of rotating machinery. The important next step in advancing the technology and for providing decision-making information to plant personnel is the system prognosis phase. The estimation of residual life of plant components (both rotating machinery and stationary systems) falls into this category. Another important issue to be addressed is that, vibration monitoring by itself may not always provide machinery degradation information. Furthermore, an attempt towards a root cause analysis of component degradation with time is seldom addressed.

The purpose of the research reported in this thesis is to develop and demonstrate a methodology for the estimation of residual life of plant components. The research focus was on the degradation monitoring and characterization of small horsepower induction motors. Both experimental and analysis techniques were developed to establish the solution to this important problem. Experimental data were acquired from a motor testing laboratory. The motors were operated continuously for a long period of time under externally imposed anomalies. The data were used to trend degradation of motors and to establish predictive models for residual life estimation. Dynamic regression models and neural network models were established to characterize the trend information and to determine the useful remaining life of small horsepower induction motors for a specified alarm level.

A PC-based analysis system was developed using the MATLAB platform. Both laboratory and industrial predictive maintenance data were used to demonstrate the applicability of this new approach. A model, describing the dynamics of induction motors, was developed to understand the characteristics of anomalies and the test data. This research has shown that just the monitoring of vibration of certain rotating machinery is not sufficient to trend the degradation of these machinery. Electrical parameters and internal changes in motor characteristics must also be monitored as part of a predictive maintenance program. The technology developed in this research may easily be extended to large horsepower motors used in nuclear and fossil power plants.

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TABLE OF SYMBOLS

$y(t)$	dependent variable at time t
$x(t)$	independent variable at time t
$\epsilon(t)$	error term at time t
$s(t)$	residual between measured value and estimated value
qd0	the quadrature-direct-zero reference axis
abc	the a-b-c reference axis
V,v	voltage
I,i	current
r	resistance
Z	impedance matrix
X	inductance
X_{ss}	total inductance in stator circuit
Xrr	total inductance in rotor circuit
L	leakage reactance
T_e	electromagnetic torque
T_l	load torque
J	moment of inertia of rotor
p	derivative with respect to time
ψ	flux linkage per second
θ	angle between the reference frame and the rotating frame
ω	angular velocity of the reference frame

ω_r	rotor angular velocity
ω_b	base angular velocity used to calculate inductive reactances
m_0	mean for normal condition
m_1	mean for degraded condition
σ_0	standard deviation for normal condition
σ_1	standard deviation for normal condition
λ	ratio between normal and degraded density functions
α	specified probability of false alarms
β	specified probability of missed alarms
β_i	actual parameters
b_i	estimated parameters
R^2	coefficient of determination
S_{xx}	autocorrelation of x
w_i	connection weights in neural networks
ρ_{xy}	correlation coefficient between two signatures x and y

Superscripts:

T	transpose of a matrix
'	rotor quantity referred to stator
^	estimated value
—	mean value

Subscripts

a	phase a
b	phase b
c	phase c
q	quadrature axis
d	direct axis
0	zero axis
s	stator
r	rotor
l	leakage (reactance)
m	mutual (reactance)

Chapter 1

INTRODUCTION

1.1 Background and Statement of the Problem

Many predictive maintenance approaches focus primarily on fault monitoring and diagnostics of rotating machinery. These results are used to trend and monitor equipment performance so that a planned maintenance program would result in improved reliability (probability that an equipment is operational at a given time) and availability. A predictive maintenance program is the most effective way to avoid catastrophic machine damage, unscheduled outage, potential safety hazards and lost production time.

The important next step in advancing the technology and providing decision-making information to plant personnel is the system prognosis phase. The estimation of residual life of plant components falls into this category, and is the focus of the research reported in this thesis. The residual life of a component is defined as the remaining useful operational life of the component from a given time.

In order to determine the residual life of components it is necessary to define the operational limits in terms of a measurable signature. The two parameters often used are the "alarm level" and the "failure level". The alarm level is the value of a signature, that represents the degradation of a process component, beyond which the performance of that component is not reliable or imminent failure may occur at any time. The "failure level", on the other hand, is the value of that signature at which point the process component is completely nonoperational. The residual life of a component is generally defined using the time-to-alarm. The average time between time-to-alarm and time-to-failure may then be used to make decisions about the replacement, repair or run-to-failure of that component.

Figure 1.1 shows the definitions of alarm level and failure level and the associated time-to-alarm and time-to-failure. For the industrial data used in this research, the time-to-alarm was estimated.

Induction motors of all sizes (fractional horsepower to hundreds of horsepower) are used extensively in industry. The purpose of this research is to develop both experimental and analysis techniques to estimate the residual life of fractional horsepower motors. Even a healthy machine will degrade with time, but a motor may also have to work under severe conditions, in which case its degradation will be accelerated. Long-term and continuous tests were performed to establish the failure characteristics of these motors by trending directly measurable quantities such as the three phase currents.

In order to establish a systematic solution to this problem, both experimental and analytical approaches were developed and demonstrated for small horsepower induction motors. This class of machinery was chosen because of the ease of experimentation and the importance of their reliability in continuous production and manufacturing industry. The general approach developed in this research may be readily extended to larger motors such as those used in power plants as drives for pumps, fans, conveyors, blowers and others.

One of the main objectives of this research was to estimate the residual life of a machine from a reference time by studying the trends in the various signatures that were

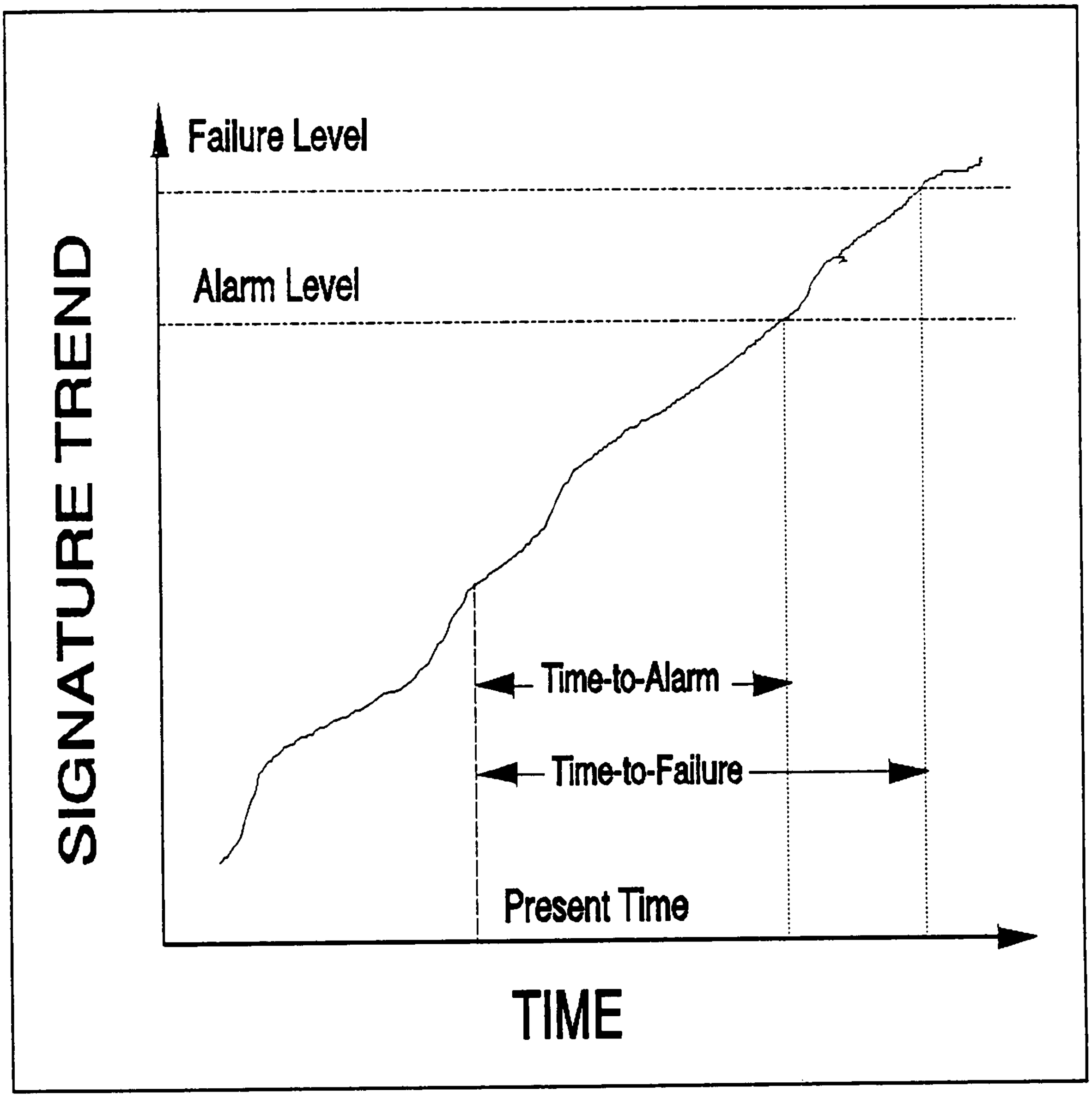

Figure 1.1 General Definition of Parameters Used in Residual Life Estimation

acquired from the machine at regular intervals. The motor may ultimately fail due to one or more causes. The objective was to trend the signals that are sensitive to specific failure modes and extract the information contained in these signals about the condition of the motor. This information, collected over a period of time, is useful in predicting how long a machine will remain operational.

1.2 Review of Previous Work

Extensive studies have been reported on the detection of various faults in large electric motors and generators. The main area of interest was insulation failures of stator and rotor windings. Diagnostic tests, both destructive and nondestructive, have been carried out for estimating the remaining life of stator insulation [11,12]. Expert systems have been developed to diagnose motor insulation condition [16,17]. Probabilistic models have also been proposed for estimating the remaining life of insulation.

Another area of interest is rotor defects. Continuous temperature and flux monitoring systems have been developed to assess rotor condition [9,14]. Broken rotor bars have been detected by using state and parameter estimation. A methodology was developed that can predict torsional fatigue crack initiation in large motor shafts [15]. Most of the above work was carried out on large motors and the methodology used cannot be applied to small and medium-size motors, mainly because of economic considerations. Furthermore, a systematic approach for residual life estimation using predictive maintenance data is not available.

An easier and more convenient method is to monitor motor currents and vibration signatures and use current waveforms and frquency spectra to identify and detect faults in both stators and rotors. Perhaps the most advanced approach to fault detection has been the use of artificial neural networks. This approach has so far been restricted to a few types of faults and the analysis has been limited to insulation defect studies.

Small horsepower motors (less than 2 hp) do not indicate degradations in their vibration signatures, unless the degree of degradation is very severe (such as the complete loss of bearing lubrication). The vendors of predictive maintenance and monitoring systems generally rely on vibration analysis for fault diagnostics. This approach is not necessarily applicable to small rotating machinery. Also, there is a visible lack of understanding of the root cause of operationsl problems in these machinery. These observations strongly support the relevance of the present research project and it would require both experimental and analytical approaches to demonstrate the feasibility of estimating residual life or time-to-failure. Statistical, time-dependent regression models and artificial neural networks were two of the data analysis methods implemented in this project. The validity of the experimental results were established using performance modeling of induction motors.

1.3 Objectives of the Research

The purpose of the proposed research was to develop technology to estimate the residual life of rotating machinery, with particular emphasis on fractional horsepower induction motors.

The objectives were accomplished by performing the following tasks :

1. Review of failure modes of small electric motors and identification of measurements that are sensitive to specific failure modes.

2. Design of various tests to understand the degradation mechanisms of fractional horsepower induction motors and generation of a test database.

3. Analysis of motor test data to observe degradation trend.

4. Development of dynamic multiple statistical regression models for residual life estimation.

5. Development of artificial neural network models for residual life estimation.

6. Development of simulation models to study the sensitivity of motor performance to changes in its design parameters.

7. Development of a PC-based residual life estimation system and its performance testing using both experimental and industry data.

1.4 Summary of the Methodology and General Features

Both experimental and analytical techniques were developed to achieve the objectives of this research project.

1.4.1 Experimental Approach

In the experimental part, data were acquired on-line from three motor-generator sets. Anomalies were introduced in the system to accelerate the degradation process. The motors were in continuous operation for a long period of time. The following experiments were performed :

1. Variation of series resistance in one of the phases, thus affecting phase imbalance.

2. Variation in the load on the motor.

4. Restriction of cooling air flow by blocking the face of the motor by various amounts.

5. Introduction of a permanent damage in the stator winding.

The results obtained were typical of motor degradation under the imposed conditions.

1.4.2 Analysis Approach

The data collected from motor experiments were analyzed using artificial neural networks and regression models to estimate residual life of motors.

Two motor current signatures were mainly used as inputs to the neural network. One was the difference between the maximum and minimum motor phase currents and the other was the maximum phase current. The output was the residual life in hours. Both sectionalized and time-regressed data were used as input information. For the sectionalized data, the motor current history was divided into sections, each of length four points. The values of motor currents in each section and the known residual life were presented in each pattern. For time-regressed data, the present point and three previous time points, together with the residual life for present time, were presented in each pattern. The four motor current points were the inputs to the neural network and the residual life was the desired output of the network. The network learned from a large number of patterns presented to it and was able to predict the residual life of the motor from any point on the motor current plot.

The statistical regression modeling involved the development of various linear and nonlinear, static and dynamic, univariate and multivariate regression models, and comparing them in terms of their prediction capabilities and goodness-of-fit. A typical linear regression model has the following form

$$y(t) = \sum_{i=0}^{n} a_i \, x(t-i) + \epsilon(t) \tag{1.1}$$

where y is the residual life, x is the measured motor current and ϵ is the error term. A PC-based software was developed for regression modeling and residual life estimation. This approach was tested extensively using both laboratory and industrial plant data.

Another task in the analytical study was the development of a nonlinear model of the induction motor and simulation of the same abnormalities that were introduced in the experimental study and verification of the results obtained in the experiments. The effects of disturbances in the external power supply (that could not be performed experimentally) on the motor performance characteristics were also simulated.

1.5 Contributions of the Research

One of the contributions of this research is the development of various types of statistical regression models and neural network models to estimate the residual life of plant components. The experimental design and motor testing are also parts of the original contribution of this thesis. Though the focus here has been on fractional horsepower induction motors, the method can be extended for application to all forms of rotating machinery.

Another significant contribution is the development of an interactive prognosis software with options for choosing a particular regression model to predict the time-to-alarm of a motor (the time when the signature being considered reaches an alarm level) and comparing the results from various models to determine the best prediction. The uniqueness of these models is that they adapt to the trend in the data and hence are able to predict the residual life from a given time instant during the operation of the motor. The specific case is the ordinary regression model which takes into account the entire life data.

The development of a steady-state nonlinear model of the induction motor with phase imbalance is another contribution of this research. This would help in understanding the machine performance when the three phases are not balanced, which is a common occurrence in operation.

1.6 Outline of the Thesis

Chapter 2 presents a brief description of induction motors from the electrical standpoint and their various failure modes. Chapter 3 contains a description of the experimental system, the experiments performed and the results. The background of dynamic modeling and the development of the necessary state-space equations are described in Chapter 4. This is followed by the results of simulations for changing motor characteristics.

Chapter 5 describes the analysis methods used in this research to evaluate the condition of the motor and to predict its life. The results using statistical methods and neural networks are discussed in Chapter 6. The extension of the developed methodology to nuclear power plant components is outlined in Chapter 7. Summary, conclusions and recommendations for future work are given in Chapter 8.

Chapter 2

REVIEW OF INDUCTION MOTOR OPERATION AND ITS FAILURE MODES

2.1 Introduction

A brief description of the construction and operation of induction motors and the electrical equivalent of the motor is presented in this chapter. This introduction is essential for understanding the development of the dynamic model described in Chapter 4. A review of the different failure modes of induction motors is also presented.

2.2 A Review of Induction Motors

2.2.1 Introduction

The induction motor is the most commonly used electrical drive. It is seldom desirable as a generator, but has a wide range of applications as a motor. Induction motors may have a wide range of power outputs, from fractional horsepower to several thousand horsepowers, and a majority of them are used in home appliances such as fans and pumps. The induction motor is mechanically simple, inexpensive, rugged and can be adapted to widely differing operating conditions by simple design changes.

2.2.2 Construction

The induction motor consists of two parts, the stator and the rotor. The stator winding is housed within the stator frame and is excited by a balanced three-phase AC source. The rotor may be either the squirrel-cage type or the wound-rotor type. The squirrel-cage type rotor has a laminated structure with skewed slots in which bars of conducting material are placed. These bars are connected by end rings which produces a solid, short-circuited cylinder appearing like a squirrel cage. In the wound rotor type, the windings are insulated from the slots and connected to slip rings in contact with brushes, which lead to an external circuit [1]. Figure 2.1 shows the cross-section of a typical three-phase induction motor. The stator of a polyphase induction motor with the rotor removed is shown in Figure 2.2. Figure 2.3 is a cutaway view of a squirrel-cage induction motor.

2.2.3 **Principle of Operation** [1]

The description of an induction motor is taken from [1,2]. Alternating balanced three-phase current is supplied to the primary winding on the stator. A magnetic flux is set up in the air gap between the stator and the rotor. This flux crosses the air gap radially and links the rotor bars which are connected by end-rings. The secondary voltage thus induced in the rotor produces currents in these bars. This secondary current lags in space position behind the rotating air gap field. A torque is thus produced, which makes the rotor rotate with a frequency lower than the supply frequency.

The primary winding, the secondary winding, the resistances and reactances in both the windings and the flux linkages in the motor are illustrated in Figure 2.4. The electrical equivalent of the squirrel-cage motor is given in Figure 2.5, where the rotor impedance is stated in terms of the stator. The effect of the windings in Figure 2.4 is

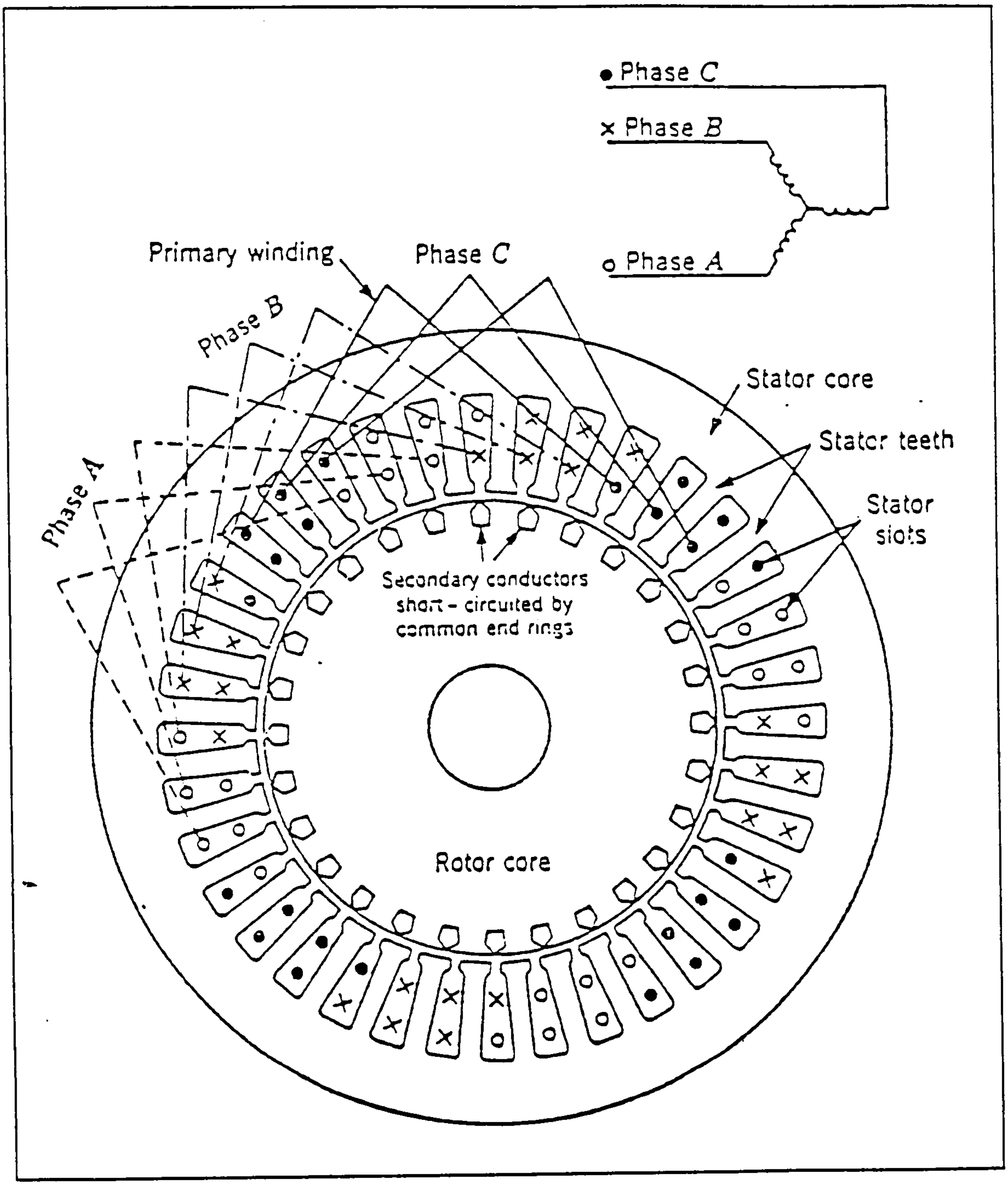

Figure 2.1 Cross-Section of a Typical Three Phase Induction Machine [1]

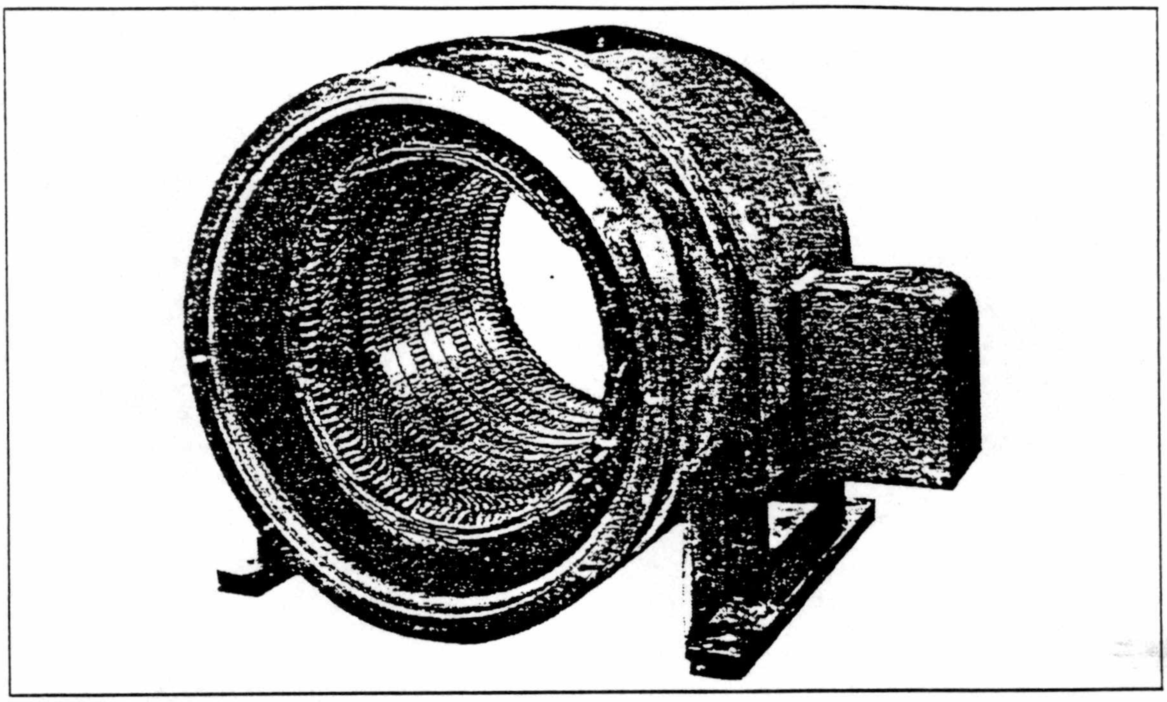

Figure 2.2 Stator of a Polyphase Induction Motor (Rotor Removed) [2]

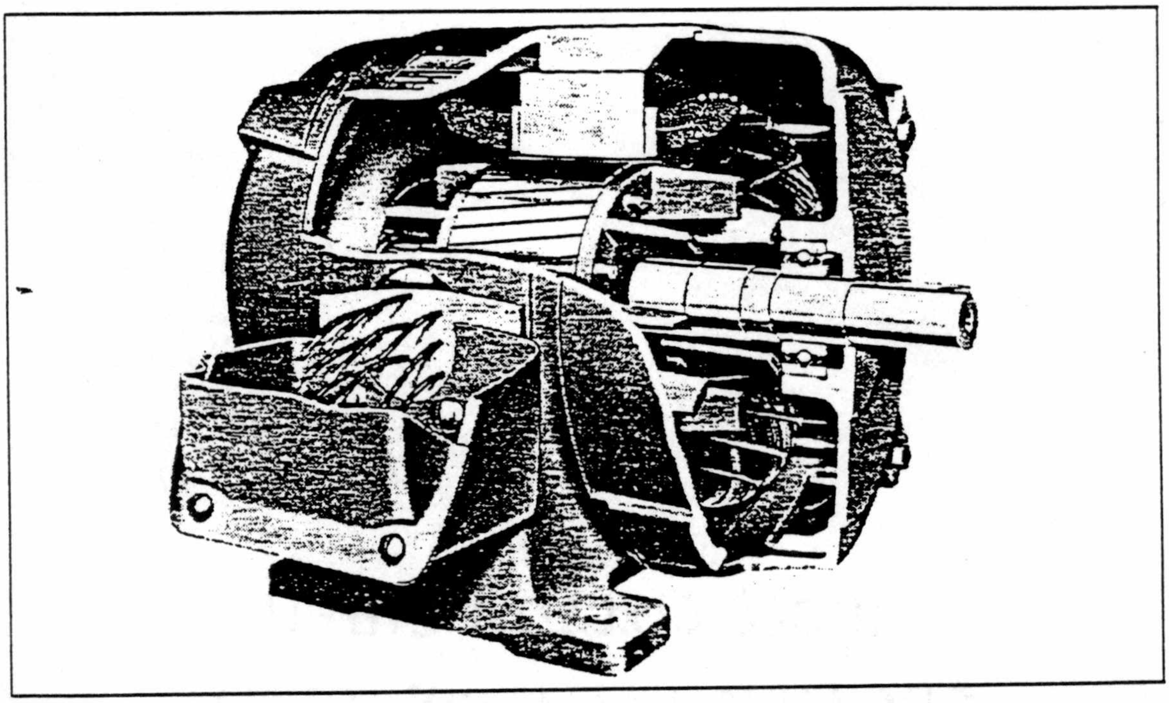

Figure 2.3 Cutaway View of a Squirrel Cage Rotor [2]

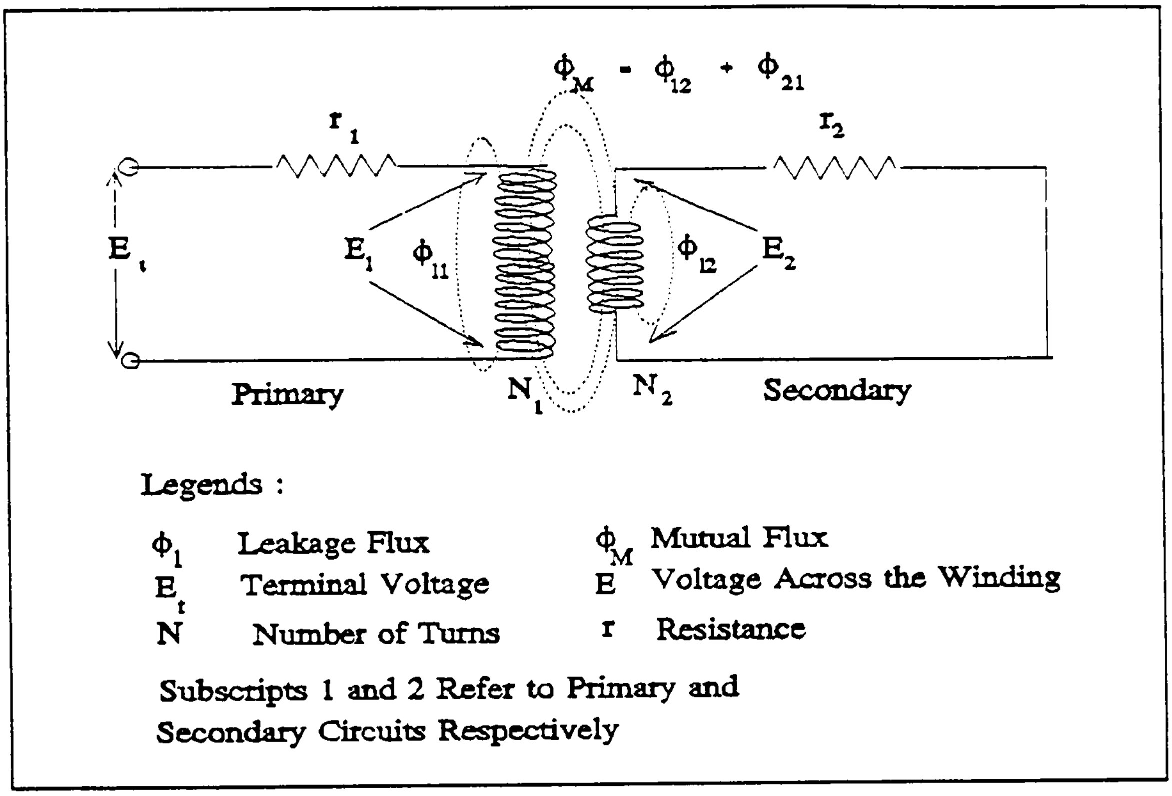

Figure 2.4 Electrical Equivalent of a Squirrel Cage Induction Motor (One Phase Shown) [3]

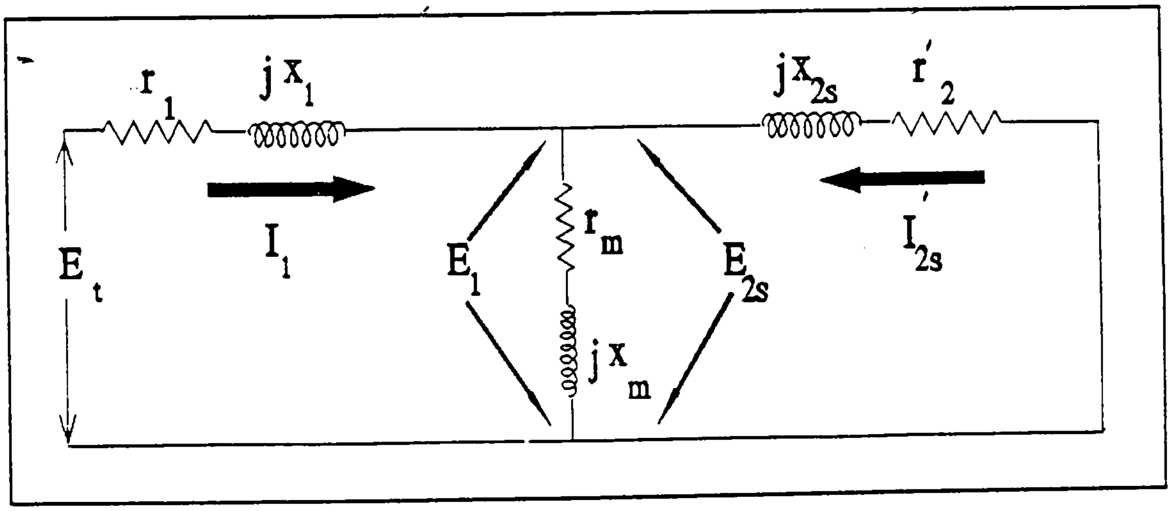

Figure 2.5 The Equivalent Circuit [3]

taken into account in Figure 2.5 by considering the ratio of the number of turns in the primary and the secondary windings. The primed rotor circuit parameters in Figure 2.5 imply that their counterparts in Figure 2.4 have been multiplied with this ratio. The relationships between the electrical variables of the motor are expressed in terms of motor parameters. These are required for the dynamic modeling of an induction motor. This is presented in Chapter 4.

2.3 Failure Modes of Induction Motors

2.3.1 Introduction

This section is organized into four sub-sections. Failure modes common in stator components, namely the frame, the core and the windings are discussed in sub-section 2.3.2. Common faults occurring in the rotor, mainly in the rotor bars and end-rings are discussed in sub-section 2.3.3. Sub-section 2.3.4 contains a discussion of the types of faults that occur not in the motor components but in the external circuit of the motor. Circuit faults often cause premature insulation failure in the stator windings leading to motor failure. These faults can be simulated in the laboratory and are used as externally imposed anomalies in this research. Faults in the bearing are also a prime cause of motor failure. This topic is beyond the scope of this research and is hence omitted. Finally, the prevalent fault detection techniques and the measurements that are sensitive to particular types of faults are discussed in sub-section 2.3.5.

2.3.2 Stator Failure Modes

The stator frame encloses the stator and protects it from the environment. It should be robust enough to withstand the mechanical vibrations in the machine and the high torsional forces transmitted to it from the air gap during starting of the machine or due to excessive load or any short circuit that might occur [4].

Insulation shrinkage of stator core laminations is a problem in large motors, but for smaller motors, this does not pose any significant problem [4].

Stator windings consist of an insulated conductor. The conductor is usually copper in larger motors and aluminum in small motors. The insulation is the most common site of failure in all electrical machines. Every strand, turn and coil is insulated from its neighbor. Insulation failure leads either to a phase-to-ground short circuit, a phase-to-phase short circuit or a three-phase short circuit.

Insulation deteriorates as a result of nuclear radiation and other environmental factors such as humidity, dust, thermal effects, electrical and mechanical effects [5]. Deterioration leads to early aging. The degradation of insulation also increases as a result of elevated temperature, high voltage, mechanical stresses or environmental contaminants. Again, these factors may affect the insulation individually, or may cause what is known as "multi-factor aging". Even though the windings are generally encased within the frame, organic products which are formed in service and trapped within the motor housing may accelerate deterioration of the winding insulation. Temperature and time are the primary factors that affect the electrical endurance properties of insulation. The life of a low-voltage motor is likely to be dictated by its operating temperature alone, while the life of a large motor may depend on voltage (electrical) and mechanical stresses.

In general, the relationship between time and temperature and their effect on insulation was described by Montsinger's 10 deg rule [6] which states that "the thermal life of insulation is halved for each increase of 10 deg C in the exposure temperature". This assumes that insulation life is halved for every 10 deg C rise throughout the temperature scale. However, Dakin [7] postulated that the rate of thermal aging of insulation obeys the Arrhenius chemical rate equation. This approach entails that thermal intervals at high temperature have less effect, percentage wise, than the same intervals at lower temperatures. Mechanical, radiation and humidity-caused aging have also been found to be of chemical nature. Apart from time and temperature, the load on the motor also influences the deterioration. An overload of as little as 10% can drastically reduce insulation life while a reduction in load can increase it dramatically.

While failures in the frame and the stator core laminations can be treated as caused by design or manufacturing defects, insulation failure is mainly an operation-related problem and can be prevented by maintaining proper operating conditions and environment.

2.3.3 Rotor Failure Modes [4, 9, 13, 14]

The rotor is subjected to the same forces as the stator, such as forces due to load, machine vibration, misalignment and environmental factors [4]. In addition, all parts of the rotor are subjected to centrifugal forces. If the weights of the rotor components are not properly distributed, excessive machine vibration may occur.

The rotor shaft is responsible for transmitting the load torque. Any driven equipment or electrical transients may cause cyclical shaft torques. These dynamic torques may have a frequency close to the system frequency, the effect being either amplification of vibration, or an attenuation of the transmitted torques.

The lamination insulation in the rotor core has to withstand a very low voltage and hence the threat to failure is less in this part of the motor compared to other parts. However, failures due to mechanical instability of the rotor core is possible [4].

Squirrel-cage rotor windings consist of conducting bars placed in slots and connected at both ends by end rings. As a result, the rotor winding is subjected to thermal expansions and contractions. Rotor cages undergo thermal excursion due to load. The energy losses produced during acceleration are directly related to the energy stored in the rotating inertia of the drive system at rated speed and may produce more pronounced thermal excursions [4].

2.3.4 Motor Circuit Failures

A study conducted by IEEE in 1989 [8] revealed that the two dominant failure points in motors were bearing and stator windings. The principle damage mechanisms leading to failure of large commercial and industrial motor stators are overheating (21%), insulation breakdown (37%), mechanical breakage (10%) and electrical faults, that is, motor circuit faults (11%).

The most prominent electrical fault is voltage imbalance. Voltage imbalance is mainly caused by imbalance in phase impedances. Resistive imbalance may be caused by a number of defects mainly found in power circuit connections, contacts and external terminals. Corrosion products, dirt and other contaminants in the switch box, bad solder joints on cable connections, loose, worn or maladjusted contacts in motor controllers or circuit breakers may also contribute to phase imbalance. Installation defects, such as replacing the faulted part of a cable with a material slightly different from the rest of the cable will invariably cause resistance and hence current imbalance. The imbalance cause "negative sequence currents" (Appendix A) in motor windings. These currents cause overheating of the machine.

The circuit reactance changes when windings become shorted with one another or with the ground. Short circuit occurs as a result of mechanical, thermal, environmental and electrical damage to the winding insulation. It is equivalent to removing some coils from the winding.

Whether there is a resistive or reactive imbalance in the circuit, the current flow in one part of the circuit is enhanced thus heating up the conductors and the surrounding insulation. Excessive heat may cause insulation to develop hotspots and the insulation deteriorates faster at these locations. Excessive heating also results in the dielectric breakdown of the insulating material.

Other faults that can occur in motor circuits are :

(i) single-phasing, i.e. when one phase is accidentally opened,

(ii) unbalanced supply, due to a faulty distribution system,

(iii) high resistance phase to ground fault, i.e., current leaking from any part of the winding to the ground through the insulation,

(iv) high resistance fault between phases,

(v) both phase-to-ground and phase-to-phase faults simultaneously,

(vi) unbalanced impedance in the rotor, due to one or more broken rotor bars, cracks in the end rings, or non-uniform slot size (hence non-uniform cross-section).

On-line monitoring of current, vibration and temperature signatures is useful in detecting the type of fault, its location and severity. A more detailed discussion of state-of-the-art fault detection techniques and their effectiveness is given in the next section.

2.3.5 Fault Detection Techniques

Certain abnormalities in an operating motor are easily seen as changes in line current signatures. For this reason, line currents are most frequently used to indicate any faulty condition in the motor. Instantaneous values of currents, RMS values, spectral features and positive and negative sequence components (explained in Appendix A) are obtained and are analyzed to identify the failure modes. Frequency spectra are influenced not only by genuine motor faults but also by faults in gearboxes, fluid couplings, loads, pulleys and belts driven by the motor. Improper resolution of the spectra may negatively affect the results of fault diagnosis.

The most common type of rotor fault is the presence of broken rotor bars. Other rotor asymmetries, due to faulty bearing, rotor ellipticity, misalignment of the shaft with the cage, magnetic anisotropy may also be present [9]. If broken rotor bars are present, harmonic fluxes are produced in the air gap which result in harmonic components in the motor line current. Generally, a detailed frequency analysis of the motor current can indicate the type of fault. However, sidebands of line frequency caused by rotating asymmetries and by broken rotor bars have similar behavior. An examination of the magnitude of the harmonic sidebands reveals the actual cause. In case of an asymmetry, the upper harmonic content is low, while in case of broken rotor bars, it is high. When one or more rotor bars are broken, the spectrum of the line current is significantly different from the spectrum of a normal motor current. In a normal motor, the amplitude at the slip frequency is generally less than 25% of the total energy content of the spectrum. As the rotor degrades, this percentage increases and can reach almost 90% for a severely degraded motor. Also, there are no slip harmonics for an undamaged rotor. When cracks appear in a rotor bar, slip harmonics also appear and may extend to several times the slip. At the same time, sidebands separated from the rotating frequency by the slip frequency also appear. Another confirmation of rotor deterioration is the presence and level of slip sidebands relative to the power line peak. Normally, these sidebands are 50-60 dB below the amplitude of the supply line peak. If the difference is less than 45 dB, rotor bar damage can definitely be ascertained. An increase in slip peak amplitude also entails a decrease in the other key peak amplitudes, not because of a decrease in mechanical load but because of an increase in the electrical load.

The level of rotor degradation can be quantified by calculating the number of broken rotor bars using the following formula [10].

$$n = \frac{2R}{10^{\left(\frac{d}{20}\right)} + p} \tag{2.1}$$

where n = estimated number of broken rotor bars

d = dB amplitude difference between line frequency and the lower slip sideband of line frequency

p = number of stator poles

R = number of rotor bars or slots.

This formula underestimates the actual number of broken rotor bars and does not take into account the effects of temperature and load. However, new software analysis take into account compensation for load variation while calculating the number of broken rotor bars.

Non-traditional methods of current sensing have been proved to be very useful in detecting stator faults. For example, the presence of the negative sequence component of current is a good indicator of a stator short circuit [11]. The positive sequence component of current is responsible for producing motor torque and depends on the slip. Only in case of a short circuit does the negative sequence current develop and its value is directly related to the number of faulted turns in the stator. Another very ingenious method of sensing stator faults is to pass all the three phases of the stator winding through the core of a current transformer. In a current transformer, the primary winding is wound on the core and secondary winding consists of a single coil connected to a load in the form of a resistance. In a symmetrical three-phase system, the vector sum of the three phase currents is zero, and no current flows in the secondary. During any fault, the phase imbalance produces current flow in the CT secondary and hence a proportional voltage across the load. However, the same voltage may appear across the load for different types of faults. A knowledge of different values of fault resistance pertaining to different failure modes is required for identifying the actual cause of failure [12].

Direct flux monitoring can help the identification of both stator and rotor cage defects that are not readily visible. This technique involves energizing the entire cage electromagnetically [13]. Stator faults are confirmed through the presence of asymmetries in the normal magnetic flux pattern within the stator laminations. Field variations that may exist along the rotor bar length as well as between one bar and another indicate rotor faults.

Temperature measurement is also a good indicator of motor faults if problems associated with measuring winding temperature can be overcome. A crack or a defect in any of the rotor bars causes its resistance to increase, hence decreasing the current compared to that in neighboring bars. The change in I^2R is immediately shown as a temperature difference. A continuous multi-point temperature monitoring system can convey this information to a computer which processes this data [14].

Among the other failure detection techniques reported in the literature are methods for predicting torsional fatigue crack initiation in shafts [15], and various standard diagnostic and destructive tests to evaluate insulation condition and to predict insulation life. But these tests are mostly effective only for large motors and are not economical and are inconvenient for carrying out on small, fractional horsepower motors. Besides, destructive tests can only be carried out when a motor is at the end of its operational life and are not applicable to motors that are still repairable and maintainable.

A comparatively new approach to motor condition monitoring is the area of applied artificial intelligence. Expert systems were developed with an extensive knowledge-base of machine diagnosis and repairs, all major motor insulation systems and their components, their most probable aging mechanisms, criteria for interpreting test results, recommendations for repairs, etc. The actual condition is provided as input and rule-based decisions are made for automatically preparing the maintenance schedules [16, 17]. Another useful area is the application of artificial neural networks in incipient fault detection. The effective number of turns in the stator winding bears a relationship with the stator current. Also, bearing wear is related to the rotor speed. With stator current and rotor speed as inputs to the neural network, the number of turns and the bearing wear can be obtained as outputs which reflect on the current and speed and hence on the condition of the motor in general [18,19].

Although an extensive amount of work has been performed in the area of failure modes of motors, an area of more practical interest to industries remains unsolved - that of predicting how long a machine is going to remain in operation and when it should be removed from service or repaired without interrupting the production line. This research attempts to provide a solution to this important problem.

Chapter 3

MOTOR TESTING LABORATORY AND THE EXPERIMENTAL APPROACH

3.1 Introduction

This chapter describes the experimental part of the research. Section 3.2 describes the apparatus, the measurements carried out and the automated data acquisition system used in the motor testing laboratory to obtain data for analysis. Section 3.3 describes the experiments performed and results of the continuous motor testing.

3.2 Electric Motor Testing Laboratory

3.2.1 The Motor-Generator Set as a Drive and Load System

The motor test stand consists of a fixture for the motor and a support platform for the generator. A belt drive system is used to provide coupling between the motor and the generator. The load applied to the generator can be varied using a fixed resistance and a rheostat. There is an additional variable resistance connected externally to one of the phases of the motor. This latter resistance is used to introduce a phase imbalance.

The motors used were generally 1.5 HP, 3-phase, 230 V, 5.3 Amps, 1725 RPM, 60 Hz, Class A type motors with Class B insulation. The generators used were 2000 W continuous duty, single phase, 120 V, 16.7 Amps, 3600 RPM, 60 Hz, Class A type generators.

3.2.2 The Test Measurements

No-load measurements were performed before loading the motor. This involved measuring the no-load currents in the three phases, the line-to-neutral voltages and the resistances at room temperature.

Motor Current Sensors :

There are three sensors for sensing motor current in the three phases. These are Fluke Current Clamps with associated power supply. The magnetic field surrounding a current-carrying conductor is concentrated in the electromagnet within the jaws of the current clamp. The voltage that appears across the jaws is converted into the corresponding current.

Vibration Sensors :

There are two CSI accelerometers for sensing vibration, one mounted inboard horizontally and the other mounted inboard vertically on the motor with magnetic mounting bases. Signal cables carry the signal to the filter. The accelerometers have frequency response upto 5 MHz.

Temperature Sensor :

A K-type thermocouple was used to measure the motor casing temperature. The junction of two dissimilar metal wires was embedded in the motor casing close to the stator winding. The voltage across the free ends of the two wires was amplified and converted to a temperature.

In addition to these measurements, voltages and resistances in the three phases were also measured periodically. Variations in the motor speed due to changes in load or imbalance conditions were also recorded.

3.2.3 Data Acquisition System

Signal Conditioning Hardware :

The signals obtained from the six sensors described above were digitized using a PC-based system. Krohn-Hite programmable filters were used to filter vibration signals before digitization. First the signals were low-pass filtered with a Butterworth filter (cutoff frequency 400 Hz, input and output gains 20). Then they were high-pass filtered with a Butterworth Filter (cutoff frequency 1 Hz, input and output gains unity) to remove the DC bias.

The temperature signal was amplified by using a Gould amplifier. The signal from the thermocouple is of the order of a few millivolts and it is amplified using two amplifiers in cascade so that the signal is of the order of a few volts.

Data Acquisition Software :

A master control program opens data files, runs a clock to track the time to digitize data, calls the subroutine to digitize, and computes statistical values of the signals. Another program makes actual calls to PCLAB routines to perform digitization. Yet another routine contains the logic to define the file names for the files to store statistical values of the signals. All the above programs were compiled individually and then linked together. The user specifies the machine number and the time interval between sampling.

The vibration and current signals were sampled at a frequency of 1024 Hz for

24 seconds. The temperature signal is sampled at a frequency of 20 Hz for 50 seconds.

The schematic of the experimental setup is provided in Figure 3.1. The signals from the six sensors were interfaced with the A/D card in the PC through a patch panel.

3.3 Laboratory Testing of Small Horsepower Motors

Various sizes of induction motors are used extensively in various manufacturing and process plants. One of the objectives of this research was to develop both experimental and analytical techniques to study the performance of small induction motors (one to two horsepower). The basic purpose of the experiments carried out in the motor testing laboratory was to enhance the degradation process of the motors so as to study the failure trend in a short period of time. The experimental data were used for residual life estimation and for studying the performance of these motors under externally imposed conditions. The following experiments were carried out in the laboratory.

(a) Continuous full-load operation with phase imbalance.

(b) Continuous full-load operation with insufficient cooling.

(c) Continuous operation with variable load and phase imbalance conditions.

(d) Continuous full-load operation with a permanent damage in the stator.

Figure 3.2 shows the trend in the three phase currents of a motor as the resistance in phase A was gradually increased to achieve a maximum imbalance of about 25%. The motor currents did not change after the imbalance was kept constant at the maximum level. Figure 3.3 shows the change in the motor casing temperature as a function of the imbalance. The phase imbalance is defined as the difference between the normal phase

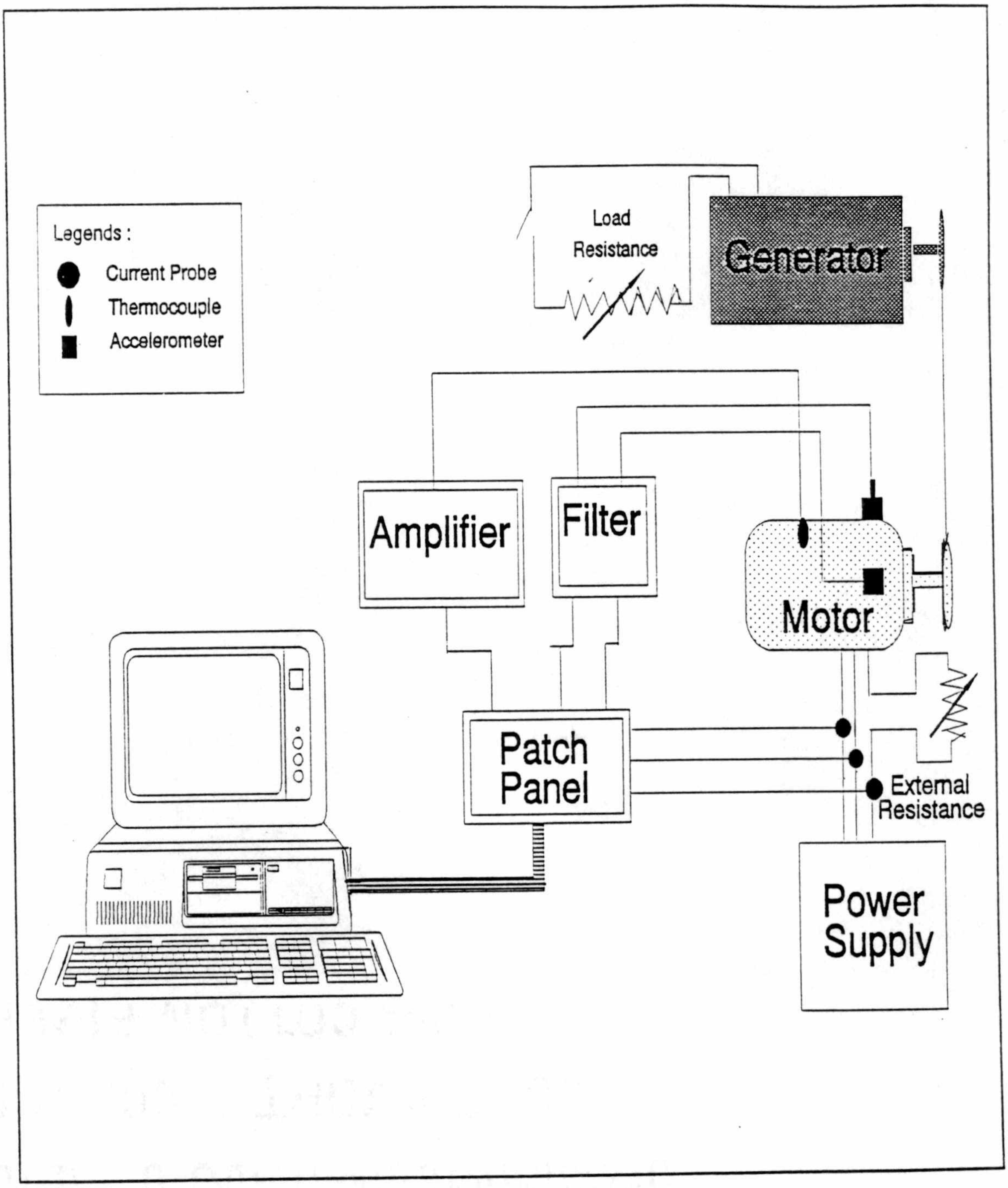

Figure 3.1 Schematic of the Experimental Setup and Data Acquisition System

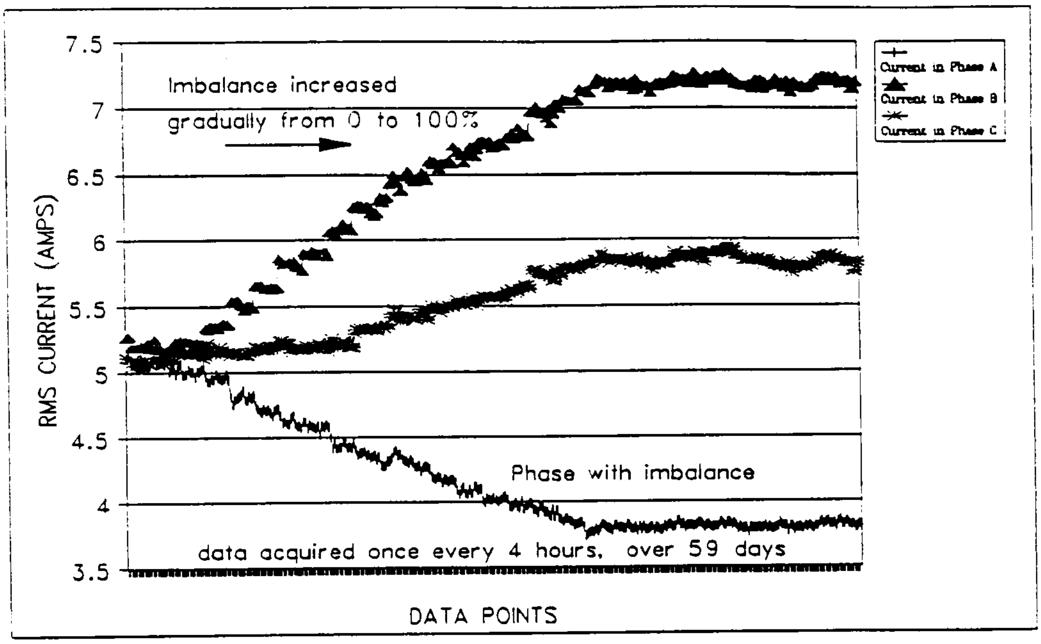

Figure 3.2 Variation in the Motor Currents Caused by External Resistance in Phase A

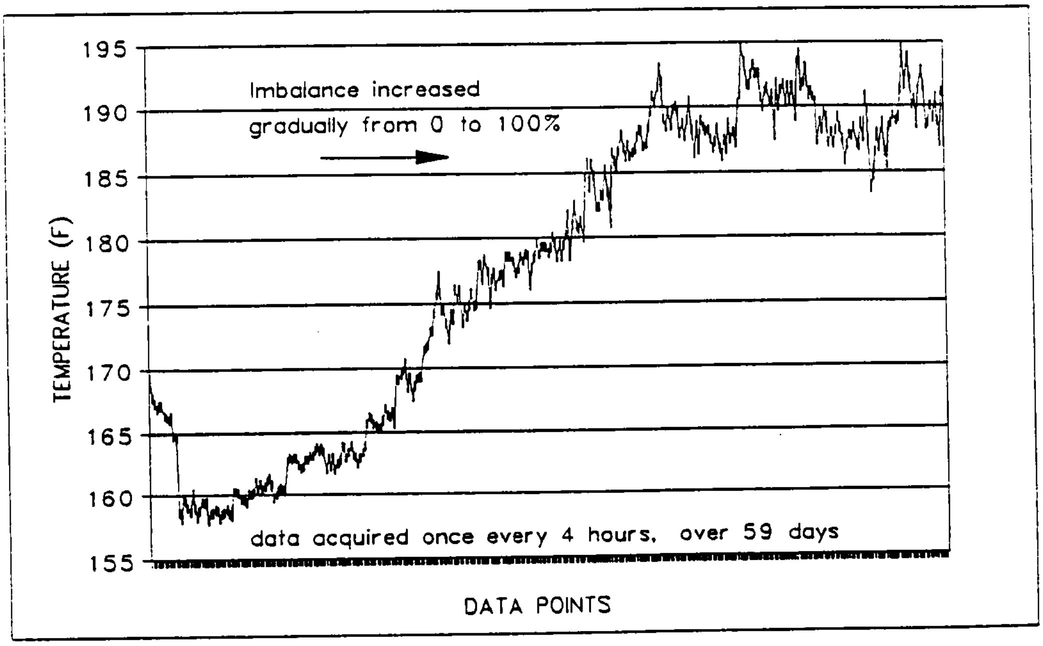

Figure 3.3 Variation in the Motor Casing Temperature Caused by External Resistance in Phase A

current (when all the phases are balanced) and the phase current when a series resistance is introduced to the phase, thus changing the total phase impedance.

The second experiment was a study of the effect of blocking the cooling air intake to the motor. The phase imbalance was increased gradually in steps and at each step the air intake to the motor was blocked by different amounts. Figure 3.4 shows the temperature variation of the motor casing as a result of varying the phase imbalance and the air intake. For a given phase imbalance, the casing temperature increased with increasing blockage, and the trend seemed to have a more nonlinear behavior at higher blockages. The general trend of the temperature variation was approximately the same for each case of imbalance. Figure 3.5 depicts the behavior of the three phase currents during the same experiment. It is seen that restricting the cooling air intake by different amounts has no effect on the phase currents. Current readings remain the same at each step imbalance regardless of the extent of the blockage. It can be concluded from this experiment that the degradation of motors due to environmental conditions may not always be reflected in the measured electrical variables.

An experiment was carried out by decreasing the load on the motor at various levels of phase imbalance. The plots of maximum motor current versus load are shown in Figure 3.6. At each value of phase imbalance, the load was decreased from 100% to 0% in steps of 20%. The behavior of the motor current with decreasing load is similar at different levels of phase imbalance. Figure 3.7 shows the casing temperature response for the above experiment. It was observed that the steady-state temperature decreased with decreasing load. However, the rate of decrease seemed to be more pronounced for

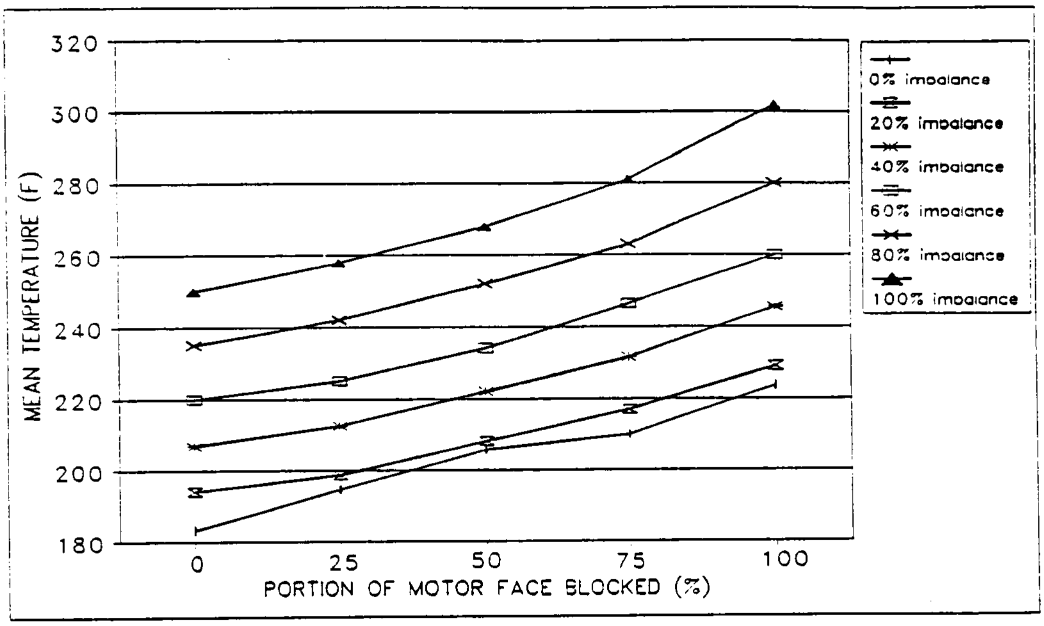

Figure 3.4 Effect of Blocking Air Intake on Temperature for Various Amounts of Phase Imbalance

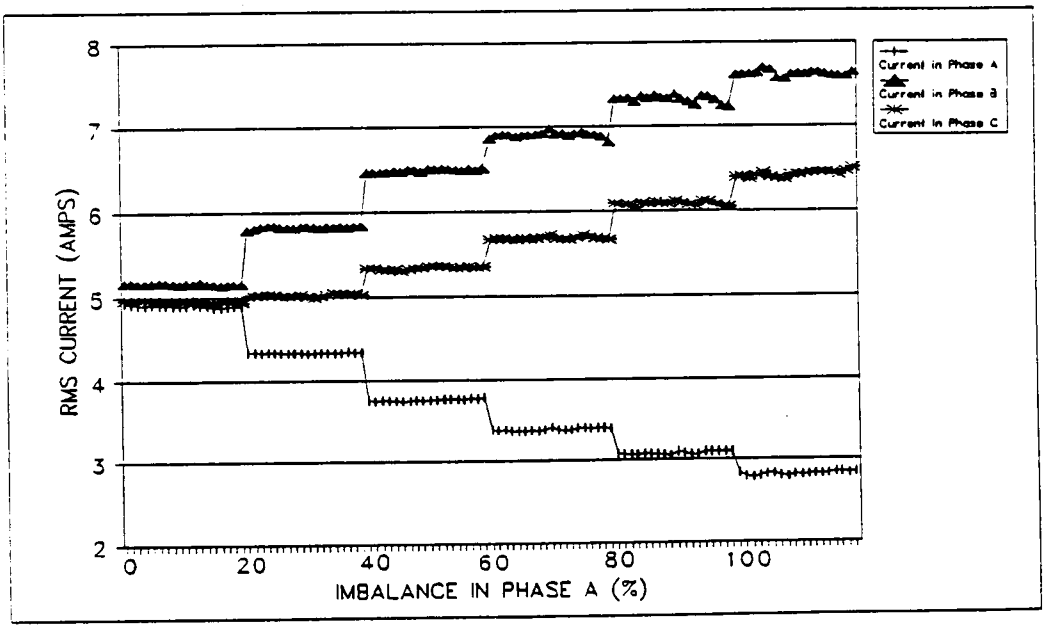

Figure 3.5 Effect of Blocking Air Intake on Motor Currents for Various Amounts of Phase Imbalance

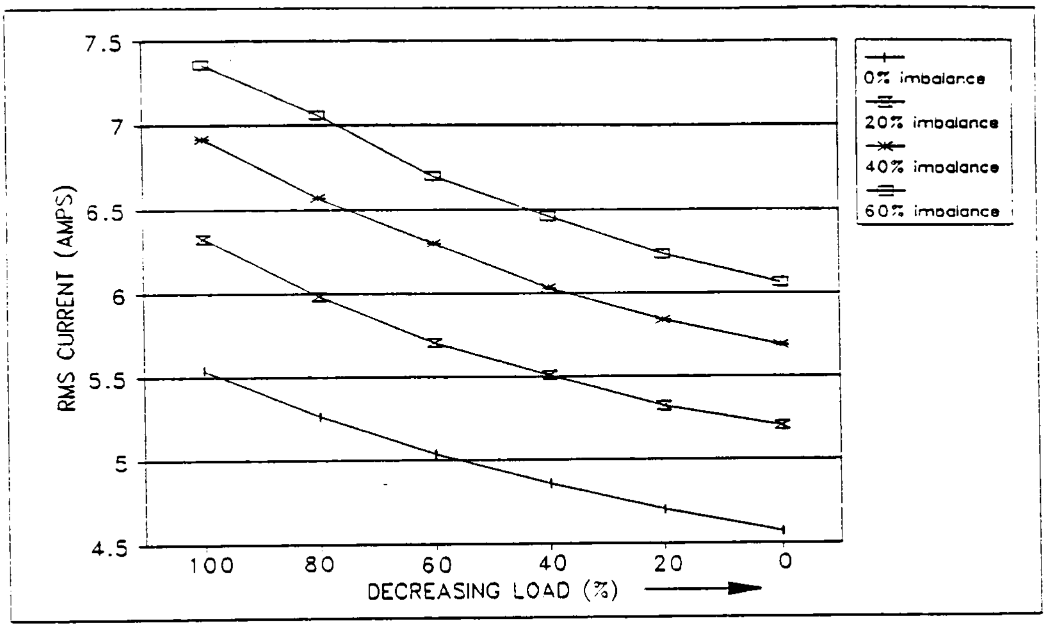

Figure 3.6 Effect of Decreasing Load on Phase B Current for Various Amounts of Phase Imbalance

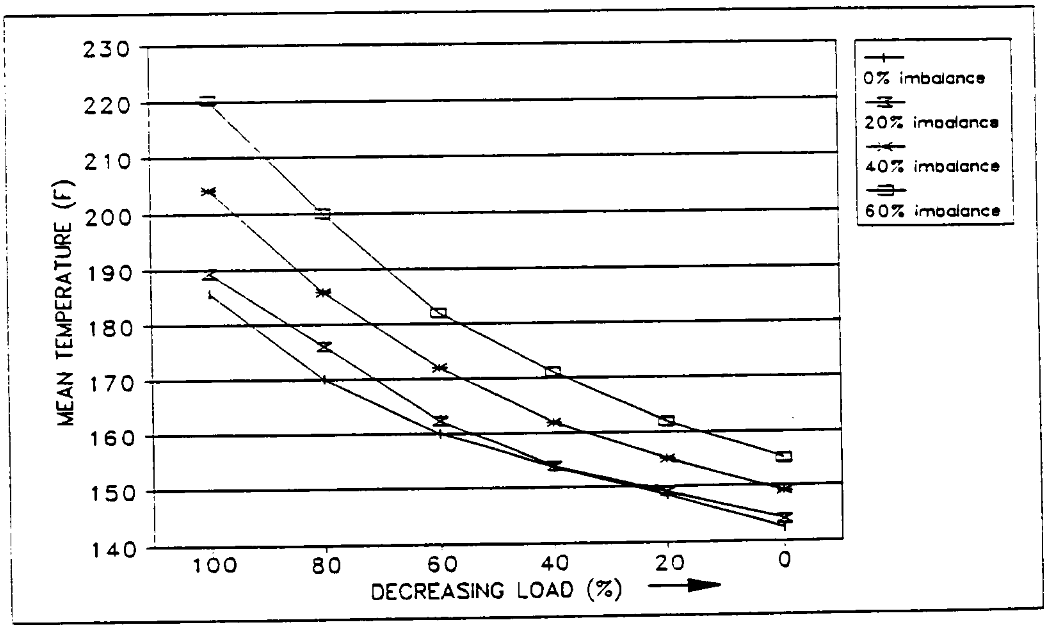

Figure 3.7 Effect of Decreasing Load on Temperature for Various Amounts of Phase Imbalance

tests with higher phase imbalances.

When a phase imbalance is present, the motor fails generally due to insulation failure in the stator. (This was observed when we opened the motors that had failed as a result of phase imbalance). It is most likely that hot spots appear in the windings carrying the maximum current. The maximum current bears a direct nonlinear relationship with the phase imbalance. Figure 3.8 shows the temperature as a function of the maximum current of a motor at different phase imbalances. It is seen that with lower phase imbalances (lower value of maximum current) the temperature rises linearly and gradually, but at higher phase imbalances the increase in temperature has a nonlinear behavior as a function of maximum phase current.

In one of the experiments, one phase of a motor was permanently damaged by reducing the number of conductor strands. As seen in Figure 3.9, the decrease in current in that phase was compensated by almost an equal increase in the currents in the other two phases. Figure 3.10 is the plot of motor casing temperature over time for the above experiment. This shows that an internal damage of small magnitude does not affect the temperature considerably. However, a definite increase in the motor casing temperature was clearly observed.

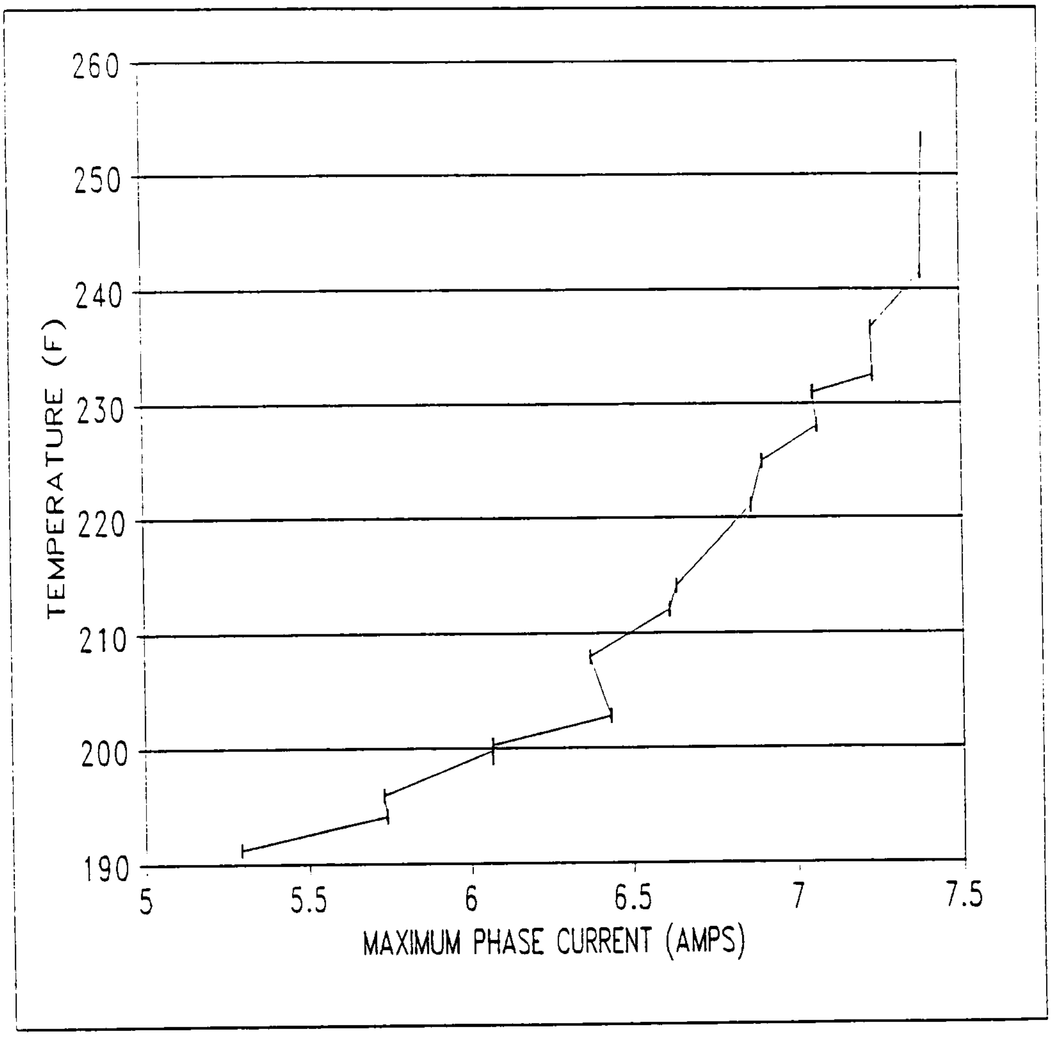

Figure 3.8 Motor Casing Temperature Shown as a Function of Maximum RMS Current for Different Imbalances

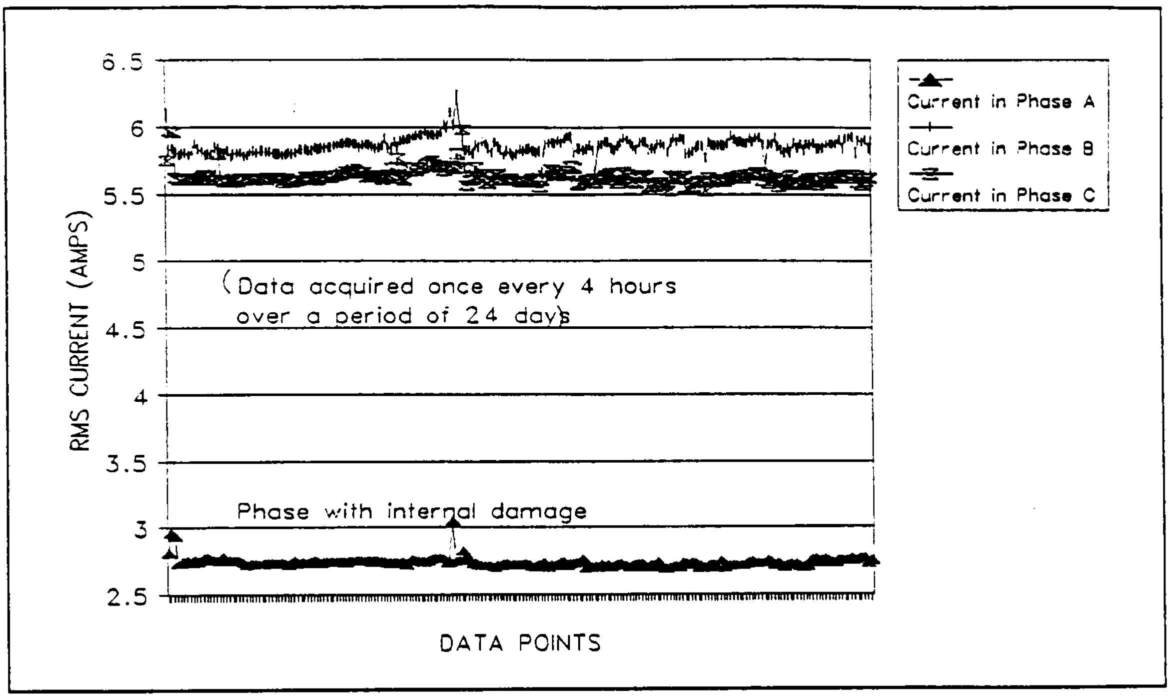

Figure 3.9 Effect of a Permanent Damage in Phase A Winding on Phase Currents

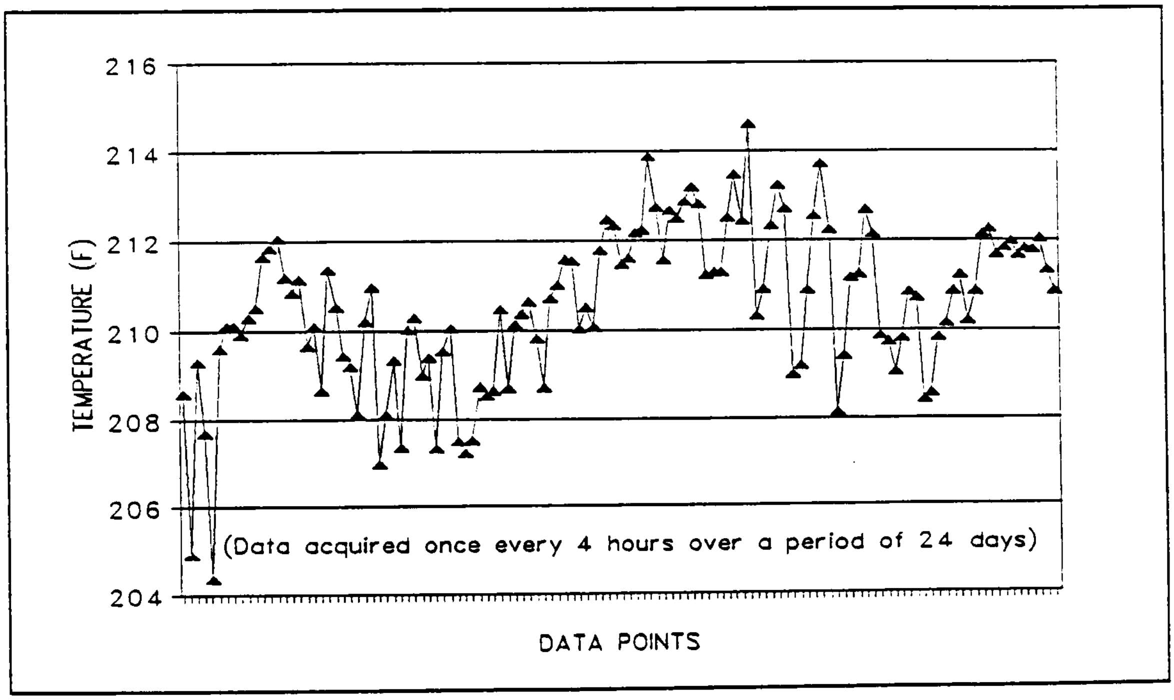

Figure 3.10 Effect of a Permanent Damage in Phase A Winding on Casing Temperature

Chapter 4

PERFORMANCE MODELING OF INDUCTION MOTORS

4.1 Introduction

In order to have a thorough understanding of the operation of an induction motor, it is essential to observe its dynamic characteristics. The differential equations describing the dynamic behavior of the electric machines are nonlinear, and can be solved using computer simulation softwares [20]. The reference axes are transformed from abc to qd0 (explained in Section 4.2) and the equations are written in the state space form. The input is the line voltage and the outputs are the three phase currents, the electromagnetic torque and the rotor speed. The dependent variables are the stator and rotor currents referred to the qd0 axes and the rotor angular frequency. The objective here is to study the sensitivity of the motor currents, torque and speed to changes in the motor parameters and the influence of external factors such as harmonics in the supply voltage. Also, simulation of motor performance helps in qualitatively verifying the results obtained from the experiments. The necessary background is provided in Section 4.2. Without going into the existing set of equations, a new set of equations pertaining to our particular area of interest (i.e., phase imbalance) are formulated in Section 4.3. The generalized balanced case is described in detail in [20]. Sections 4.4 and 4.5 discuss the results of simulation for the balanced and unbalanced conditions, respectively. The effect of harmonics in the power supply on motor currents, torque and speed are discussed in

Section 4.6.

4.2 Transformation of Variables

The variables of all three phase machines are generally stated in terms of the phases a,b and c. This notation is inconvenient for modeling and simulation purposes. The transformation of variables are used in the analysis of AC machines to eliminate time-varying inductances. In most of the digital computer programs used for transient and dynamic stability studies of power systems and power system components, the variables are represented in a reference frame rotating at synchronous or arbitrary speed. Hence, the variables associated with the induction motor must be transformed to the synchronously or arbitrarily rotating reference frame by a change of variables [20].

Let **f** represent any measurable electrical quantity, for example, voltage, current, flux linkage or electric charge. Then, the transformation of the 3-phase variables to the rotating reference frame (qd0 axis) is formulated as follows :

$$f_{qd0s} = K_s f_{abcs} \tag{4.1}$$

where f_{qd0s} is the electrical quantity referred to the qd0 axis and f_{abcs} is the same electrical quantity referred to the abc axis. The subscript 's' indicates association with stationary circuit elements. In matrix form,

$$(f_{qd0s}) = [f_{qs}\ f_{ds}\ f_{0s}]^T \tag{4.4}$$

$$[f_{abcs}] = [f_{as}\ f_{bs}\ f_{cs}]^T \tag{4.3}$$

K_s, the transformation matrix, is given by

$$K_s = \sqrt{\frac{2}{3}} \begin{bmatrix} \cos\theta & \cos\left(\theta - \frac{2\pi}{3}\right) & \cos\left(\theta + \frac{2\pi}{3}\right) \\ \sin\theta & \sin\left(\theta - \frac{2\pi}{3}\right) & \sin\left(\theta + \frac{2\pi}{3}\right) \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \tag{4.4}$$

θ is the angle between the rotating reference frame and the stationary reference frame at any instant (radians) and is expressed as

$$\theta = \int_0^t \omega(\xi) d\xi + \theta(0) \tag{4.5}$$

where ω is the speed of the rotating reference frame and ξ is a dummy variable of integration. It can be shown that

$$(K_s)^{-1} = (K_s)^T \tag{4.6}$$

For a singly-fed motor (one with power supply only on the stator side and not on the rotor side) with balanced or unbalanced stator conditions, the stationary reference frame ($\omega = 0$) is the most convenient reference frame for simulation purposes [20]. Thus the θ in Equation (4.4) becomes zero. The transformation equations considering the stationary reference frame can be visualized as trigonometric relationships between the variables as shown in Figure 4.1. Note that the zero axis variables are not associated with the reference frame but are related arithmetically to the abc variables.

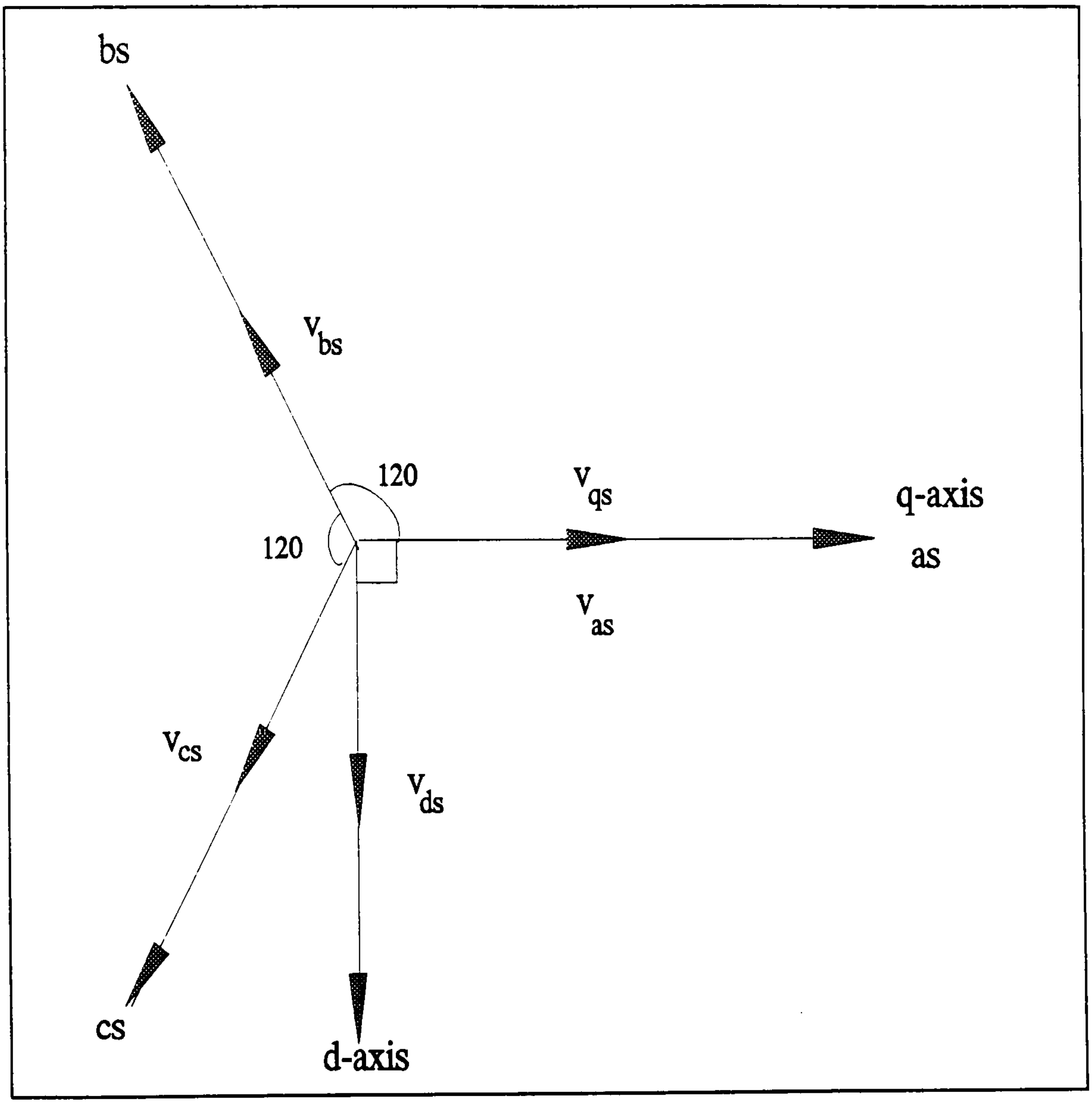

Figure 4.1 Transformation of a-b-c to d-q axes

4.3 State Space Equations

In the equations that follow, v denotes voltage, ψ denotes the flux linkage per second, i denotes current and r denotes resistance. The subscripts q, d, and 0 refer to the quadrature, the direct and the zero axis respectively. The subscript s stands for stator and the subscript r stands for rotor. The superscript ' impies that the rotor circuit elements and quantities are referred to the stator. Following Kirchoff's voltage law, the voltage equations for the resistive-inductive circuit of an induction motor are given below in terms of flux linkages per second [20].

$$v_{qs}=r_s i_{qs}+\frac{\omega}{\omega_b}\psi_{ds}+\frac{p}{\omega_b}\psi_{qs} \tag{4.7}$$

$$v_{ds}=r_s i_{ds}-\frac{\omega}{\omega_b}\psi_{qs}+\frac{p}{\omega_b}\psi_{ds} \tag{4.8}$$

$$v_{0s}=r_s i_{0s}+\frac{p}{\omega_b}\psi_{0s} \tag{4.9}$$

$$v_{qr}'=r_r' i_{qr}'-\frac{\omega-\omega_r}{\omega_b}\psi_{dr}'+\frac{p}{\omega_b}\psi_{qr}' \tag{4.10}$$

$$v_{dr}'=r_r' i_{dr}'-\frac{\omega-\omega_r}{\omega_b}\psi_{qr}'+\frac{p}{\omega_b}\psi_{dr}' \tag{4.11}$$

$$v_{0r}'=r_r' i_{0r}'+\frac{p}{\omega_b}\psi_{0r}' \tag{4.12}$$

where ω is the rotor angular frequency and is a function of current, ω_b is the base electrical angular velocity used to calculate the inductive reactances and p=d/dt. The flux linkages per second are, in turn, related to the currents and inductive reactances as follows:

$$\psi_{qs}=X_{ls}i_{qs}+X_m\left(i_{qs}+i_{qr}'\right) \tag{4.13}$$

$$\psi_{ds}=X_{ls}i_{ds}+X_m\left(i_{ds}+i_{dr}'\right) \tag{4.14}$$

$$\psi_{0s}=X_{ls}i_{0s} \tag{4.15}$$

$$\psi_{qr}'=X_{lr}'i_{qr}'+X_m\left(i_{qs}+i_{qr}'\right) \tag{4.16}$$

$$\psi_{dr}'=X_{lr}'i_{dr}'+X_m\left(i_{ds}+i_{dr}'\right) \tag{4.17}$$

$$\psi_{0r}'=X_{lr}'i_{0r}' \tag{4.18}$$

where X_{ls} is the stator leakage inductance, X_m is the mutual inductance and X_{lr} is the rotor leakage reactance referred to the stator. The above Equations (4.13 - 4.18) are illustrated in the equivalent circuit diagram Figure 4.2.

In case of a singly-fed induction motor,

$$v_{qr}'=v_{dr}'=v_{0r}'=0$$

and since there is no electrical imbalance in the rotor, the zero sequence current (Appendix A) in the rotor is absent. Hence

$$i_{0r}'=0$$

Also, when the system is balanced, the nonzero elements of the diagonal matrix $\mathbf{r}_s$ are equal and $\mathbf{K}_s\mathbf{r}_s(\mathbf{K}_s)^{-1} = \mathbf{r}_s$.

In the special case where the phase resistances are unequal, the resistance matrix associated with the variables is a function of $\mathbf{K}_s$. If the stationary reference frame ($\theta=0$) is chosen due to the reason discussed earlier, then $\mathbf{K}_s$ becomes

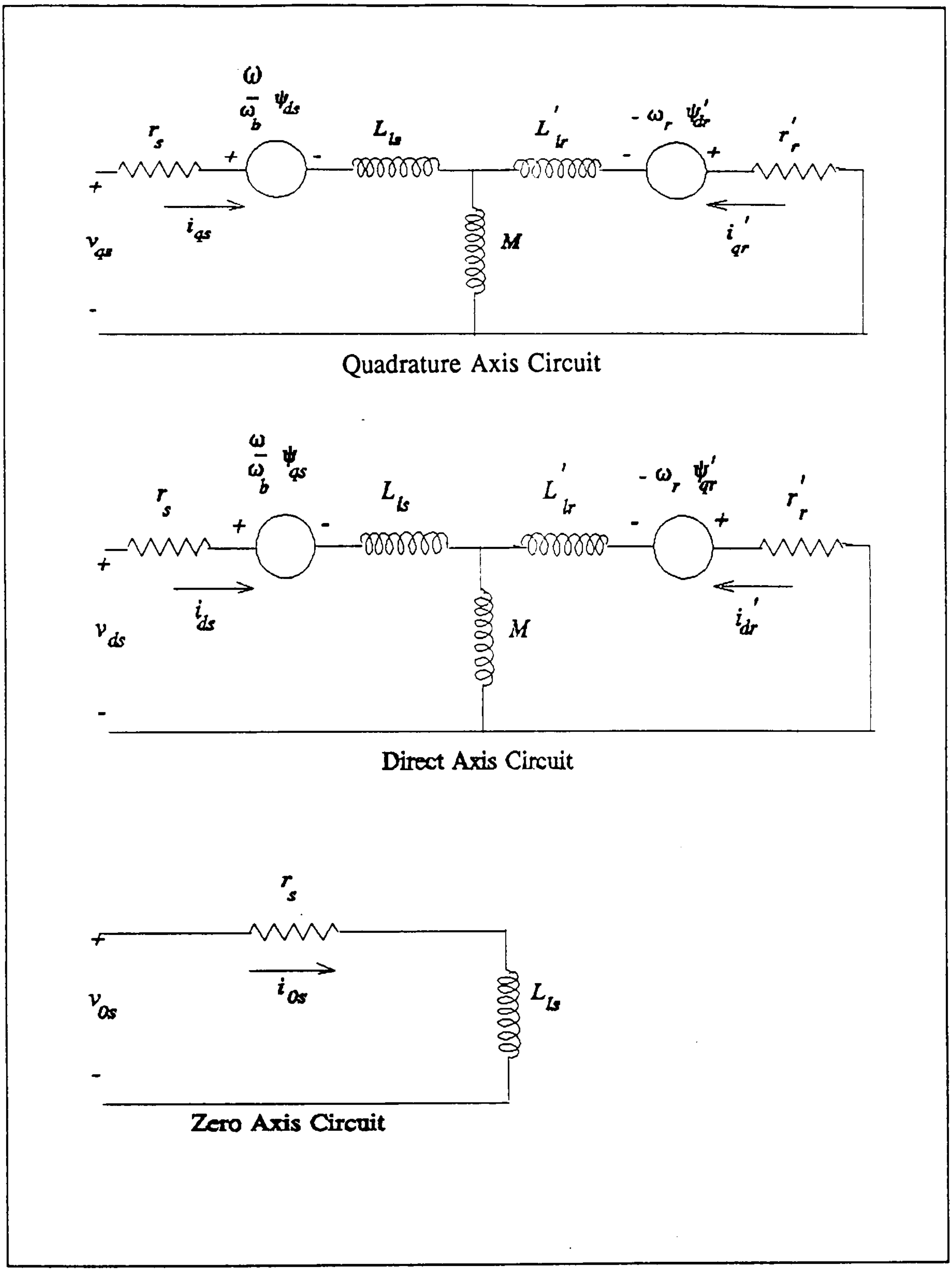

Figure 4.2 Equivalent Circuit in Terms of State Variables [20]

$$K_s = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & -\frac{\sqrt{3}}{2} & \frac{\sqrt{3}}{2} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \tag{4.19}$$

In this case, the resistive matrix becomes

$$\underline{K}_s \underline{r}_s \underline{K}_s^{-1} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & -\frac{\sqrt{3}}{2} & \frac{\sqrt{3}}{2} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} r_{as} & 0 & 0 \\ 0 & r_{bs} & 0 \\ 0 & 0 & r_{cs} \end{bmatrix} \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & 0 & \frac{1}{\sqrt{2}} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} & \frac{1}{\sqrt{2}} \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$\underline{K}_s \underline{r}_s \underline{K}_s^{-1} = \begin{bmatrix} \frac{2}{3} r_{as} + \frac{1}{6} r_{bs} + \frac{1}{6} r_{cs} & \frac{1}{2\sqrt{3}} \left(r_{bs} - r_{cs} \right) & \frac{\sqrt{2}}{3} r_{as} - \frac{1}{3\sqrt{2}} \left(r_{bs} + r_{cs} \right) \\ \frac{1}{2\sqrt{3}} \left(r_{bs} - r_{cs} \right) & \frac{1}{2} \left(r_{bs} + r_{cs} \right) & \frac{1}{\sqrt{6}} \left(-r_{bs} + r_{cs} \right) \\ \frac{\sqrt{2}}{3} r_{as} - \frac{1}{3\sqrt{2}} \left(r_{bs} + r_{cs} \right) & \frac{1}{\sqrt{6}} \left(-r_{bs} + r_{cs} \right) & \frac{1}{3} \left(r_{as} + r_{bs} + r_{cs} \right) \end{bmatrix} \tag{4.20}$$

The experiments carried out in this research involved adding an external resistance in one of the phases (phase A) leaving the other two phases intact. Henceforth, the unchanged resistances in phase b and phase c are referred to as r_s and the changed resistance in phase A as r_{as}. The resistive matrix finally becomes

$$\underline{K}_s \underline{r}_s \underline{K}_s^{-1} = \begin{bmatrix} \frac{2}{3} r_{as} + \frac{1}{3} r_s & 0 & \frac{\sqrt{2}}{3} \left(r_{as} - r_s \right) \\ 0 & r_s & 0 \\ \frac{\sqrt{2}}{3} \left(r_{as} - r_s \right) & 0 & \frac{1}{3} r_{as} + \frac{2}{3} r_s \end{bmatrix} \tag{4.21}$$

Equations (4.7) through (4.12) are modified to incorporate the required condition of phase imbalance by substituting $\mathbf{r_s}$ with $\mathbf{K_s r_s K_s^{-1}}$. Also ψ in the Equations (4.7-4.12) are substituted from Equations (4.13) through (4.18), and we arrive at the following

$$\begin{bmatrix} v_{qs} \\ v_{ds} \\ v_{0s} \\ 0 \\ 0 \end{bmatrix} = Z \cdot \begin{bmatrix} i_{qs} \\ i_{ds} \\ i_{0s} \\ i_{qr}' \\ i_{dr}' \end{bmatrix} \tag{4.22}$$

where

$$Z = \begin{bmatrix} \frac{2}{3}r_{as}+\frac{1}{3}r_s+\frac{p}{\omega_b}X_{ss} & 0 & \frac{\sqrt{2}}{3}(r_{as}-r_s) & \frac{p}{\omega_b}X_m & 0 \\ 0 & r_s+\frac{p}{\omega_b}X_{ss} & 0 & 0 & \frac{p}{\omega_b}X_m \\ \frac{\sqrt{2}}{3}(r_{as}-r_s) & 0 & \frac{1}{3}r_{as}+\frac{2}{3}r_s+\frac{p}{\omega_b}X_{ls} & 0 & 0 \\ \frac{p}{\omega_b}X_m & -\frac{\omega_r}{\omega_b}X_m & 0 & r_r'+\frac{p}{\omega_b}X_{rr}' & -\frac{\omega_r}{\omega_b}X_{rr}' \\ \frac{\omega_r}{\omega_b}X_m & \frac{p}{\omega_b}X_m & 0 & \frac{\omega_r}{\omega_b}X_{rr}' & r_r'+\frac{p}{\omega_b}X_{rr}' \end{bmatrix}$$

Rewriting,

$$v_{qs}=\left(\frac{2}{3}r_{as}+\frac{1}{3}r_s\right)i_{qs}+\frac{p}{\omega_b}X_{ss}i_{qs}+\frac{\sqrt{2}}{3}(r_{as}-r_s)i_{0s}+\frac{p}{\omega_b}X_m i_{qr}' \tag{4.23}$$

$$v_{ds}=r_s i_{ds}+\frac{X_{ss}}{\omega_b}pi_{ds}+\frac{X_m}{\omega_b}pi_{dr}' \tag{4.24}$$

$$v_{0s}=\frac{\sqrt{2}}{3}(r_{as}-r_s)i_{qs}+\left(\frac{1}{3}r_{as}+\frac{2}{3}r_s\right)i_{0s}+\frac{p}{\omega_b}X_{ls}i_{os} \tag{4.25}$$

$$0=\frac{p}{\omega_b}X_m i_{qs}-\frac{\omega_r}{\omega_b}X_m i_{ds}+\left(r_r'+\frac{p}{\omega_b}X_{rr}'\right)i_{qr}'-\frac{\omega_r}{\omega_b}X_{rr}'i_{dr}' \tag{4.26}$$

$$0=\frac{\omega_r}{\omega_b}X_m i_{qs}+\frac{p}{\omega_b}X_m i_{ds}+\frac{\omega_r}{\omega_b}X_{rr}'i_{qr}'+r_r'i_{dr}'+\frac{p}{\omega_b}X_{rr}'i_{dr}' \tag{4.27}$$

Transposing the differential terms to the left hand side, we obtain

$$\frac{p}{\omega_b}(X_{ss}i_{qs}+X_m i_{qr}')=v_{qs}-\left(\frac{2}{3}r_{as}+\frac{1}{3}r_s\right)i_{qs}-\frac{\sqrt{2}}{3}(r_{as}-r_s)i_{0s} \tag{4.28}$$

$$\frac{p}{\omega_b}(X_{ss}i_{ds}+X_m i_{dr}')=v_{ds}-r_s i_{ds} \tag{4.29}$$

$$\frac{p}{\omega_b}X_{ls}i_{0s}=v_{0s}-\frac{\sqrt{2}}{3}(r_{as}-r_s)i_{qs}-\left(\frac{1}{3}r_{as}+\frac{2}{3}r_s\right)i_{0s} \tag{4.30}$$

$$\frac{p}{\omega_b}(X_m i_{qs}+X_{rr}'i_{qr}')=\frac{\omega_r}{\omega_b}X_m i_{ds}-r_r'i_{qr}'+\frac{\omega_r}{\omega_b}X_{rr}'i_{dr}' \tag{4.32}$$

$$\frac{p}{\omega_b}(X_m i_{ds}+X_{rr}'i_{dr}')=-\frac{\omega_r}{\omega_b}X_m i_{qs}-\frac{\omega_r}{\omega_b}X_{rr}'i_{qr}'-r_r'i_{dr}' \tag{4.33}$$

The above equations are now written in the matrix form

$$\frac{1}{\omega_b}\begin{bmatrix} X_{ss} & 0 & 0 & X_m & 0 \\ 0 & X_{ss} & 0 & 0 & X_m \\ 0 & 0 & X_{ls} & 0 & 0 \\ X_m & 0 & 0 & X_{rr}' & 0 \\ 0 & X_m & 0 & 0 & X_{rr}' \end{bmatrix} \frac{d}{dt}\begin{bmatrix} i_{qs} \\ i_{ds} \\ i_{0s} \\ i_{qr}' \\ i_{dr}' \end{bmatrix} = \begin{bmatrix} v_{qs} \\ v_{ds} \\ v_0 S \\ 0 \\ 0 \end{bmatrix} - \underline{Z_2}\begin{bmatrix} i_{qs} \\ i_{ds} \\ i_{0s} \\ i_{qr}' \\ i_{dr}' \end{bmatrix} \tag{4.34}$$

where

$$\underline{Z_2} = \begin{bmatrix} \frac{2}{3}r_{as}+\frac{1}{3}r_s & 0 & \frac{\sqrt{2}}{3}(r_{as}-r_s) & 0 & 0 \\ 0 & r_s & 0 & 0 & 0 \\ \frac{\sqrt{2}}{3}(r_{as}-r_s) & \left(\frac{1}{3}r_{as}+\frac{2}{3}r_s\right) & 0 & 0 & \\ 0 & -\frac{\omega_r}{\omega_b}X_m & 0 & r_r' & -\frac{\omega_r}{\omega_b}X_{rr}' \\ \frac{\omega_r}{\omega_b}X_m & 0 & 0 & \frac{\omega_r}{\omega_b}X_{rr}' & r_r' \end{bmatrix}$$

This can be rewritten in the final state-space form as

$$\frac{d\underline{I}}{dt}=\omega_b\underline{X}^{-1}\underline{V}-\omega_b\underline{X}^{-1}\underline{Z_2}\underline{I} \tag{4.35}$$

where

$$\underline{X}^{-1}=\frac{1}{D}\begin{bmatrix} X_{rr}' & 0 & 0 & -X_m & 0 \\ 0 & X_{rr}' & 0 & 0 & -X_m \\ 0 & 0 & \frac{D}{X_{ls}} & 0 & 0 \\ -X_m & 0 & 0 & X_{ss} & 0 \\ 0 & -X_m & 0 & 0 & X_{ss} \end{bmatrix}$$

and

$$D=X_{ss}X_{rr}'-X_m^2=(X_{ls}+X_m)(X_{lr}'+X_m)-X_m^2=X_{ls}X_{lr}'+X_m(X_{ls}+X_{lr}')$$

The electromagnetic torque is given by [20]

$$T_e = 0.75\times \textit{pole} \times L_m\times(i_{dr}'\ i_{qs}-i_{qr}'\ i_{ds})$$

where pole denotes the number of poles of the motor. As seen from the above equation, electromagnetic torque developed is nonlinear. The current equations contain terms which are products of the rotor frequency and current, both of which are dependent variables, and hence the current equations are also nonlinear.

The final state space equations used in the simulation are

$$\frac{di_{qs}}{dt}=\frac{\omega_b^2}{D}\left[L_{rr}'v_{qs}-L_{rr}'\left(\frac{2}{3}r_{as}+\frac{1}{3}r_s\right)i_{qs}-L_m^2\omega_r i_{ds}-L_{rr}'\frac{\sqrt{2}}{3}(r_{as}-r_s)i_{0s}+L_m r_r' i_{qr}'-L_m L_{rr}'\omega_r i_{dr}'\right] \tag{4.37}$$

$$\frac{di_{ds}}{dt}=\frac{\omega_b^2}{D}\left[L_{rr}'v_{ds}+L_m^2\omega_r i_{qs}-L_{rr}'r_s i_{ds}+L_m L_{rr}'\omega_r i_{qr}'+L_M r_r' i_{dr}'\right] \tag{4.38}$$

$$\frac{di_{0s}}{dt}=\frac{\omega_b}{X_{ls}}\left[v_{0s}-\frac{\sqrt{2}}{3}(r_{as}-r_s)i_{qs}-\left(\frac{1}{3}r_{as}+\frac{2}{3}r_s\right)i_{0s}\right] \tag{4.39}$$

$$\frac{di_{qr}'}{dt}=\frac{\omega_b^2}{D}\left[-L_m v_{qs}+L_m\left(\frac{2}{3}r_{as}+\frac{1}{3}r_s\right)i_{qs}+L_{ss}L_m\omega_r i_{ds}+L_m\frac{\sqrt{2}}{3}(r_{as}-r_s)i_{0s}-L_{ss}r_r' i_{qr}'+L_{ss}L_{rr}'\omega_r i_{dr}'\right] \tag{4.40}$$

$$\frac{di_{dr}'}{dt}=\frac{\omega_b^2}{D}\left[-L_m v_{ds}+L_{ss}L_m\omega_r i_{qs}+L_m r_s i_{ds}+L_{ss}L_{rr}'\omega_r i_{qr}'-L_{ss}r_r' i_{dr}\right] \tag{4.41}$$

From Reference [20]

$$\frac{d\omega}{dt}=\frac{T_e-T_l}{J\times\dfrac{2}{pole}} \tag{4.42}$$

where J is the inertia of the rotor in kg-m^2 and T_l is the applied load torque in N-m.

4.4 Simulation for Balanced and Unbalanced Conditions of an Induction Motor

The dynamic model of a three phase induction motor was used to study the sensitivity of the motor variables to changes in its characteristic parameters. In particular, the behavior of the machine under normal and abnormal conditions was studied. A simulation software called SIMNON was used in this analysis. It features state space representation for dynamic systems, hybrid linear and nonlinear simulation and interactive graphics. The system is modeled by a set of state space equations. The three phase voltages were the inputs and torque and speed were the outputs of the motor. The state variables were the currents and the angular speed.

The response of a three phase, 230 volts, 5.7 Amps, 1725 rpm, 2 horsepower induction motor was simulated for normal and abnormal conditions to study the effects of applying full load torque at a certain time with the three phases balanced, that with a resistive imbalance in one of the phases and also to study the effect of harmonics present in the supply voltage on motor current, torque and speed. The computer code written in SIMNON incorporates the final form of the state space equations given above. This code is provided in Appendix B. Simulation under the balanced condition was achieved by modifying the same code to include some generalizations. Two other computer codes generate the 3rd and 5th harmonics in the supply voltage. These modifications are also presented in Appendix B.

Figure 4.3 illustrates the result for the balanced condition. It shows the motor current, torque and speed variables for the first 3 seconds of the simulation. All the three waveforms undergo a transient phase for the first 0.6 second. After that, the

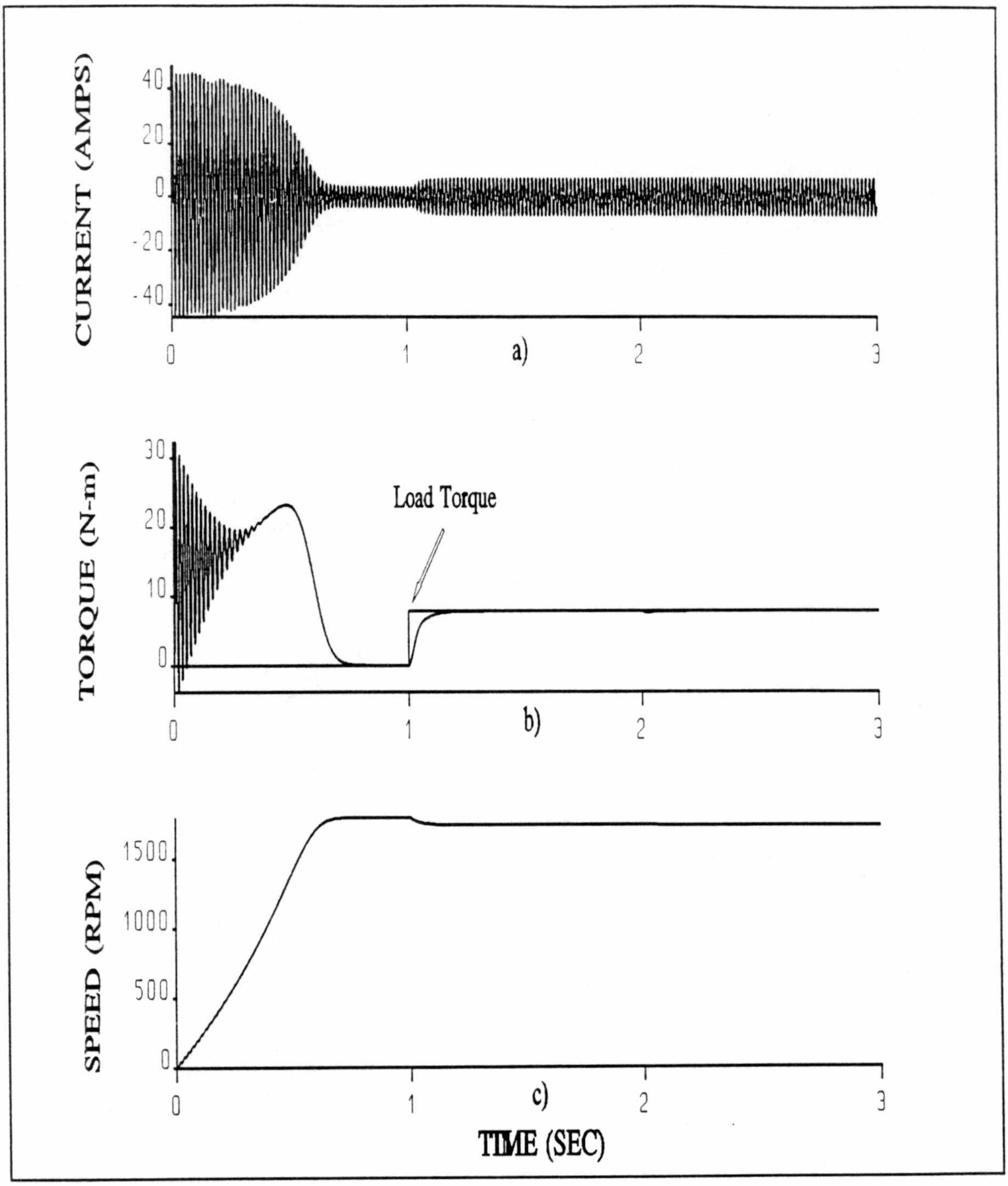

Figure 4.3 Simulation Results Under Balanced Condition
(Load Applied at 1 sec)
a) Phase Current (Amps)
b) Load Torque and Electromagnetic Torque (N-m)
c) Speed (RPM)

current settles down at the no-load current value of about 2.3 Amps. The electromagnetic torque developed is zero, as there is no load and the motor does not have to deliver any power. The speed is the no-load speed of 1800 rpm. When the full load torque is applied at 1 second after starting, the current increases to the rated current of 5.7 Amps, the electromagnetic torque builds up to the load torque to supply adequate power to the load and the speed falls to the rated full load speed of 1725 rpm.

The unbalanced condition was simulated by adding an additional resistance in phase A, 4 seconds after starting the motor. The result of this is shown in Figures 4.4 and 4.5. Immediately after adding the imbalance, the current in phase a decreases and the currents in the other two phases increase. Though the change is not very prominent from the plots produced by SIMNON because of the scale, the result is as expected and compares very well with the experimental results. Also, as a result of the imbalance, speed decreases to slightly below the speed under normal load and both speed and torque begin pulsating. The decrease in the speed can be observed from the measurement, but the fluctuations produced in the speed and torque are not readily observable. The detrimental effect of a phase imbalance is, revealed clearly in the simulation of motor dynamic behavior.

4.5 Effect of Harmonics in the Power Supply

Harmonics were introduced in the supply voltage. For all practical purposes, the total harmonic distortion (THD) in the voltage can be 5%-6% of the rated voltage. First, a 5% third harmonic was added to the supply voltage and its effect on current, torque

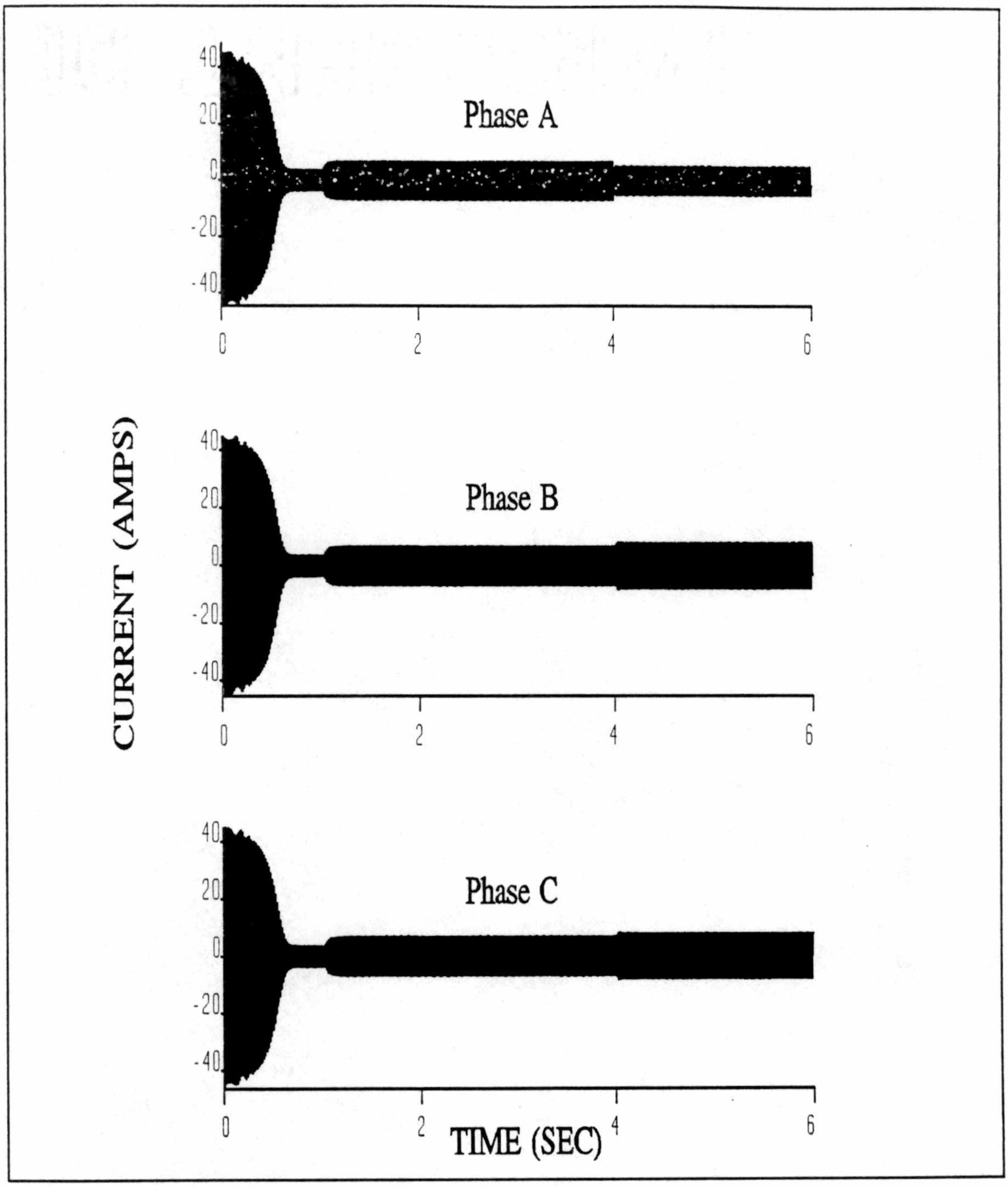

Figure 4.4 Currents in Phase A, Phase B and Phase C (Amps) as a Result of Applying a Load at 1 sec and Introducing a Resistance in Phase A at 4 sec

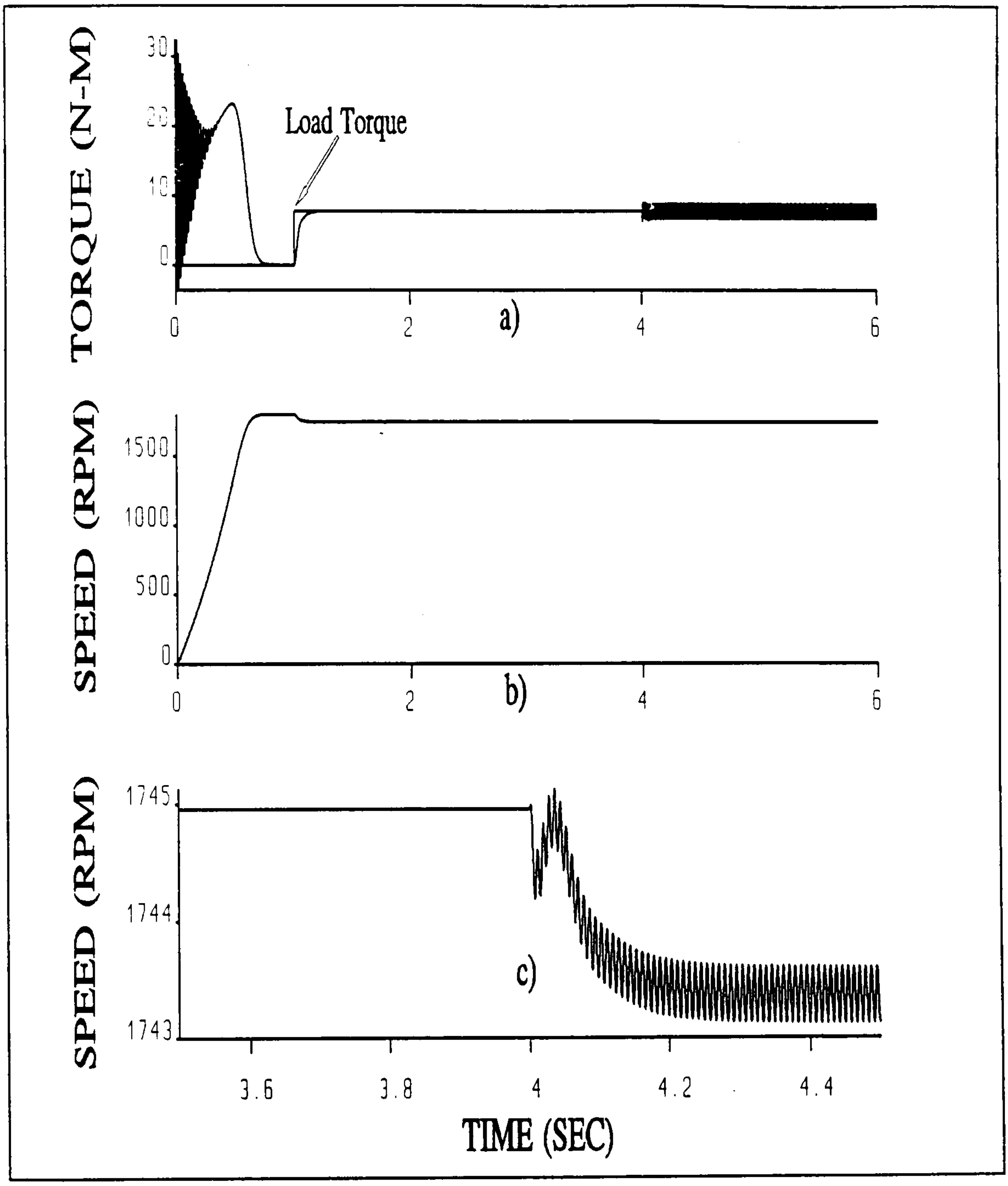

Figure 4.5 Effect of Phase Imbalance Introduced at 4 sec on Torque and Speed (Load Torque Applied at 1.0 sec)
a) Electromagnetic Torque and Load Torque (N-m)
b) Motor Speed (RPM)
c) Detailed plot of the Motor Speed Variation (RPM)

and speed are noted. Second, a fifth harmonic of 1% of the rated voltage was added to the above third harmonic. Currents in phase A with sinusoidal voltage, with a 5% third harmonic in voltage and with 5% third harmonic and 1% 5th harmonic are shown for comparison in Figure 4.6. Figures 4.7 and 4.8 compare the torques and the speeds, respectively for the same cases described above. With the introduction of harmonics, the current waveform no more remains perfectly sinusoidal but develops a distortion near the peak of the sine wave. The torque fluctuates with time about the full load torque of 7.8 N-m and the speed waveform has ripples about the full load speed of 1745 rpm. It is seen that the introduction of the fifth harmonic does not add to the amplitude of the distortions but has a smoothing effect on both.

The presence of harmonics in the power supply of high performance motors is of considerable concern in industrial processes, because of the increase in induced vibration in large motors, and the consequent reduction in their service life.

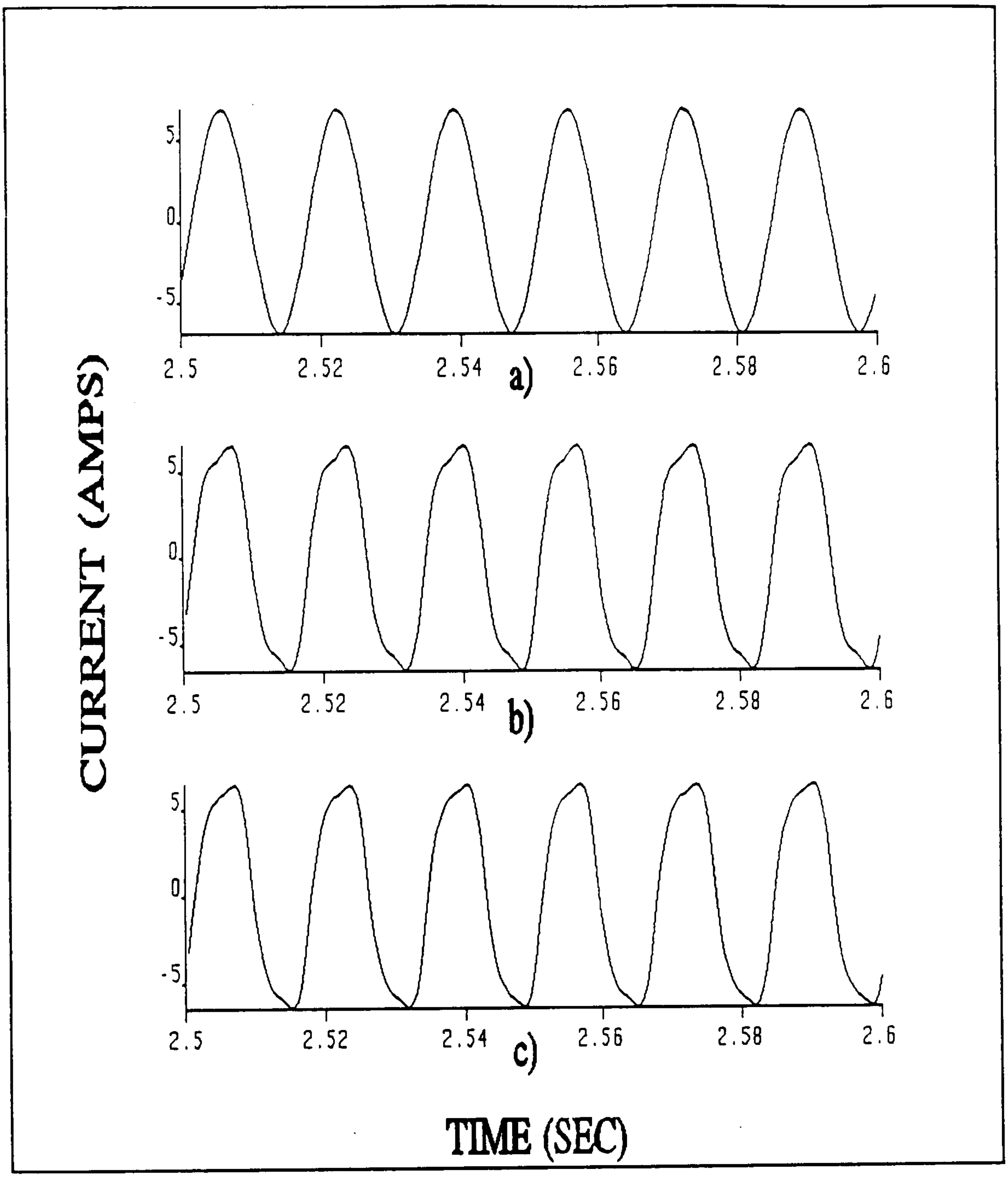

Figure 4.6 Effect of Harmonics on Current
a) Phase Current Without Harmonics
b) Phase Current With 5% third Harmonic
c) Phase Current With 5% third Harmonic and 1% 5th Harmonic

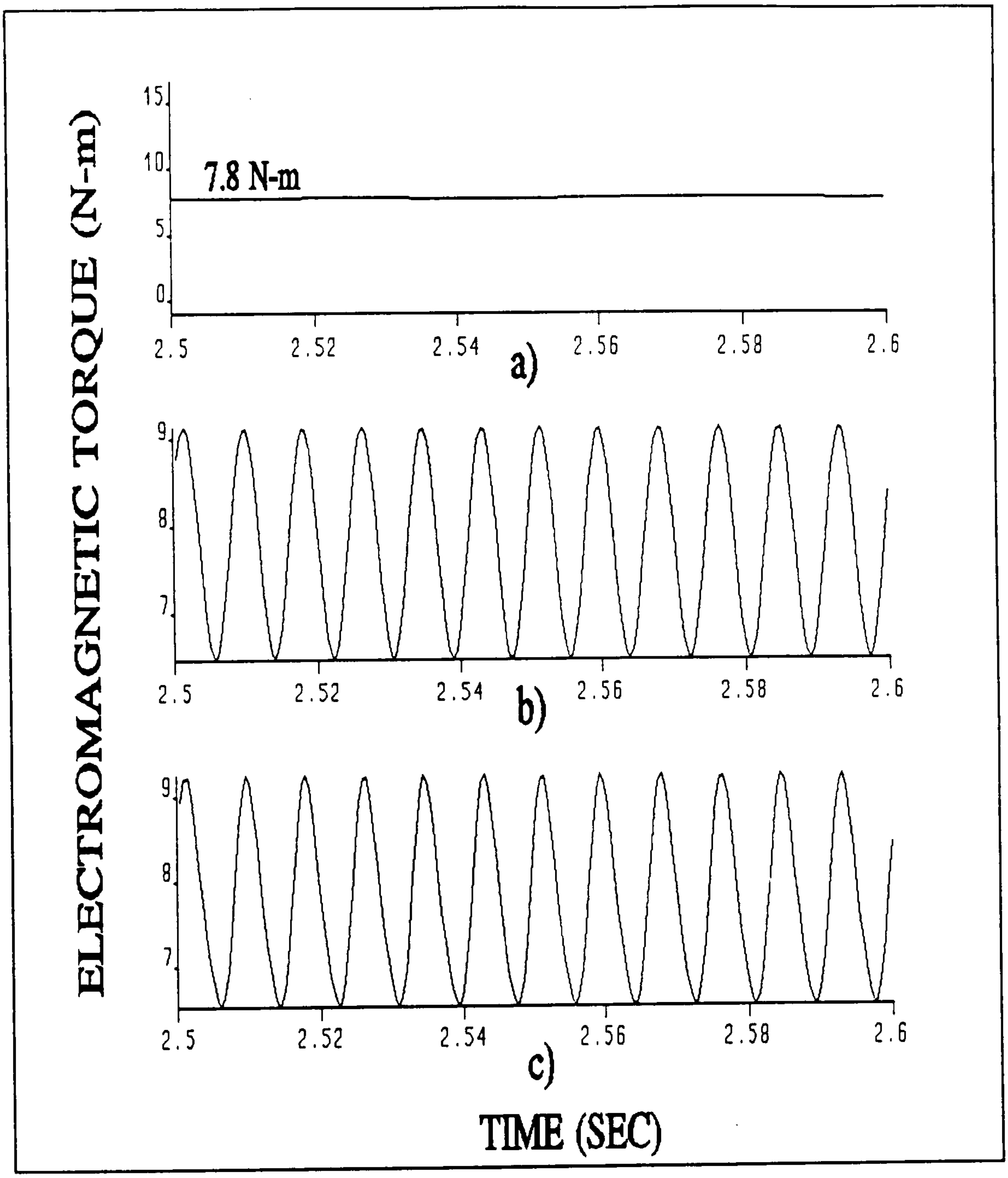

Figure 4.7 Effect of Harmonics on Electromagnetic Torque
a) Without Harmonics
b) With 5% third Harmonic
c) With 5% third Harmonic and 1% 5th Harmonic

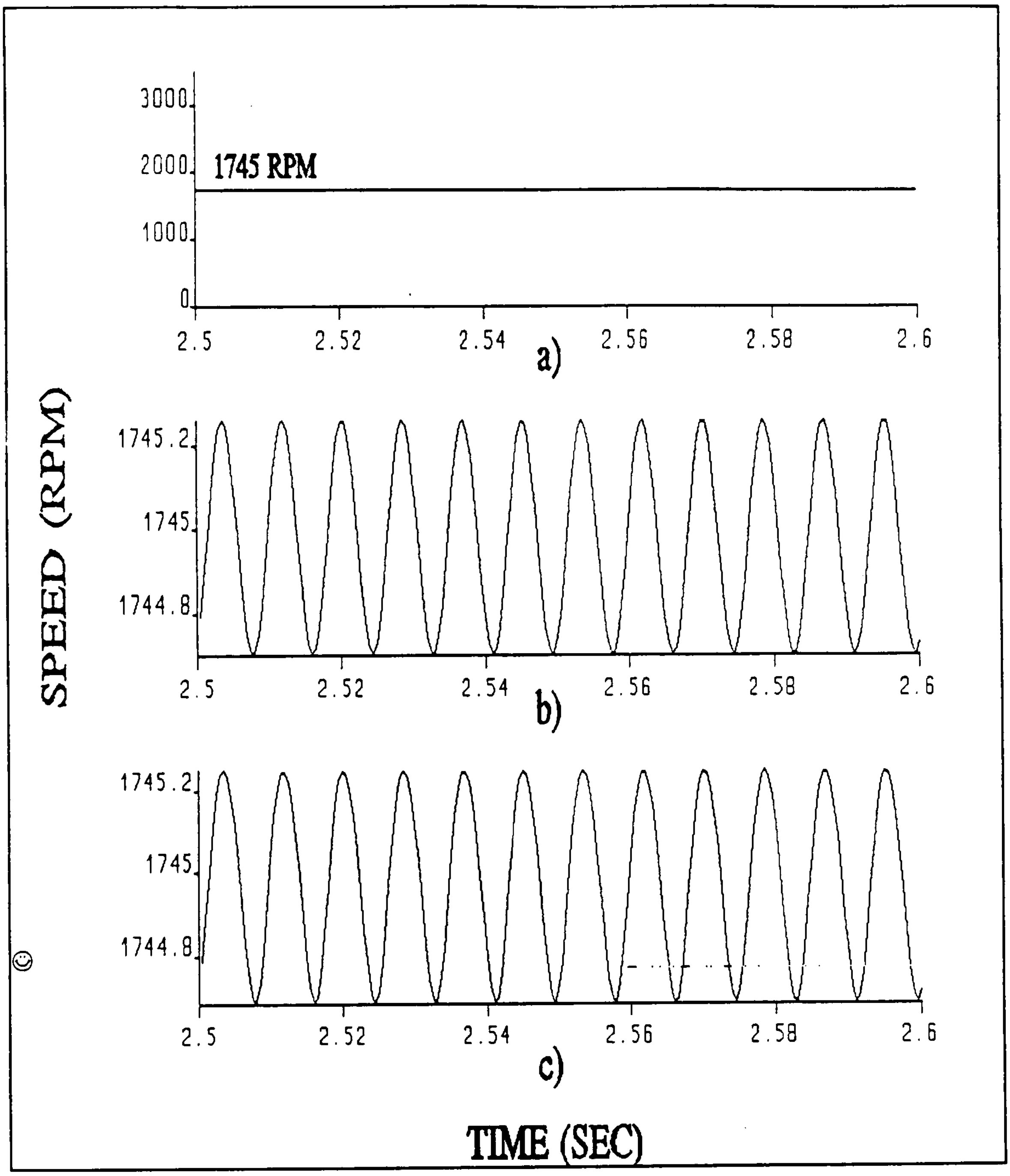

Figure 4.8 Effect of Harmonics on Motor Speed
a) Without Harmonics
b) With 5% third Harmonic
c) With 5% third Harmonic and 1% fifth Harmonic

Chapter 5

METHODS FOR ESTIMATING RESIDUAL LIFE OF PLANT COMPONENTS

5.1 Introduction

In order to have better control over plant performance and to avoid unnecessary and unscheduled shutdowns, it is important to estimate the remaining life of plant components. This chapter describes the methods that were developed and used to estimate the life of an induction motor using various motor signatures. These methods can be extended to electric motors used in nuclear and fossil power plants, process industry, as well as stationary components such as piping, pressure vessels and heat exchangers.

Two statistical methods are first described. One of them is the empirical data-driven modeling approach, and the other is a statistical Sequential Probability Ratio Test (SPRT). The SPRT is a technique that allows the visualization of a degradation trend (if there is any), even if it is not apparent from the trend in the signatures measured. It classifies a component or a sensor as normal or degraded depending on the behavior of a likelihood ratio described in Section 5.2.

The regression analysis primarily consists of fitting a model to a sequence of data points using a least-squares-estimation method. This model enables us to predict the trend in a signature for a future time. The model may be fit over the entire range of data or to the data in a selected range (referred to as the window) and the model may adapt itself to the changing trend in data as the window is moved. An error analysis provides a goodness-of-fit and quantifies the confidence in the prediction. Both static and dynamic regression models, with nonlinear features are used to establish the residual life of small induction motors.

Section 5.3 describes a non-parametric approach to the estimation of residual life of electric motors. Artificial neural network models were developed using motor trend data from a number of input-output patterns. The inputs are motor signatures and the output is the residual life. When provided with data not presented before, the network "recalls" the knowledge gained during training and predicts a residual life corresponding to this data window.

5.2 The Sequential Probability Ratio Test

A sensor or component cannot be judged as failed unless a number of continuous observations have been made. It is inconvenient to calculate the mean and the variance for each of the samples and use them to check whether a component has degraded or not. The sequential probability ratio test (SPRT), originally developed by Wald, makes use of the degree of failure and the continuous behavior of components instead of the updated mean and variance to detect failures [22].

A Gaussian (normal) probability density function is assumed for the signature to be trended. Let x be a process variable. The SPRT is applied to the residual $s(t_m)$ between the measured value and the estimated value of x at any time t_m

$$s(t_m) = x(t_m) - \hat{x}(t_m) \tag{5.1}$$

Let m_0 and σ_0^2 be the mean and the variance respectively, for the normal condition and m_1 and σ_1^2 be the mean and the variance respectively, for the degraded condition. The Gaussian density function modeling the normal mode signal error is

$$p_0(s, m_0, \sigma_0^2) = \frac{1}{\sqrt{2\pi\sigma_0^2}} \exp\left[-\frac{(s-m_0)^2}{2\sigma_0^2}\right] \tag{5.2}$$

The likelihood ratio, that is, the ratio between the degraded density function and the normal density function, is given by

$$\lambda = \frac{p_1(s, m_1, \sigma_1^2)}{p_0(s, m_0, \sigma_0^2)} \tag{5.3}$$

This ratio is updated at every sampling instant. For a sequence of independent samples, the joint density function is the product of the individual density functions. An overall likelihood ratio updated at instances i = 1, 2, 3,...m is expressed as follows:

$$\lambda_m{}' = \frac{p_1(s_1, m_1, \sigma_1^2)\; p_1(s_2, m_1, \sigma_1^2) \ldots\ldots p_1(s_m, m_1, \sigma_1^2)}{p_0(s_1, m_0, \sigma_0^2)\; p_0(s_2, m_0, \sigma_0^2) \ldots\ldots p_0(s_m, m_0, \sigma_0^2)} \tag{5.4}$$

Taking natural logarithm on both sides of the above equation makes its form additive.

$$\lambda_m = \sum_{i=1}^{m} \ln\left[\frac{p_1(s_i, m_1, \sigma_1^2)}{p_0(s_i, m_0, \sigma_0^2)}\right] \tag{5.5}$$

This equation may be rewritten as

$$\lambda_m = \lambda_{m-1} + \ln\left[\frac{p_1(s_m, m_1, \sigma_1^2)}{p_0(s_m, m_0, \sigma_0^2)}\right] \tag{5.6}$$

But

$$\ln\left[\frac{p_1(s_m, m_1, \sigma_1^2)}{p_0(s_m, m_0, \sigma_0^2)}\right] = \ln\left(\frac{\sigma_0}{\sigma_1}\right) + \left[\frac{(s_m-m_0)^2}{2\sigma_0^2} - \frac{(s_m-m_1)^2}{2\sigma_1^2}\right] \tag{5.7}$$

Substituting this in Equation (5.6) the general form of the SPRT with both bias and noise degradations is given by

$$\lambda_m = \lambda_{m-1} + \ln\left[\frac{\sigma_0}{\sigma_1}\right] + \frac{s_m^{\,2}}{2}\left[\frac{1}{\sigma_0^{\,2}} - \frac{1}{\sigma_1^{\,2}}\right] + s_m\left[\frac{m_1}{\sigma_1^{\,2}} - \frac{m_0}{\sigma_0^{\,2}}\right] + \frac{1}{2}\left[\frac{m_0^2}{\sigma_0^2} - \frac{m_1^2}{\sigma_1^2}\right] \tag{5.8}$$

To check for only bias or mean degradations, we set $\sigma_1^2 = \sigma_0^2 = \sigma^2$ and $m_0 = 0$ and obtain

$$\lambda_m = \lambda_{m-1} + \frac{m_1}{\sigma^2}\left(s_m - \frac{m_1}{2}\right) \tag{5.9}$$

To detect excessive noise in the signals, we set $m_1 = m_0 = 0$ and obtain

$$\lambda_m = \lambda_{m-1} + \frac{s_m^2}{2}\left[\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}\right] + \ln\left[\frac{\sigma_0}{\sigma_1}\right] \tag{5.10}$$

For a normal sensor the likelihood ratio would decrease and eventually reach a specified negative bound, A. When the ratio reaches A, it is decided that the sensor is normal, and the ratio is reset to zero. For a degraded sensor the ratio would increase and eventually reach a specified positive bound B and when it does this, the sensor is declared to be degraded and the ratio is again reset to zero. These two cases for the normal and the degraded conditions are portrayed qualitatively in Figure 5.1. The behavior of the likelihood ratio is illustrated in Figure 5.2. The bounds A and B are

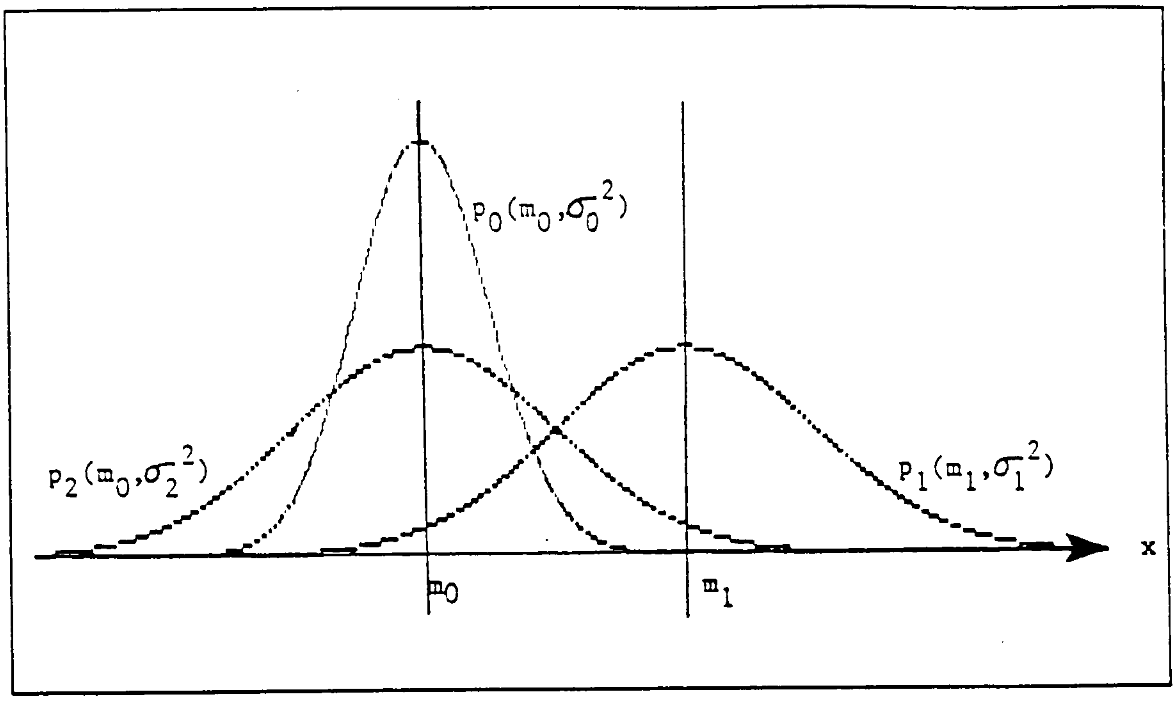

Figure 5.1 Gaussian Density Functions Representing Normal and Degraded Measurements [22]

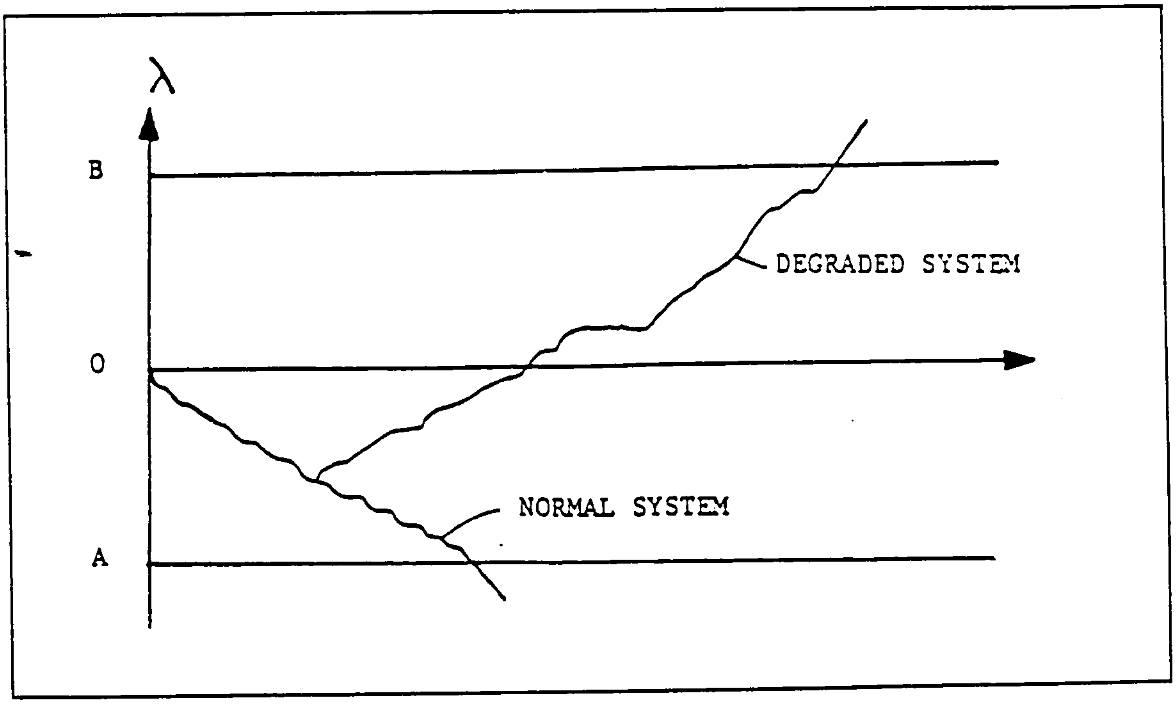

Figure 5.2 Trajectory of the Probability Ratio Function [22]

calculated as

$$A = \ln\left(\frac{\beta}{1-\alpha}\right) \tag{5.11a}$$

$$B = \ln\left(\frac{1-\beta}{\alpha}\right) \tag{5.11b}$$

where α = specified probability of false alarms

β = specified probability of missed alarms

These are given by

$$\alpha = \int_{x_0}^{\infty} p_0(x)\,dx \tag{5.12a}$$

$$\beta = \int_{-\infty}^{x_0} p_1(x)\,dx \tag{5.12b}$$

where x_0 = true measurement,

$p_0(x)$ = normal mode density function, and

$p_1(x)$ = degraded mode density function.

The false and missed alarm probabilities are specified for the application under study.

Several signatures may be used as the random sequences. Examples are the root-mean-square (RMS) values of a signal, the RMS values at certain frequency bands, the AC component (actual signal - the DC value of the signal) of a signal, and the residual sequence derived from a time series model. But the random sequence must have an uncorrelated Gaussian distribution.

SPRT may be used as a sensitive and qualitative tool for detecting incipient degradation in a machine, even when it is functioning normally. If an anomaly is detected by this technique, the motor signatures should be further investigated using regression analysis or neural networks technique.

5.3 Regression Models for Residual Life Estimation

Regression analysis is a statistical method which describes the relationship between the variable to be predicted and one or more other variables that affect the behavior of the variable to be predicted. The relationship is expressed as an equation that predicts a dependent variable as a function of independent variables and parameters. The parameters are adjusted so that a measure of fit is optimized. The variation in the dependent variable can be visualized as a sum of two components: a systematic variation and a random variation. The systematic variation is the variation in the dependent variable explained by its relationship with the independent variable(s). The systematic relationship may be linear or nonlinear in nature, and a first or second degree polynomial equation may be used to describe this relationship. A regression model may have the form

$$Y_i = \beta_0 + \beta_1 X_i \tag{5.13}$$

or

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 \tag{5.14}$$

In general, the static regression model has the form

$$Y_i = f(X_i) \quad , \; i = 1,2,\ldots N \tag{5.15}$$

where Y_i is the dependent variable, X_i is the independent variable and β_i are the model parameters.

A random variation is variation in Y unexplained by the relationship of Y with

X. It is the effect of many other factors not taken into account in the present study. All these unexplained factors operate collectively on each individual in a unique fashion. The effect of the random variation is conceptualized by including a term ε_i so that the generalized regression model has the form

$$Y_i = f(X_i) + \varepsilon_i \tag{5.16}$$

At each measurement, we can observe the values of X and Y but cannot observe ε_i.

Based on the samples of observed values (X_i, Y_i) we compute estimates of the parameters of the relationship and obtain a regression equation of the form

$$\hat{Y}_i = b_0 + b_1 X_i \tag{5.17}$$

or

$$\hat{Y}_i = b_0 + b_1 X_i + b_2 X_i^2 \tag{5.18}$$

where b_0, b_1 and b_2 are the estimated parameters. For each observation, we can estimate the impact of all the other variables lumped together as the "random error" by computing the residuals.

$$e_i = Y_i - \hat{Y}_i \text{ , } i = 1,2,\ldots N \tag{5.19}$$

The method most commonly used to estimate the parameters is to minimize the sum of squares of differences between the actual measured value and the value predicted by the equation. The estimates are called "least-squares estimates" and the criterion value is called the "error sum of squares" [23]. For example, for the model of Equation (5.17), the sum of squared errors (SSE) is

$$SSE = \sum_{i=1}^{N} (Y_i - b_0 - b_1 X_i)^2 \tag{5.20}$$

where N is the number of measurements. By minimizing the SSE, the parameters of a simple linear static model are obtained as

$$b_1 = S_{xy} / S_{xx} \tag{5.21}$$

$$b_0 = \bar{y} - b_1 \bar{x} \tag{5.22}$$

where

$$S_{xy} = \sum_{i=1}^{N} y_i (x_i - \bar{x}) \tag{5.23}$$

$$S_{xx} = \sum_{i=1}^{N} (x_i - \bar{x})^2 \tag{5.24}$$

and

$$\bar{X} = \frac{1}{N} \sum_{i=1}^{N} X_i \ , \quad \bar{Y} = \frac{1}{N} \sum_{i=1}^{N} Y_i$$

The residual life of a motor bears a relationship with many of the signals that are monitored. Some particular signals may have more effect on the life of the motor than the others, but all of them represent the effect on the motor in a combined way to degrade it faster. In lifetime estimation, the effect of the lesser factors may be overlooked. The relationship between the signal(s) $x_i(t)$ and the residual life y(t) of the motor may be linear or nonlinear. Again, considering the past trend in the signature(s) improves the prediction of future trends, and the set of previous points that gives the best estimate has to be decided. Expressing mathematically, the generalized dynamic multivariate linear regression model takes the form

$$y(t) = \sum_{i=0}^{n} b_{1i} x_1(t-i) + \sum_{i=0}^{n} b_{2i} x_2(t-i) + \dots + \sum_{i=0}^{n} b_{mi} x_m(t-i) + \varepsilon_i \tag{5.25}$$

where x_i, $i=1,2,\ldots,m$ are the signatures acquired from the motor, b_{ki}, $k=1,2,\ldots,m$; $i=1,2,\ldots,n$, are the model parameters, and ε is an error term [23]. When $n=0$, a static regression model is obtained and has the form :

$$y(t) = \sum_{i=1}^{m} b_i \, x_i(t) + \varepsilon_i \tag{5.26}$$

A nonlinear model may contain terms of the form $x_1(t).x_2(t)$, $x(t)^2$ and $x(t).x(t-1)$ where x(t) is a single variable. Regardless of the model, a least-squares minimization was used to estimate the regression model parameters.

The above method requires the knowledge of residual life of the motor at any given time instance t. In practice, an on-line model that makes use of the available lifetime information upto that time is required. A time dependent piecewise linear regression model serves this purpose. This model adapts itself to the data with time and predicts life at some future point based on the parameters estimated from the current window. The residual life is estimated by establishing an alarm level and extrapolating the latest regression model. This model is referred to as the adaptive dynamic regression model. Towards the beginning of life of the motor, the trend in the signatures is smaller, and hence predicting residual life from an early stage may give larger errors than later estimates. As the machine degrades, the trend is more systematic and the estimation of the residual life is closer to the expected value. Linear fits for both ordinary regression and adaptive regression are shown in Figures 5.3 and 5.4. A comparison of the two figures clearly reveals the flexibility of the adaptive model with regard to window size and position. The adaptability may be potentially superior for particular applications.

Prediction of the life of electric motors is our objective, and the various models discussed above must be compared in terms of their prediction capabilities in order to decide which model is best suited to prediction of this kind. A good model should fit the data adequately and also should predict the response well enough. An important criterion for judging a model is the estimate of the error variance, s^2. This statistic, also called the residual mean square, plays an important role in hypothesis testing in multiple regression, confidence bounds, etc [23]. This term is mathematically defined as

$$s^2 = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{degrees\ of\ freedom} \tag{5.27}$$

where degrees of freedom is the number of data points reduced by the number of parameters estimated. A candidate model with the smallest value of s^2 should be chosen. Another important statistic for model fitting is the Coefficient of Determination. It is denoted by R^2 and is defined as the proportion of variation in the response data that is

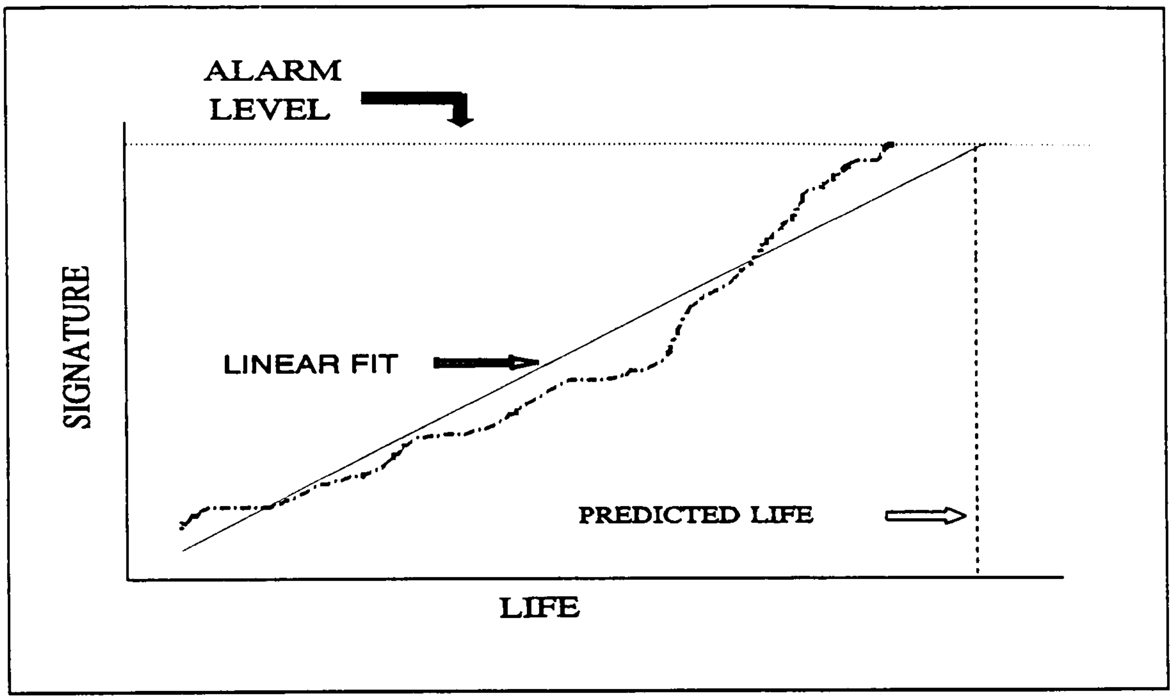

Figure 5.3 Linear Fit For Ordinary Regression

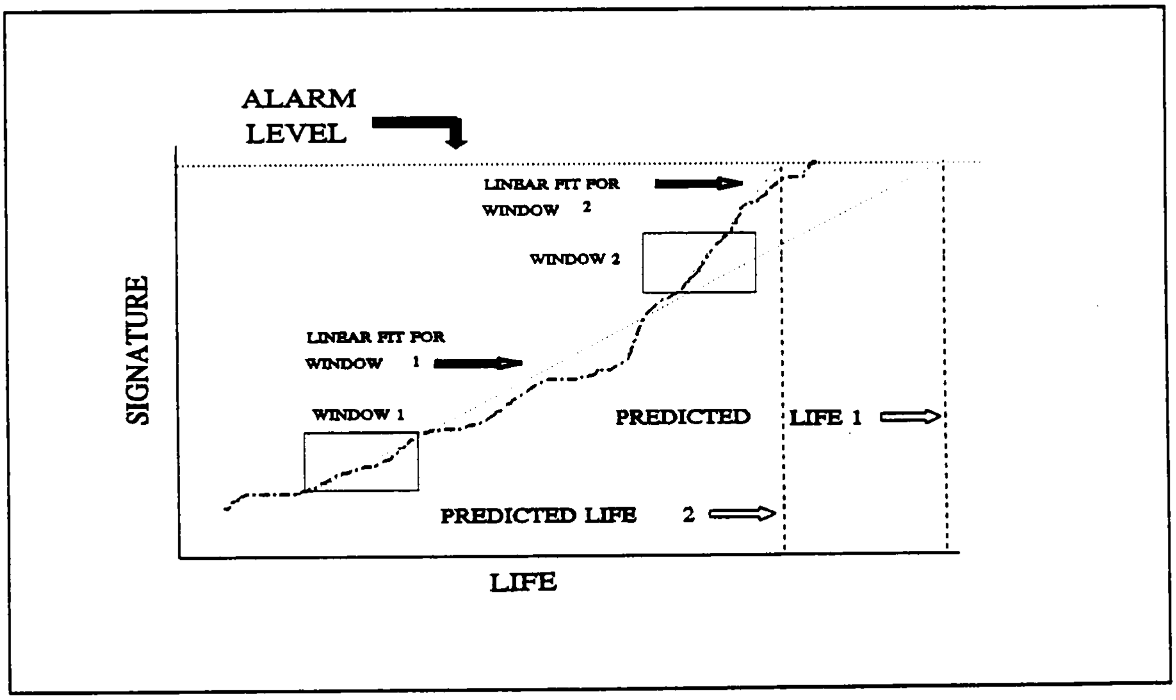

Figure 5.4 Linear Fit For Adaptive Regression

explained by the model.

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{5.28}$$

Clearly R^2 lies between 0 and 1 and is closer to 1 for a better model. The Coefficient of Variation (CV) is a reasonable criterion for representing quality of fit and measuring spread of noise around the regression line. the CV is defined as

$$CV = (s/\bar{y}) \times 100 \tag{5.29}$$

Use of this term has an advantage over the use of s, the estimate of error standard deviation, as the latter is not scale free.

The point estimate of the dependent variable is subject to sampling error, and should be allowed some margin for error to result in an estimate with some confidence. The size of the margin for error is decided depending on whether the predicted value is to be used as an estimate of the average value of Y at a specified value X or as an estimate of the actual value of Y for an observation with that value of X. Because of our specific objective, that is prediction, we are interested in some type of bound on a single response observation for a particular value of a signature. The margin for error M, in this case, is given by

$$t_{\alpha/2,df}\, s \sqrt{1 + \frac{1}{n} + \frac{(x_i - \bar{x})^2}{S_{xx}}} \tag{5.30}$$

where t is the student statistic depending on the desired level of confidence and the degrees of freedom. The predicted value plus/minus the margin for error gives the bound within which the actual value is expected (with a certain confidence) to fall.

5.4 Artificial Neural Networks for Residual Life Estimation

Artificial neural networks are non-parametric models that attempt to map the relationship between two sets of information. They consist of a large number of highly interconnected processing elements (PEs) commonly called nodes or PEs. The network is usually organized into three layers: the input layer, the hidden layer and the output layer with varying number of PEs in each layer as shown in Figure 5.5. PEs are the artificial counterpart of the neurons in human nervous system. A PE has a number of inputs coming from other PEs. It combines the values of the weighted inputs, modifies the combination with a transfer function, and produces an output. This is illustrated in Figure 5.6. Some of the common transfer functions used are linear, step, and sigmoid. These functions are shown in Figure 5.7. The network output is compared with the desired output and the weights are updated iteratively till the error is minimized. The process of adjusting the weights as a function of time is known as "learning". The larger the learning rate, the bigger is the change in weights, and the error converges quickly. However, if the learning rate is too large, it may lead to oscillations in the error function. In order to prevent this oscillation, another term called the momentum term is introduced and it determines the effect of past changes on the direction in which the weight change is currently taking place.

The residual life of a motor may be estimated by using a neural network model trained with data from motor measurements. The successful implementation of this

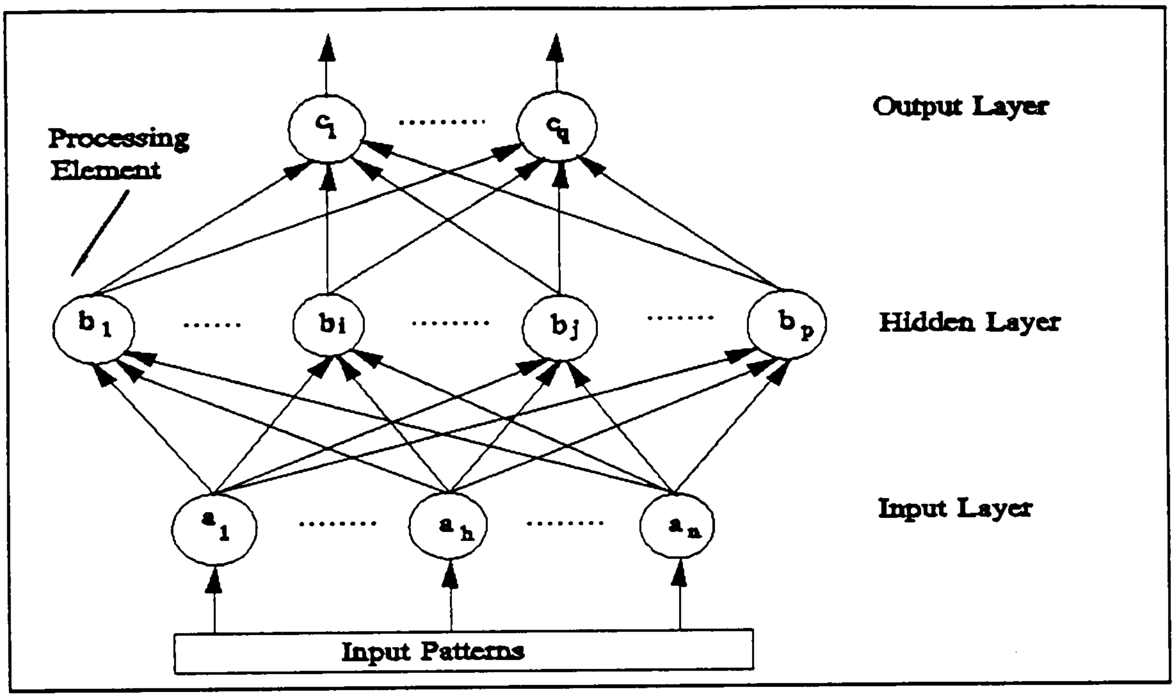

Figure 5.5 A Three-Layer Artificial Neural Network

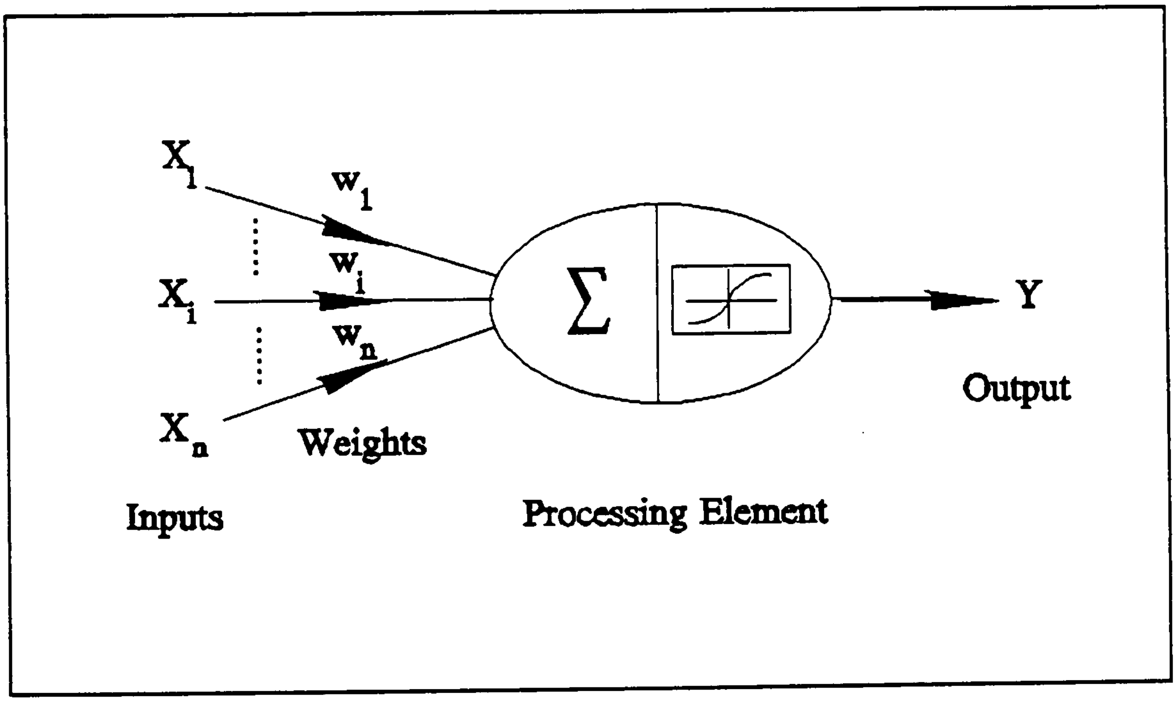

Figure 5.6 A Typical Processing Element

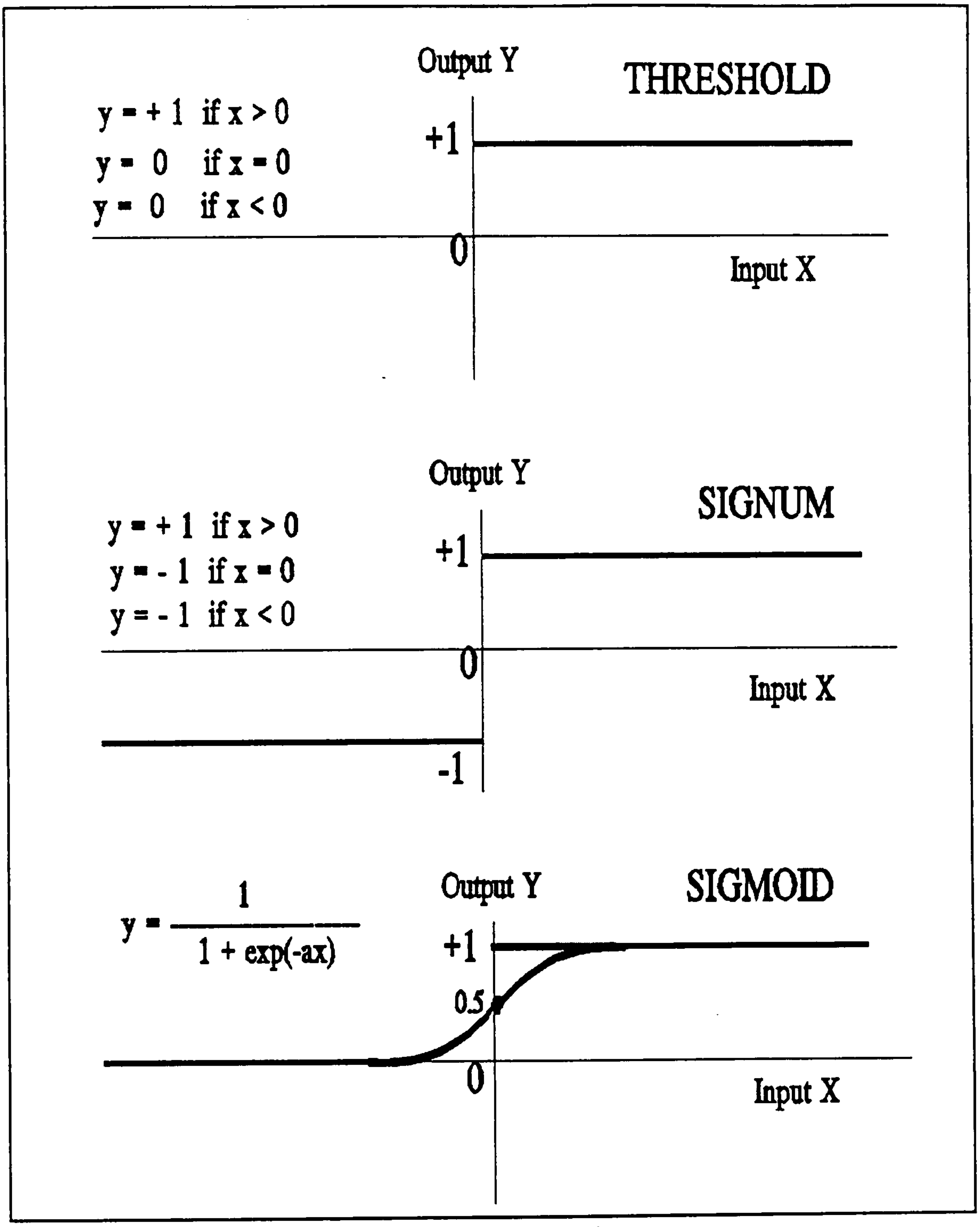

Figure 5.7 Some Typical transfer Functions Used in Neural Networks

method involves proper selection of input signals, data pre-processing and selection of training data. Also, the accuracy of estimation depends on the choice of the number of hidden layers, the number of nodes in a particular hidden layer and parameters such as the coefficient of learning and the momentum. Choice of the type of network and the learning rule also contribute significantly to the results obtained.

The connection weights $\{w_i\}$ in Figure 5.6 are generally determined using the well-known backpropagation training algorithm and a set of supervised training patterns for input and output values. For details of network training algorithms and their performance see Reference [24].

Chapter 6

RESULTS OF APPLICATION TO RESIDUAL LIFE ESTIMATION OF SMALL INDUCTION MOTORS

6.1 Introduction

This chapter presents the results of applications of the methods described in Chapter 5 to the problem of residual life (or time-to-alarm) estimation of small horsepower motors. A PC-based analysis software was developed in the MATLAB environment. Results of application to both laboratory data and industrial motor data are discussed. The influence of data window selection on forecasting and the choice of model to provide optimal results are also discussed.

6.2 Application of the Sequential Probability Ratio Test

During the early part of the life of a motor (or any plant component) or during subsequent operation, the signatures monitored may not reveal the internal degradation of the motor. Yet the motor may be deteriorating and steadily progressing towards failure. The Sequential Probability Ratio Test (SPRT), described in Section 5.2, is a unique method of detecting degradation of equipment with little or no apparent failure trend.

A computer code was written in PC MATLAB to implement the above task. The user is required to provide the data file name and the parameters necessary to calculate the alarm levels in an interactive way depending on the application. There is a provision for specifying a portion of the file for learning, calculating normal mean and variance of the data, and also for skipping a portion of the data. The program checks the data for either bias degradation, or noise degradation, or both bias and noise degradations. It also plots the trajectory of the likelihood ratio. As long as the trajectory tends toward the lower bound, the equipment from which the data are acquired is considered to be normal. When the ratio becomes less than this value, it is set to zero. If the trajectory progresses towards the upper bound, then the machine is declared to be in a degraded state. Once it crosses the upper limit, the ratio is again set to zero. Hence it is evident that the number of times the trajectory of the ratio crosses the upper or the lower bound determines the extent to which the machine is degraded or normal. The program counts these numbers and helps in tracking the conditions of different machines.

An extensive test for establishing the performance of SPRT would require a variety of data containing normal as well as bias and/or noise degraded condition. Due to the unavailability of this type of data from our experiments, synthetic data with all the above conditions were generated using MATLAB (Appendix C). The normal data were defined to be random noise with a Gaussian distribution. The abnormal data were generated by increasing the mean or the variance of the data by different amounts. Several data files were created, all of length 1000 points, the first 200 of which were normal and the rest containing anomalies as stated above. The data with different bias degradations are shown in Figure 6.1 and those with gradually increasing bias after the first 200 points are shown in Figure 6.2. Figure 6.3 shows data with different noise degradations.

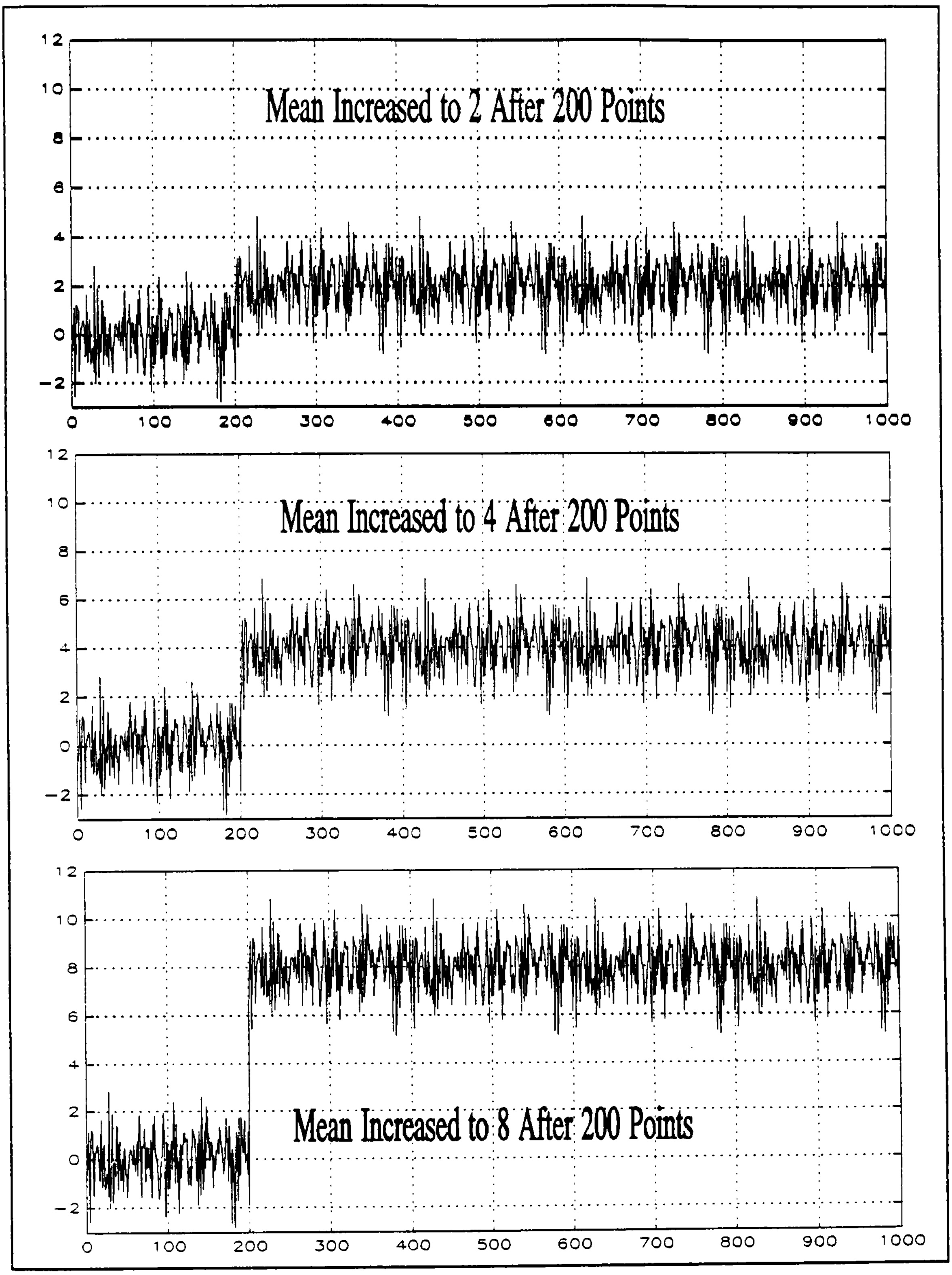

Figure 6.1 Synthetic Data with Different Bias Degradations

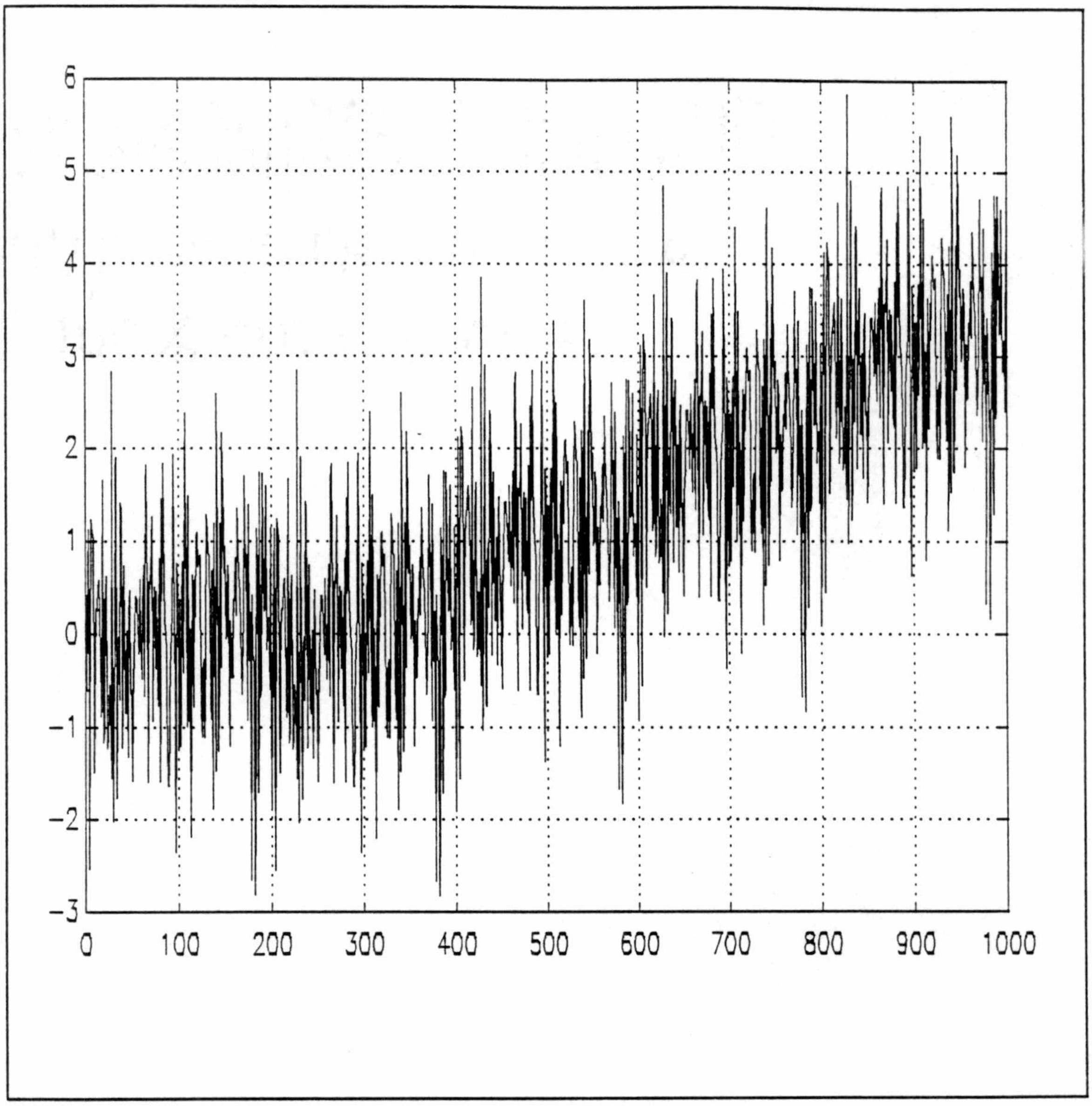

Figure 6.2 Synthetic Data with Gradually Increasing Bias After 200 Points

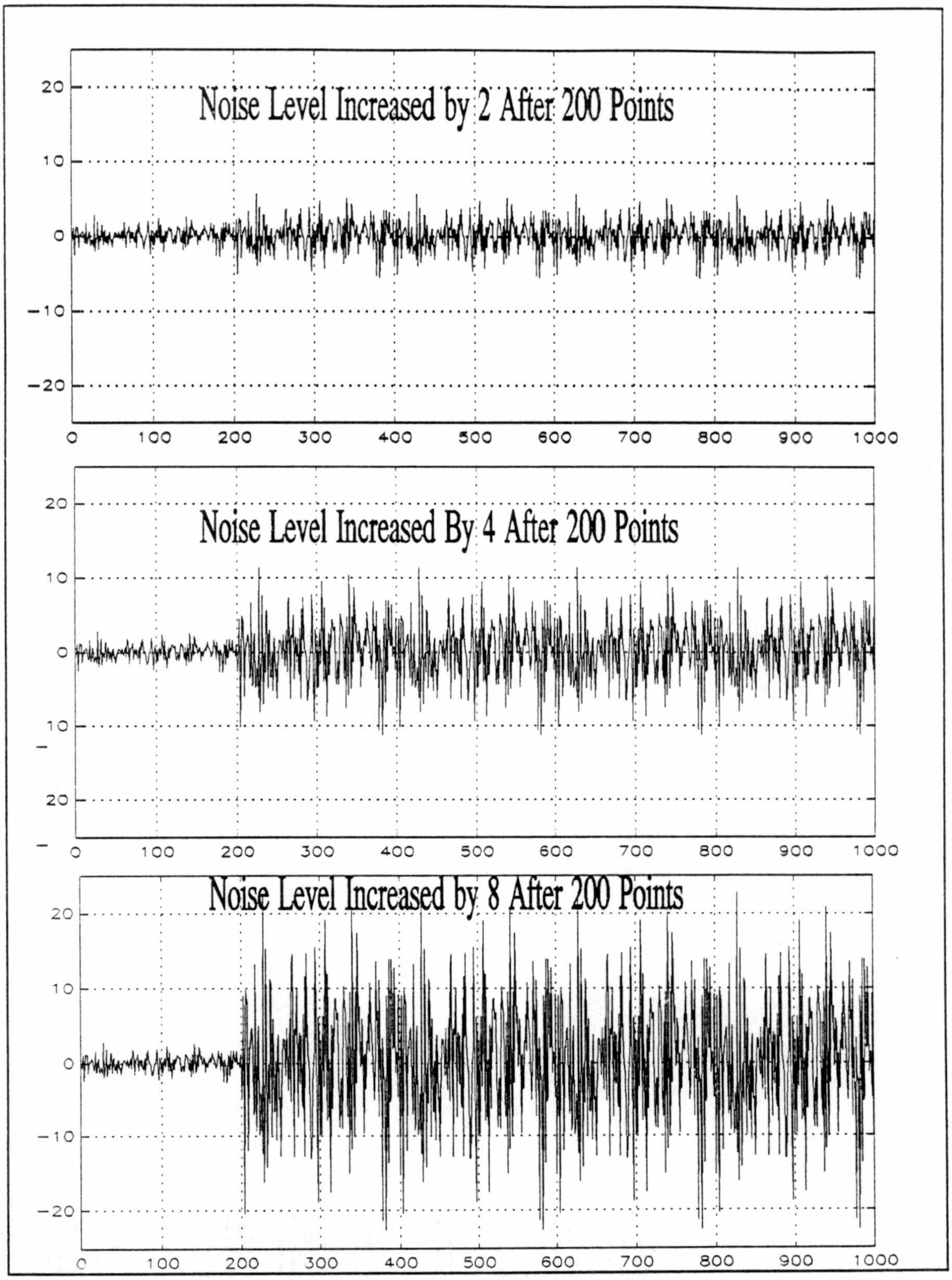

Figure 6.3 Synthetic Data with Different Noise Degradations

Table 6.1 shows the effect of the allowable bias (mean1) on the behavior of the trajectory for different levels of bias degradation. Table 6.2 shows the same for data with gradually increasing bias. Table 6.3 shows the effect of the allowable noise (var1) for different levels of noise degradation. As expected, for the same degraded mean, the number of times the likelihood ratio trajectory touches the upper bound (implying failure) is greater for data with greater bias than with those with smaller bias. For example, for a degraded mean level of 1, the ratio exceeds the upper bound 136 times when the mean of the abnormal data is 2, 298 times when the mean is 4 and 559 times when the mean is 8, respectively. Also, for a particular degraded mean, the number of times the trajectory reaches the lower bound (implying normalcy) is more with less bias than with more bias. The same trends are observed in case of noise degradation also.

Another interesting point to note is the relationship between the choice of the level of degraded mean and the actual level of bias or noise of the test data. As is clear from the table, choosing the correct degraded mean or variance for a particular existing bias or noise in the data is very important in deciding whether the machine is normal or degraded. An improper choice will alter the decision significantly. For example, in the case where the abnormal data has a bias of 2, a degraded mean of 8 would lead us to judge the machine as perfectly normal whereas a degraded mean of 1 would affect our decision negatively. However, in each case, it is seen that there is a point where the number of crossings at the upper limit is equal to the number of crossings at the lower limit, and this point depends on the bias or noise of the abnormal data. This point is

Table 6.1 Effect of Allowable Degraded Bias on the Behavior of the Ratio Trajectory for Different Levels of Bias Degradation

Data File Name	Meanl	Lower Count	Upper Count
BIAS1.DAT (BIAS DEGRADATION OF +2)	1	11	136
	2	41	168
	4	185	60
	6	575	12
	8	883	0
BIAS2.DAT (BIAS DEGRADATION OF +4)	1	11	298
	2	41	440
	4	130	536
	6	208	401
	8	347	160
	10	683	28
	12	927	4
BIAS3.DAT (BIAS DEGRADATION OF +8)	1	11	559
	2	41	799
	4	130	799
	6	192	799
	8	200	799
	10	200	779
	12	208	728
	14	259	540
	16	451	276
	18	763	68
	20	951	8

TABLE 6.2 Effect of Allowable Degraded Bias on the Behavior of the Ratio Trajectory for Gradually Increasing Bias

Data File Name	Mean1	Lower Count	Upper Count
RAMP.DAT (WITH GRADUALLY INCREASING BIAS)	0.5	6	63
	1	23	101
	5	520	59
	10	974	1

TABLE 6.3 Effect of Allowable Degraded Bias on the Behavior of the Ratio Trajectory for Different Levels of Noise Degradation

Data File Name	Var1	Lower Count	Upper Count
NOISE1.DAT (NOISE DEGRADATION OF +2)	1	0	12
	2	2	59
	4	9	71
	6	13	67
	8	20	59
	10	23	52
NOISE2.DAT (NOISE DEGRADATION OF +4)	2	2	223
	4	9	264
	6	13	279
	8	16	278
	10	10	275
	12	21	270
	24	33	267
	30	36	267
	50	192	259

shown in Figure 6.4 for three levels of bias degradation. Similar plots may help us to decide the correct value of the degraded mean for a particular bias or noise. The SPRT analysis may be designed to make it sensitive to small levels of degradation, so that such incipient changes in the behavior of the plant components may be detected early in life.

6.3 Application of Regression Models for Residual Life Estimation

6.3.1 Supervised Empirical Models

Residual life of a motor bears a relationship with many of the signals that were monitored. Two of the signals monitored were motor current and motor casing temperature. The vibration signal did not appear to have any trend and was discarded as a candidate for residual life estimation for this case. When an imbalance was introduced in one of the three phases and was gradually increased, the difference between the maximum and the minimum currents as well as the temperature continued to increase and the motor gradually proceeded towards failure. Residual life was thus inversely related to the maximum current difference and also the temperature. Statistical models may be formulated to estimate these relationships and to observe the degree to which either the current difference, or the temperature, or both together are responsible for affecting the residual life. Based on the sample of observed values, we compute the estimates of the parameters of models and obtain different regression equations which describe the systematic relationship between the residual life and motor current, or temperature, or both. There is still a random error, which cannot be attributed to any measurement.

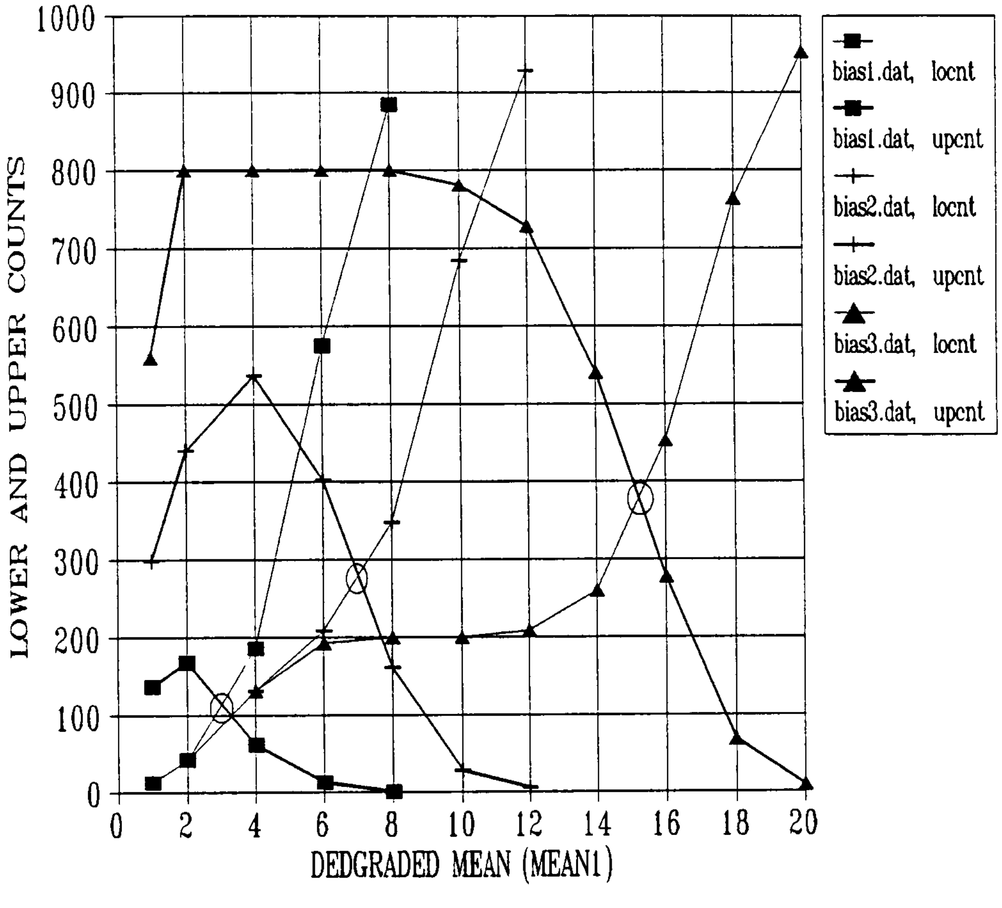

Figure 6.4 Effect of Degraded Mean Selection on the Behavior of the Ratio Trajectory

First we discuss the results of regression analysis using the various univariate and multivariate, linear and nonlinear models. These results were obtained using a statistical software package called SAS [25]. The data were acquired from motors that ultimately failed, so that the residual life of a motor at any point in time was known after the motor had failed. The data file consists of the maximum current difference, the temperature acquired daily from the machine, and the corresponding residual life. The model and the instructions for the desired analysis are provided in the SAS code. Execution of the SAS program results in a table with the data provided along with the estimated residual life and the error at each observation. Values of the root-mean-square error, the coefficient of variation and the coefficient of determination for the model, the estimated values of the parameters and their standard errors follow. Confidence limits on the estimated values, a plot showing the relationship between the actual and the predicted values of the dependent variable, and a scatter diagram with the distribution of error can also be obtained through proper instructions. For a detailed knowledge of SAS, the reader is referred to [25]. For comparison, the results of a few models are shown in a tabular form in Table 6.4, where

y = the residual life of the motor in hours,

$x(t)$ = maximum current difference in Amps at time t,

$T(t)$ = Temperature (deg F) at time t,

b_0 = intercept on the Y-axis and

b_i = estimates of the parameters, $i = 1, 2, \ldots n$.

The smaller the root-mean-square error and the coefficient of variation, the better

Table 6.4 Comparison of Various Regression Models Using SAS

MODEL EQUATIONS	Intcpt	Std Error	Coeff	Std Error	Sum of Sq Dev	RMS Error	Coeff of Var	Coeff of Determ
y = b0 + b1.x(t)	825	7.95	-224.6	4.4	1065538	20.19	4.43	0.9868
y = b0 + b1.x(t) + b2.x(t-1)	813.69	8.44	-122.87 -99.22	37.84 36.7	1068062	18.59	4.07	0.9891
y = b0 + b1.x(t) + b2.x(t-1) + b3.x(t-2)	801.59	9.77	-90.15 -49.19 -80.32	38.98 41.81 37.06	1069525	17.65	3.87	0.9905
y = b0 + b1.T(t)	4489.7	159.46	-2388	94.36	1023897	39.97	8.76	0.9482
y = b0 + b1.T(t) + b2.T(t-1) + b3.T(t-2)	4346.8	148.78	-2241 -21 -44	95.14 31.25 23.11	1037975	35.6	7.8	0.9613
y = b0 + b1.x(t) + b2.x(t-1) + b3.x(t-2) + b4.T(t) + b5.T(t-1) + b6.T(t-2)	1435	212.96	-24.96 -87.99 -73.92 -427.4 0.53 19.82	32.69 31.83 28.99 133.84 12.38 9.86	1074738	12.99	2.85	0.9953
y = b0 + b1.x(t).x(t-1)	766.92	7.4	-129.46 -31.01	10.24 3.25	1075927	10.68	2.34	0.9964
y = b0+b1.x(t)+b2.x(t-1) +b3.x(t-2)+b4.x(t).x(t-1)	751.92	5.28	-36.78 -20.73 -74.41 -28.92	15.71 16.45 14.47 2.13	1078289	6.887	1.51	0.9986

is the model. Also, the best model has the highest coefficient of determination. Comparing these figures from the table, it is seen that the dynamic model which takes into account time-regressed values of current difference or temperature into account has a smaller root-mean-square error and a smaller coefficient of variation than the static model. Again, the dynamic models explain the variation in the residual life in a much better way. Also it is seen that the current difference is a much better measurement to influence the residual life than the temperature. But when time-regressed values of both current difference and temperature were taken into account, the result was better than when current difference alone was used. But even the best linear multivariate model has an RMS error of 12.99 hours. The nonlinear univariate model, on the other hand, has an RMS error of only 10.68 hours. A nonlinear model of a higher order however, does not improve the RMS error, though it improves the coefficient of variation and the coefficient of determination to a small extent.

The nonlinear model of second order is superior to the linear univariate model also in another respect. The scatter diagram is a plot of the residual error or, in other words, the difference between the actual and the estimated residual life vs. current difference (dependent variable). Ideally it should not have any trend. Scatter diagrams for the linear and nonlinear models obtained by executing SAS codes are shown in Figures 6.5 and 6.6 respectively. In the figures, 'res' is the residual error and P3 is the residual life. 'A' is the location of the residual error corresponding to a particular residual life. The residual error for two successive points may be the same, and 'B' is the common location of two such residuals. It is observed that the scatter diagram for

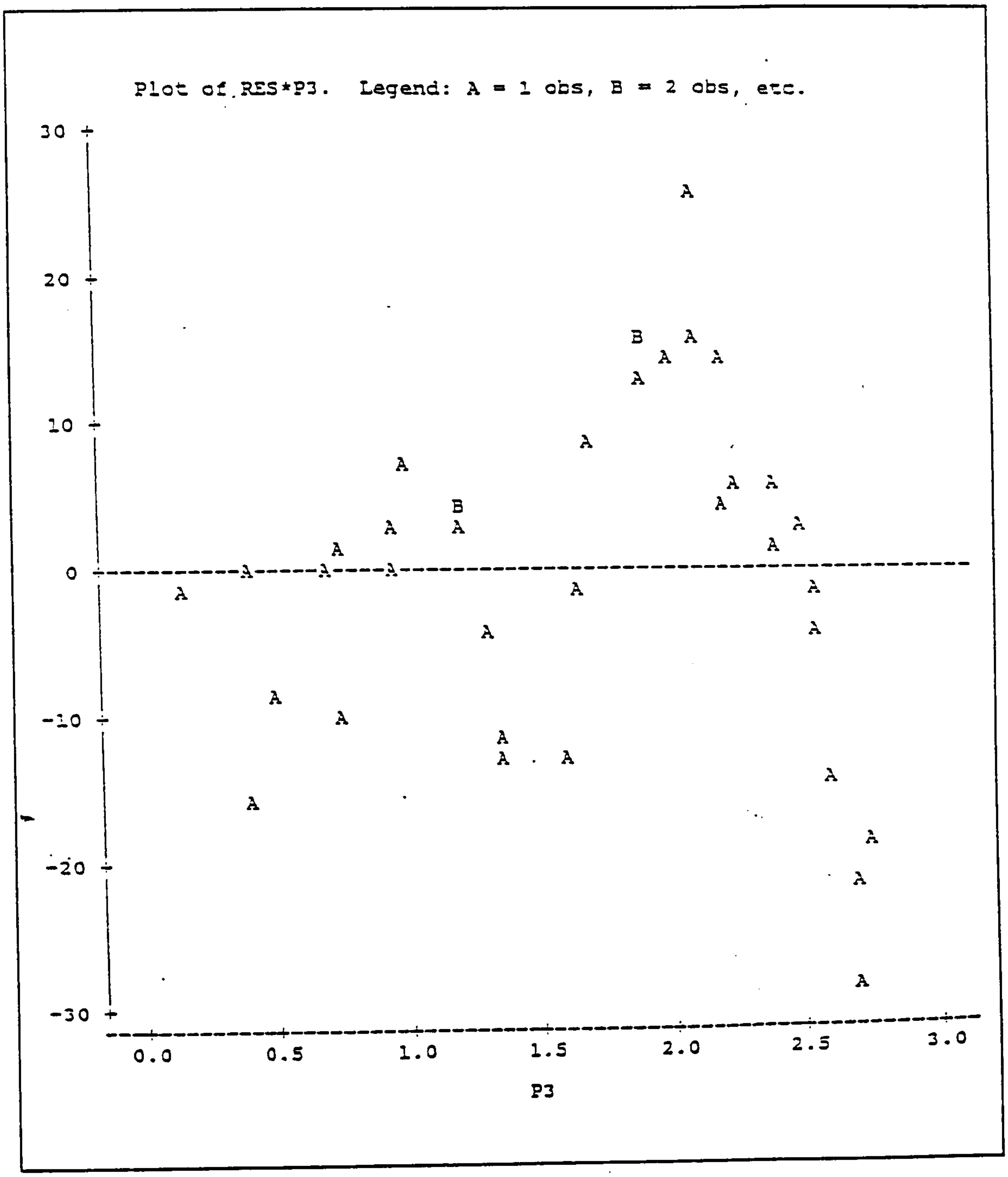

Figure 6.5 Distribution of Error for Linear Model

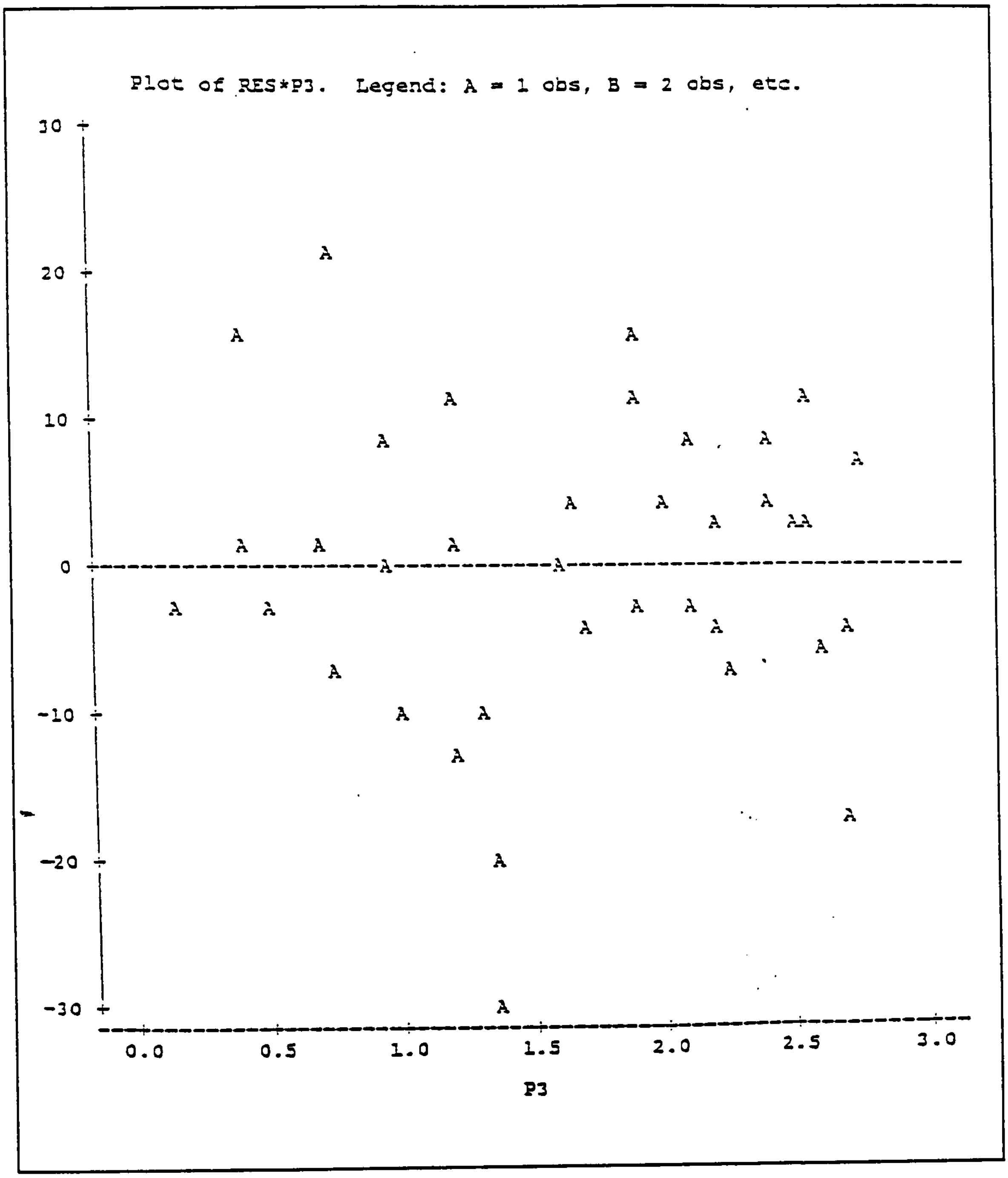

Figure 6.6 Distribution of Error for Nonlinear Model

the linear model (shown in Figure 6.5) has a clearer trend than the scatter diagram for the nonlinear model (shown in Figure 6.6).

An attempt was made to predict the lifetime corresponding to data points not in the data set both within and outside the range of the data points that were in the data set using SAS. This was done by replacing the value to be estimated with a dot in the input data set. The output from SAS contained the estimated value in place of the dot. Only the best model was tested. Interpolation estimated a life of 588.4 hours compared to the actual value of 584 hours, while extrapolation estimated a life of 714 hours compared to the actual value of 728 hours. Extrapolated estimation was even worse when tried with two points outside the range. The model estimated 665 hours instead of 680 hours and 704 hours instead of 728 hours.

It is evident from these results that ordinary regression models, whether univariate or multivariate, linear or nonlinear, static or dynamic, are stringent as far as prediction is concerned. They employ the available data to estimate the parameters, and based on these parameters, fit a model to the data in the least-square-error sense. In order to predict a future point, this fit is extrapolated. The drawback of these models is that they do not take into account the changing pattern of the trend in any of the signatures.

6.3.2 Adaptive Regression Models for Residual Life Estimation

Ideally, it is more practical to have a model, and hence parameters, that adapt themselves with the changing trend, so that the predicted value follows the actual value more closely. We propose a piecewise-linear dynamic model that considers only the data in the latest window, and estimates parameters for that window. The window size can vary, depending on how many previous points are to be considered. An alarm level in the signature is set, and the model fit from the latest window is extrapolated to meet this alarm level. The life corresponding to the point where the extrapolated signature meets the alarm level is the predicted "alarm life" of the motor. The residual life can be obtained by subtracting the present age of the motor from the expected overall lifetime.

The poor quality of plots obtained from SAS, the unfamiliarity of our research sponsors with SAS together with its lack of flexibility to cope with the requirements, necessitated the use of another mathematical software called MATLAB. The earliest attempt to realize adaptive regression model in PC MATLAB considered a linear, univariate case with an option to choose the window size. It could estimate lifetimes at future points using the estimated parameters from the given window. The estimation depended on the position of the data window with respect to the alarm level. Windows from a later stage in the life of the motor gave better estimates than windows from earlier stages. This is demonstrated in Figures 6.7 and 6.8. The code is given in Appendix C. The modified program (also provided in Appendix C) requires the user to enter the data filename, and offers the choice of

- i) single or multiple signatures,
- ii) static or dynamic model,
- iii) linear or quadratic model,
- iv) size of the window used for model fitting,
- v) adaptive or ordinary regression model, and

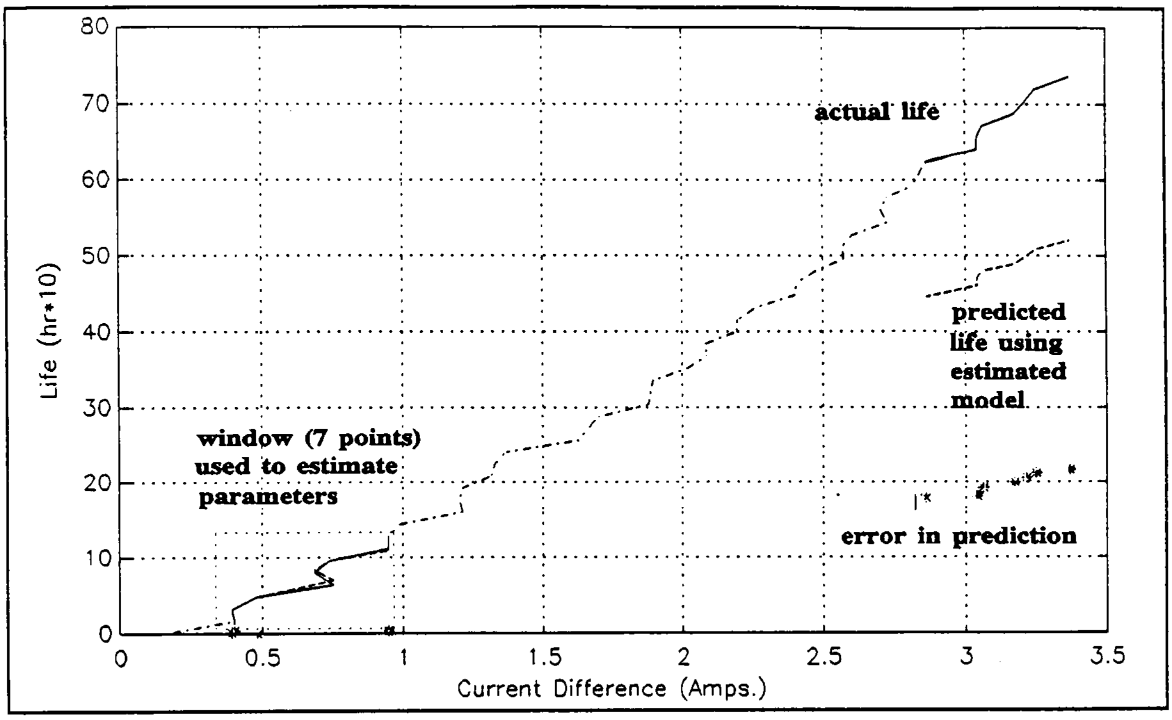

Figure 6.7 Estimation of Life at Future Points Based on Information From an Earlier stage in the Life of the Motor

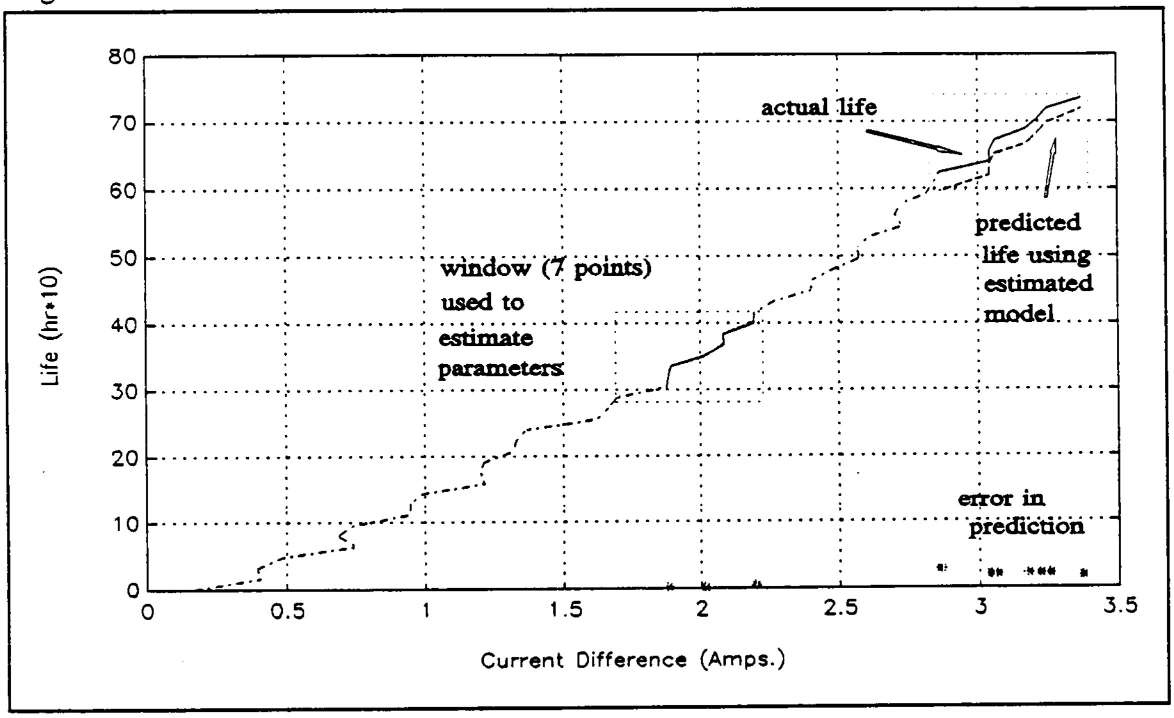

Figure 6.8 Estimation of Life at Future Points Based on Information From a Later stage in the Life of the Motor

vi) alarm level(s) for the signature(s).

For the univariate adaptive linear models, the program updates the life of the motor using the estimated parameters and the values of the signature from the last available window till the value of the independent variable reaches the pre-specified alarm level. The parameters are first estimated for a particular model for a specified window size. Then the next point in time y(t+1) is found by adding a fixed small time interval 'Δt' to the present value of time y(t). Next, for example, for a fourth order linear model, the signature value is updated in the following way:

$$x(t+1) = \frac{y(t+1) - b_0 - b_2x(t) - b_3x(t-1) - b_4x(t-2)}{b_1} \qquad (6.1)$$

where $y(t+1) = y(t) + \Delta t$ and b_0, b_1, b_2, b_3 and b_4 are the estimated parameters of the model. The predicted value of the signature is updated till it reaches the alarm level and then the life corresponding to this signature value is declared as the predicted time-to-alarm. The code also provides a plot of predicted future points till the alarm level is reached. For the linear multivariate models and the static quadratic model it predicts the "alarm life" of the motor directly from the alarm level and the estimated parameters. Using multiple signatures, however, poses a problem as different signatures reach their alarm levels at different times. Therefore, only similar signatures (ones that have the same alarm levels) can be used for testing multivariate regression models. Using nonlinear models of order higher than the quadratic model does not improve the fit or the prediction significantly. A nonlinear dynamic model could not be used due to difficulty in recursive extrapolation.

It is not, however, sufficient to predict the life of the motor based on the models discussed above. Error analysis should be carried out and the quality of fit should be judged before declaring a particular model as the 'optimal model'. Also, we should be sure to a certain extent as to the correctness of our prediction. To achieve this objective, different statistics have been included in the program which helps us to compare the goodness of fit and the quality of prediction using different models. These are the RMS error, the coefficient of determination, the coefficient of variation, and 95% confidence interval on the predicted value. Since the model with the lowest RMS error may not have the highest coefficient of determination as well as the lowest coefficient of variation, it may not be easy to judge a particular model as the best. In that case, a compromise must be sought between the three statistical indices.

Both prediction and goodness-of-fit depend to a large extent on the order of the model chosen and the window size. Regression analysis was carried out on laboratory data as well as field data to study the effect of these two factors. The effect of window size on the statistical parameters and prediction using laboratory data are shown in Figures 6.9 through 6.12. The results using the field data are presented in Table 6.5. A study of the results lead to the following conclusions :

* For any particular window size, the RMS error and the coefficient of variation decrease and the coefficient of determination increases with higher order model. In other words, a higher order model provides a better goodness-of-fit.

* For a particular model, the above three factors improve significantly when a smaller window size is chosen.

* The prediction using static quadratic model was always conservative. The other parameters compared with those obtained using the simple linear model.

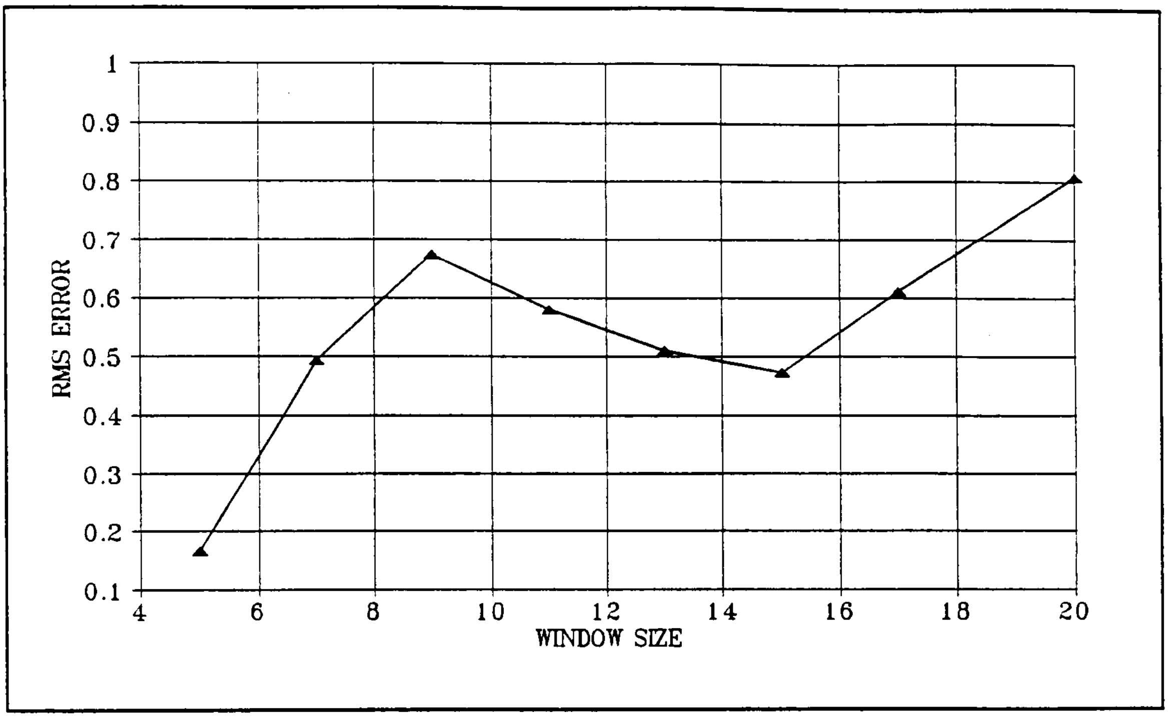

Figure 6.9 Effect of Window Size (Number of Points) on RMS Error

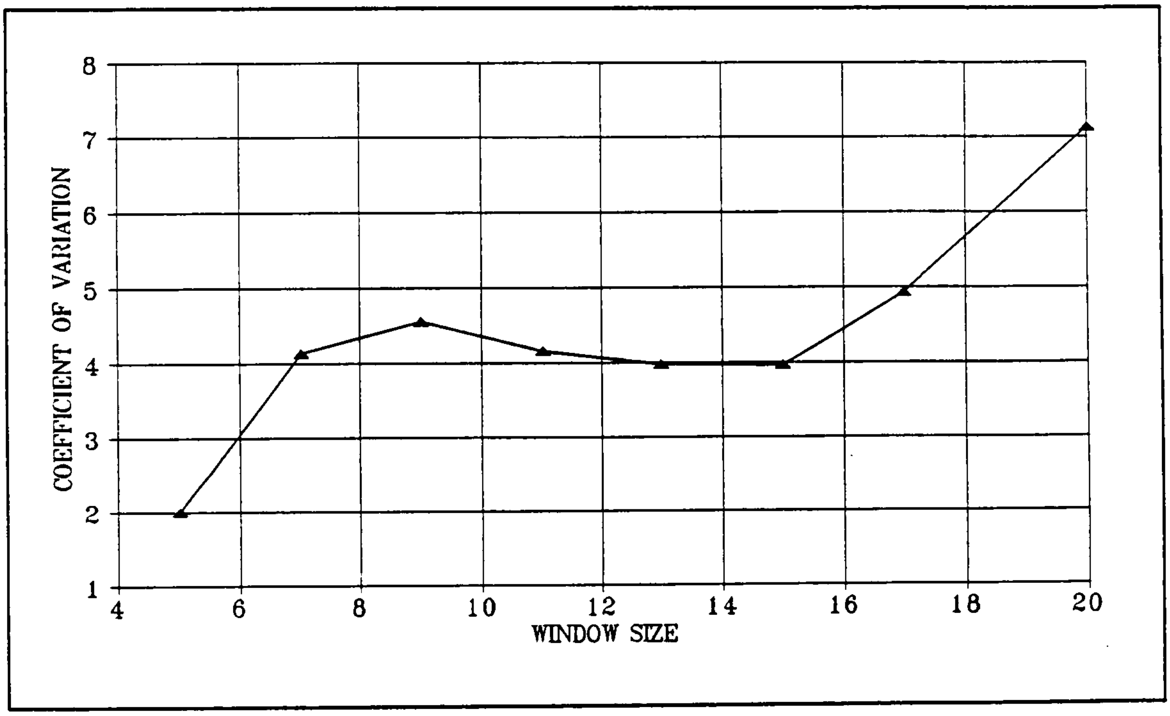

Figure 6.10 Effect of Window Size (Number of Points) on Coefficient of Variation

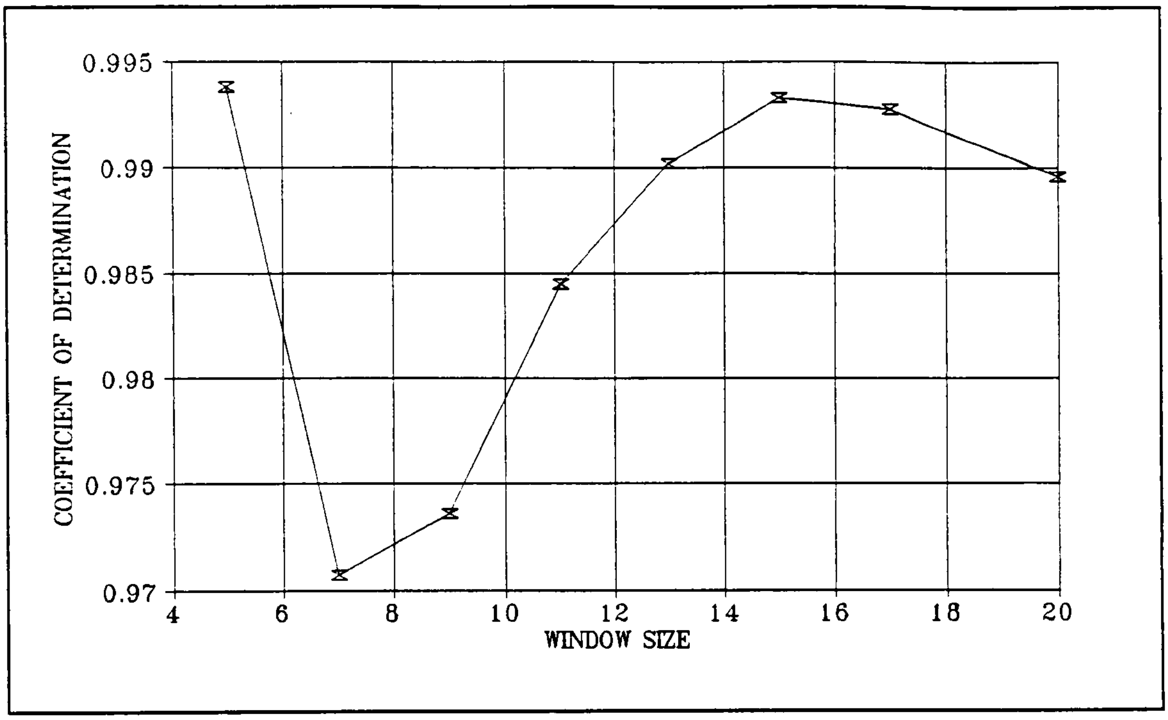

Figure 6.11 Effect of Window Size (Number of Points) on Coefficient of Determination

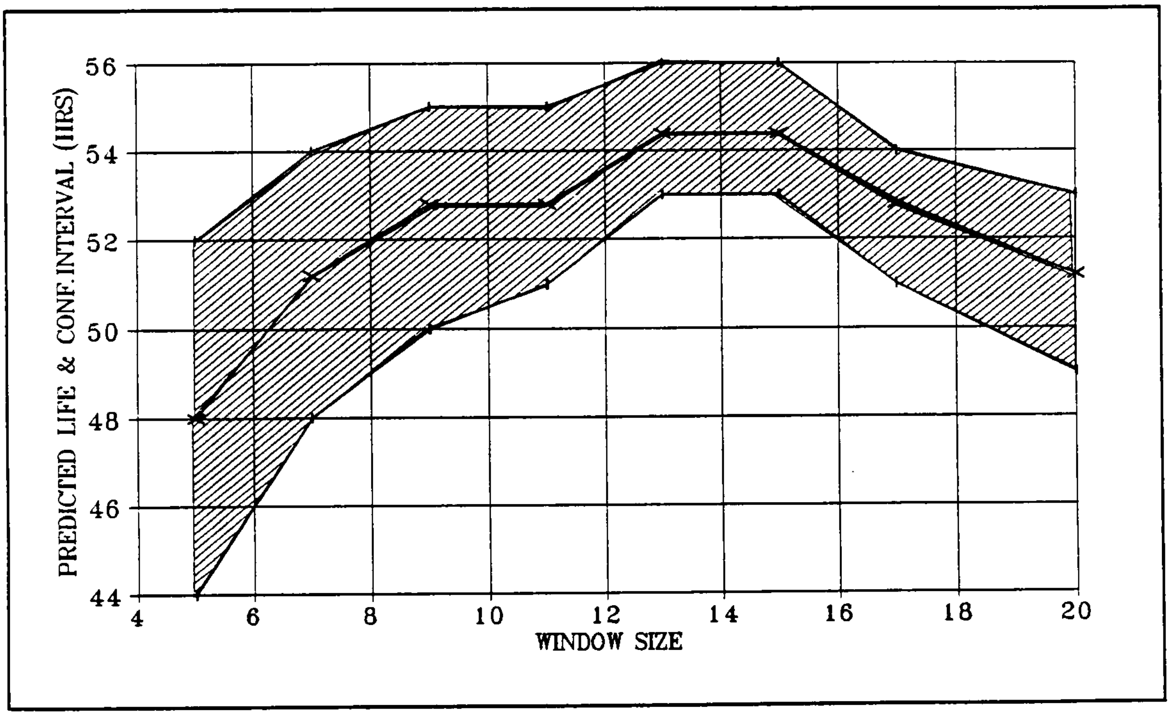

Figure 6.12 Effect of Window Size (Number of Points) on Predicted Life and Confidence Interval

Table 6.5 Results Showing the Effect of Different Window Sizes and Models

Window Size	Model Number	RMS Error	Coefficient of Determination	Coefficient of Variation	Predicted Life Till Alarm (hrs)
33	1	6.5	0.48	44.5	49
	2	6.2	0.53	43.3	49
	3	6.1	0.54	43.5	48
	4	5.8	0.57	42.9	47
	5	6.4	0.49	44.9	38
30	1	6.5	0.37	41.3	45
	2	5.9	0.46	38.9	48
	3	5.4	0.52	37.5	46
	4	5.0	0.57	36.2	52
	5	6.5	0.37	42.1	45
20	1	2.6	0.61	16.9	43
	2	2.4	0.75	13.9	43
	3	2.1	0.79	13.1	54
	4	2.1	0.81	12.9	52
	5	2.5	0.63	17.0	35
10	1	1.6	0.68	7.2	40
	2	1.0	0.84	5.5	37
	3	0.6	0.93	3.7	39
	4	0.6	0.96	3.3	39
	5	1.3	0.72	7.2	33

Model Number	Equation
1	$y(t)=b0+b1.x(t)$
2	$y(t)=b0+b1.x(t)+b2.x(t-1)$
3	$y(t)=b0+b1.x(t)+b2.x(t-1)+b3.x(t-2)$
4	$y(t)=b0+b1.x(t)+b2.x(t-1)+b3.x(t-2)+b4.x(t-3)$
5	$y(t)=b0+b1.x(t)+b2.x(t)^2$

* No conclusion can be made about which model or what window size gives the best life prediction. The overall conclusion is to choose the model that gives the best quality of fit.

The above three conclusions were confirmed when the analysis was carried out with two other data sets.

6.3.3 Residual Life Estimation Using Industrial Data

A database containing vibration signatures from a 7.5 HP motor, used for driving a pump, was acquired from one of the member companies of the Measurement and Control engineering Center at The University of Tennessee. These data consisted of vibration RMS values from accelerometers mounted at the outboard position of the motor.

Some interesting plots of future prediction trends were obtained when different window sizes and models were considered using these data. Figure 6.13 shows a plot of the entire data and the prediction using the simple ordinary (not adaptive) static univariate model. Figure 6.14 shows the prediction plot when a window size of 20 and a third order model were chosen. In Figure 6.15, the prediction oscillates more because of selection of a higher order model that tends to follow the dynamics more closely than a lower order regression model.

Sometimes it becomes necessary to know if the various signatures collected from a machine are correlated. Figure 6.16 shows plots of three different vibration signatures from one of the motors at an industrial plant. Such plots do not help in understanding the correlation between any two signatures. Correlation analysis requires a quantitative

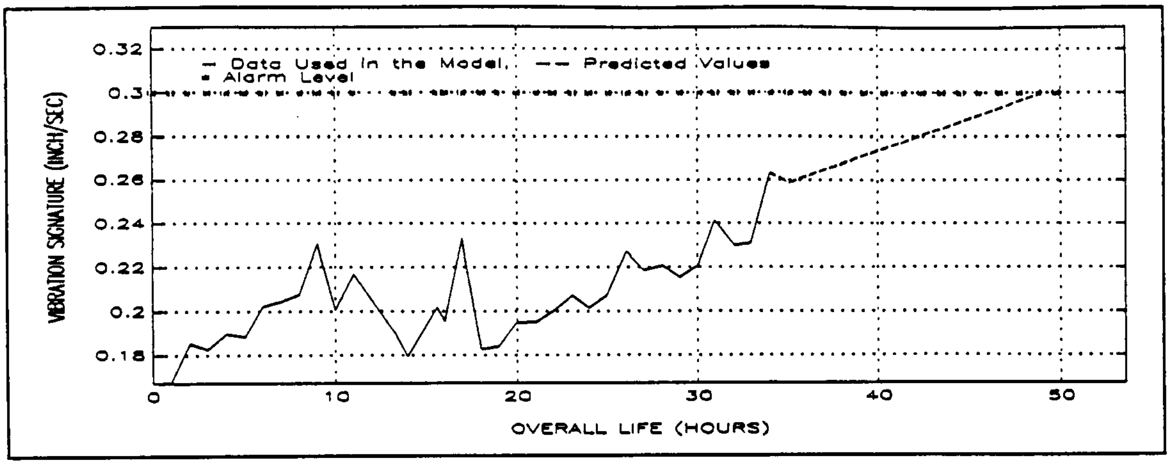

Figure 6.13 Life Prediction using Field Data and a Simple Regression Model

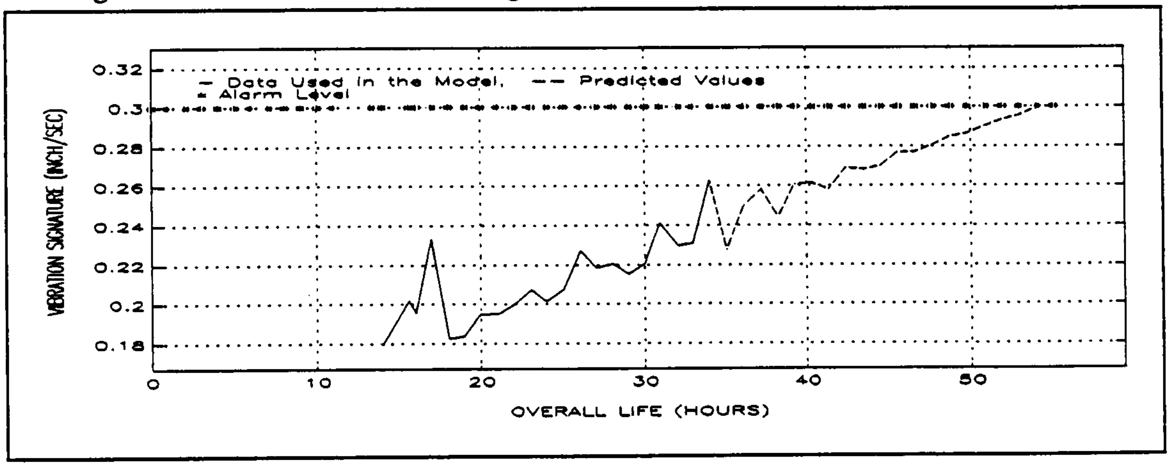

Figure 6.14 Life Prediction using Field Data and a Third Order Regression Model with 20 Data Points

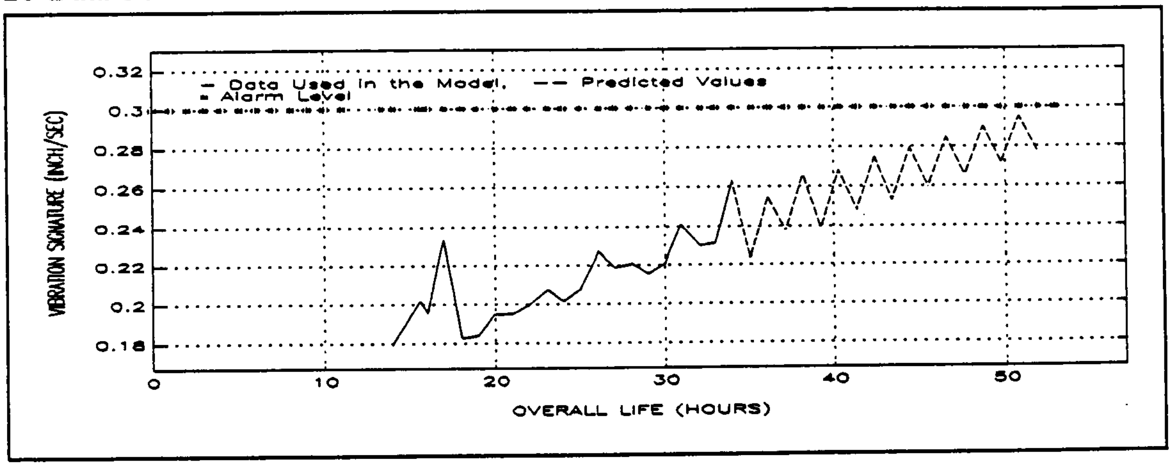

Figure 6.15 Life Prediction using Field Data and a Fourth Order Regression Model with 20 Data Points

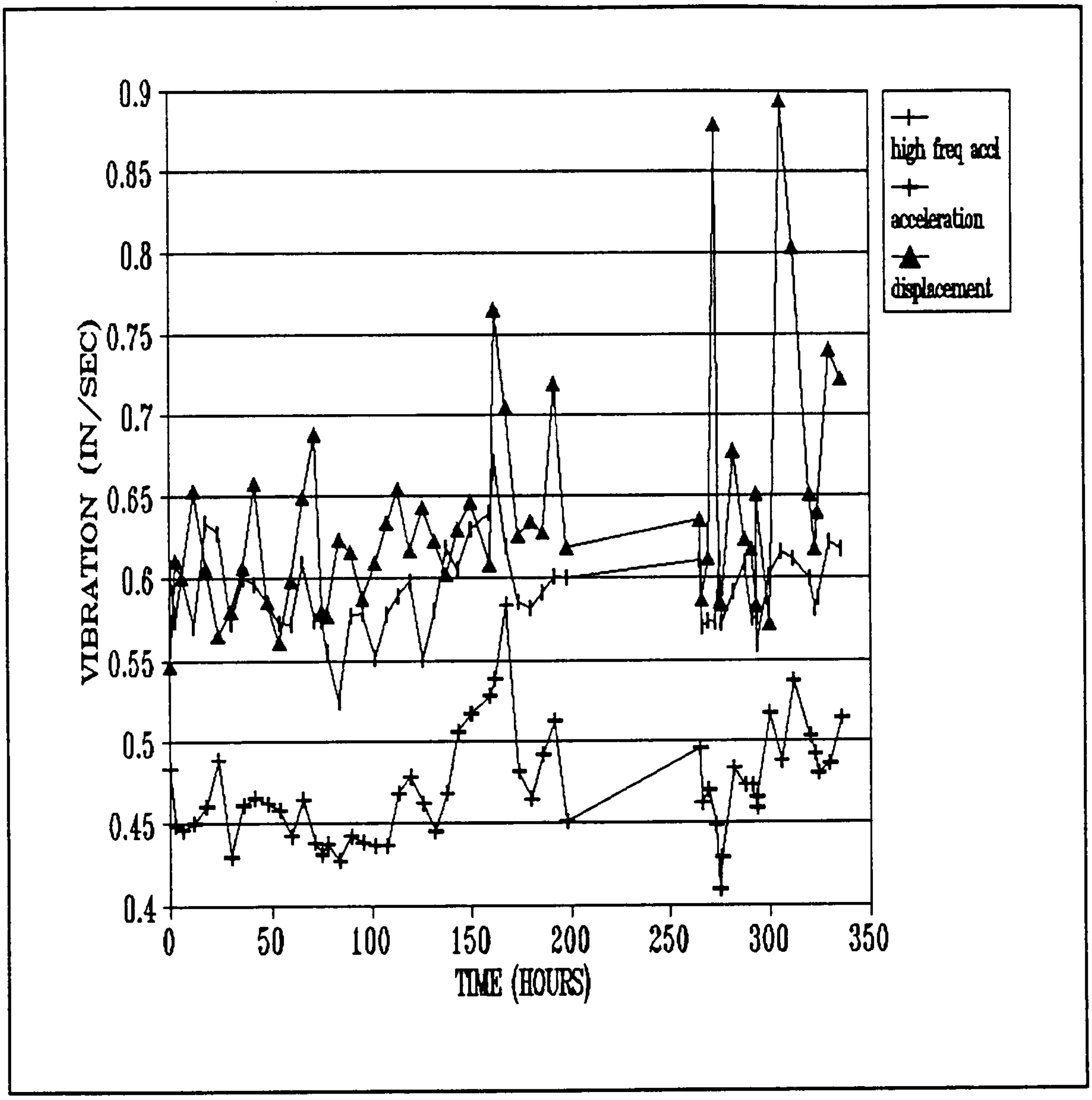

Figure 6.16 Three Vibration Signatures From a 7.5 HP Motor

parameter. This was done with a separate computer program that used two files containing two different signatures collected over the same period of time and at equal intervals. The computer code is given in Appendix C. The output of this analysis is the correlation coefficient between the two. The results obtained using this calculation are given in Table 6.6. The correlation coefficient between two signatures $\{x_i\}$ and $\{y_i\}$ is defined as

$$\rho_{xy} = \frac{\sum_{i=1}^{N} x_i y_i}{\sqrt{\sum_{i=1}^{N} x_i^2 \cdot \sum_{i=1}^{N} y_i^2}}, \quad -1 \leq \rho_{xy} \leq 1 \tag{6.2}$$

A large magnitude of ρ_{xy} indicates that the two are correlated. A large positive value of ρ_{xy} indicates that the two signatures vary in the same direction. The three vibration signatures used in the plot were used. The practical importance of this is that if the two signatures are highly correlated, one of the signatures reaching the alarm level can be confirmed by the level reached by the other.

6.4 Results of Residual Life Estimation Using Artificial Neural Networks

Artificial neural networks were used to estimate the residual life of motors from the signatures collected over a period of time and the available life data. Multiple-input single-output feedforward networks were used for this purpose. The input patterns were vectors of present and three previous values of motor currents. Because this was a case of supervised learning, the actual residual life at each point was also provided in the input pattern. The network output was the residual life of the motor. A single

Table 6.6 Correlation Coefficient Between Three Vibration Signatures From an Industrial Motor

SIGNATURE 1	SIGNATURE 2	CORRELATION COEFFICIENT
Displacement	Acceleration	0.9946
Displacement	Control Point Acceleration	0.9945
Acceleration	Control Point Acceleration	0.9985

intermediate layer was used and the number of nodes in that layer was adjusted using a trial and error approach until the error between the predicted residual life and the actual residual life was a minimum.

In this research two motor current signatures were used as inputs to the neural network. One was the difference between the maximum and minimum currents and the other was the maximum current. The output was the residual life in hours. Both sectionalized and time-regressed data were used. For sectionalized data, the entire current plot against the entire lifetime was divided into sections, each having four points. The values of currents in each section and the residual life from the last of these points were presented in each pattern. For time-regressed data, the present value and three previous time points, together with the residual life from the present time were incorporated in each pattern. The four motor current points were the inputs to the neural network and the residual life was the desired output of the network. The network learned from a large number of patterns presented to it and was able to predict the residual life of the motor from any point on the current plot.

For both the methods, the RMS values of the currents (or difference of currents) were used. From every data point, the actual residual life was calculated. The current values and the corresponding residual life were then normalized, i.e. scaled, so that all values were between 0.1 and 0.9. This was done in the following manner.

First the maximum and the minimum values in the data set were found.

a = maximum - minimum

b = 0.8/a

$c = 0.9 - b * \text{maximum}$

$d = b * x + c$

where 'x' is the present value of the motor current or the residual life, d is the corresponding value of 'x' in the 0.1-0.9 scale, and a, b, and c are parameters used in the normalization of the data.

The hyperbolic tangent transfer function and the normal cumulative learning rule seemed to be appropriate to the specific application and use of other transfer functions and learning rules did not improve the results obtained.

The results are presented in Table 6.7 showing the training RMS errors. Figure 6.17 shows the actual life and the predicted life using time-regressed data. Figure 6.18 shows the same for sectionalized data. Results using mean temperature and the square of the maximum current were not satisfactory.

One problem of estimating residual life with neural networks is that it is an after-the-fact attempt. Data are not available from motors that have not failed. If the neural network is to predict the residual life of the motor at some point in the future, the lack of supervised training during the period from the present to that future point will lead to a bad estimate.

Another problem is that in order to establish the best model among a few, for a particular class of motors, a very large database is required. Not only that, the database should consist of data acquired from exactly similar motors operating under the exact same conditions. Motors with same name-plate specifications, of the same age (started and serviced at the same time), run under identical conditions are bound to have different

Table 6.7 Results using Artificial Neural Network

Motor Identi-fication Number	Inputs	Type of Data Pattern	Number of Training Patterns	# of Testing Patterns	# of nodes in Hidden Layer	RMS Error in hours
4	maximum difference in current	regressive	28	37	24	10
4	maximum difference in current	sectionalized	7	9	12	9.9
4	maximum current	regressive	25	32	12	14
5	maximum difference in current	regressive	20	24	16	5.67

Note : Every pattern consists of the current point and three points back in time and the desired residual life.

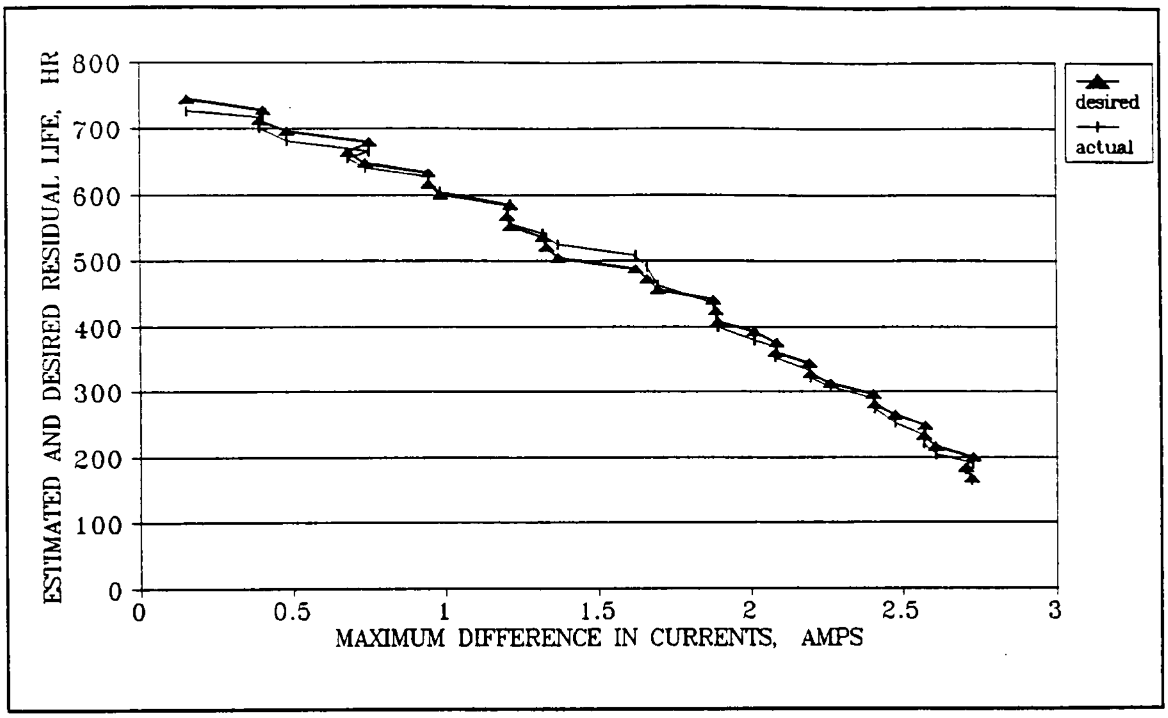

Figure 6.17 Actual and Predicted Life Using Time-regressed Data

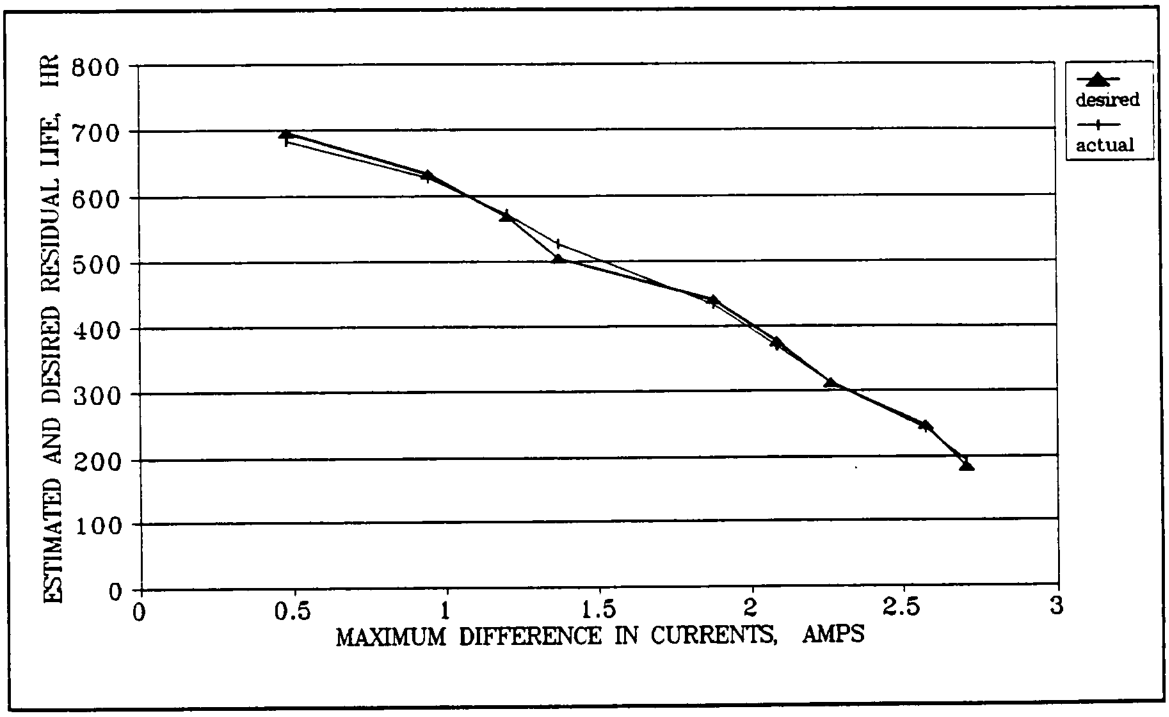

Figure 6.18 Actual and Predicted Life Using Sectionalized Data

residual lives at any instant because of the unknown internal conditions specific to the motor. Such data would confuse the neural network and the estimate would not be as expected. Due to the above reasons, the use of artificial neural networks to this particular problem requires further study.

Chapter 7

INDUCTION MOTORS IN NUCLEAR POWER PLANTS

Induction motors constitute a major part of the auxiliary systems at all power generating sites in the world. They convert a significant portion of all electrical energy produced in a country. Moreover, the total generating capacity of a country depends on their reliable operation on a continuous basis. There are approximately 100,000 small and medium (100 HP and above) auxiliary motor drives in applications ranging from slurry pump motors to reactor coolant pump motors to forced draft fan motors in the U.S. alone [26].

Although a small number of dc motors and synchronous motors are used in nuclear power plants, more than 90% of all motors used in nuclear generating stations are ac squirrel-cage induction motors. A large number of boiler-feed-pump motors are used in generating units of sizes 150 MW and above. Pressurized water reactor (PWR) plants also employ a considerable number of induction motors. The main applications of these motors in power plants are cooling tower fans, boiler feed pumps, startup boiler feed pumps, boiler feed booster pumps, condensate booster pumps, condensate pumps, circulating water pumps, boiler circulating pumps, recirculating pumps in boiling water reactors (BWRs), and reactor coolant pumps in PWRs. In addition, there is a large number of motor-operated valves, dampers and other short-time duty motors. Motor circuit protection and control is an important issue at all generating sites. However, it is seen that majority of the failures in nuclear power plant motors are bearing related (41-44%) and stator related (26-36%).

The nuclear industry and the regulatory community are aware of the importance of predictive maintenance of electrical motors in nuclear plants. Every power plant should have a well-planned and comprehensive surveillance and maintenance program and it should be implemented properly for reliability enhancement of the plant. Good maintenance practices in other utilities should be correlated and applied to nuclear plant maintenance programs. Nuclear plant technical specifications and the regulations imposed by the Nuclear Regulatory Commission require the operability of a large number of redundant safety-related systems. The number of candidate motors for predictive maintenance is thus greatly enhanced.

Generally 100-200 HP or even larger motors are used in utility applications. The reliability of these motors are critical to plant performance. The NRC has sponsored a study on the range of motor types and sizes with an objective to identify the failure modes most likely to impair plant operation and safety. The data are available from information sources including Licensee Event Reports, In-Plant Reliability Data System, and the Nuclear Plant Reliability Data System.

The author is hopeful that the methodology developed here can be used to predict residual life of large motors used in nuclear and fossil power plants and in the process industry, and can contribute significantly to the predictive maintenance programs at these plants.

Chapter 8

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

8.1 Summary

It is important to monitor the condition of all plant components in order to ensure that their sudden failures do not interfere with the normal operation of a plant. Condition monitoring and incipient fault detection are important in scheduling maintenance activities and to avoid the catastrophic damages that may result from a policy of run-to-failure. Machine prognosis can be carried out by monitoring the trends in selected signatures, and for this prediction, it is necessary to estimate the residual life of plant components.

The purpose of the research was to develop and demonstrate a methodology for the estimation of residual life of plant components. The research focus was on the monitoring of fractional horsepower induction motors. Both experimental and analysis techniques were developed to establish the solution of the problem. Experimental data were acquired from a motor testing laboratory. Adaptive, time-dependent regression models and artificial neural network models were developed. These were tested with both experimental and industrial data. Modeling of induction motor dynamics was performed to understand the development of certain anomalies. This technology can be extended to other machinery, including large horsepower motors used in nuclear and fossil power plants.

8.2 Conclusions

A new approach to analyze data from small horse-power induction motors was undertaken with a view to predict residual life of motors. A database was created from the data acquired from a motor testing laboratory. This database was used to estimate the overall life and the residual life of motors and the results were compared with the actual failure time of these motors. In addition, industrial field data were also used to demonstrate the applicability of the technique developed in this research.

Anomalies were introduced in the motors mainly in the form of phase imbalance and load in order to accelerate the degradation process. Motor phase currents proved to be the most sensitive signatures measured for fractional horse-power motors. They were used as inputs to neural networks and as independent variables in regression models developed for estimating the residual life of motors. Vibration signatures did not have any trend and this was expected as no mechanical instability was introduced in the system. Temperature also revealed information about the degraded condition of the motor but was not as useful as motor current with regard to failure time estimation.

The dynamics of a typical induction motor was studied in detail and the responses of motor phase currents, developed torque and speed to a phase imbalance condition were observed through dynamic modeling. Also, the sensitivity of the motor performance to the presence of harmonics in the line voltage was also observed. The behavior of the motor for the normal balanced condition and for the unbalanced condition were compared.

A PC-based software was developed for empirical regression modeling of the trend data. It offers a number of models to be used in the prediction of motor life. Computation of all the parameters necessary for determining the quality of fit and prediction were included so that different models could be compared. A new adaptive model, whereby the model fit adapts itself to the changing trend of the data, was implemented. Another code based on the SPRT technique helps to determine whether an equipment (machine or sensor) is normal or is experiencing degradation long before any significant trend appears in its signatures. Artificial neural networks were also used to estimate residual life in a supervisory training mode.

The methodology developed here is applicable to a wide range of electrical machinery, covering almost every industry. Some of the plants that can benefit from an extended version of this work are nuclear power plants, hydro-electric plants, fossil power plants, consumer products industry, textile industry, machine tools industry, automobile industry, to name a few.

The present study also indicated that vibration monitoring is not always effective for prognosis of small horsepower motors. Furthermore, at steady operating conditions of a motor at high temperatures, the measured parameters may not indicate incipient failure of the motor. The internal degradation must be monitored using some other signature, possibly by a 'virtual trending' approach.

8.3 Recommendations for Future Research

Although considerable progress has been made in this research, much more remains to be done. Most motors fail due to insulation degradation. Assessing the condition of the insulation while the motor is still in operation requires further investigation. The condition of insulation can be stated in terms of the insulation resistance, but measuring insulation resistance involves a destructive test and is not practical for online applications. There must be a relationship between the measured signatures and the insulation resistance, and the work on establishing this relationship is highly recommended.

Another recommendation is to establish a large and accurate database either through individual experiments or from an industrial plant. Only then the complete validity of the models can be verified. Another scope is to develop a generic regression or neural network model that would estimate the residual life of a wide range of motors reasonably well. Yet another approach is to categorize the different motors based on information and measurements and develop one model for each category.

Establishing alarm levels is another difficulty faced in industrial applications. Since the regression models predict motor life based on the time taken for a signature to reach its alarm level, the estimation is time-to-alarm rather than time-to-failure. For the same reason, multivariate models could not be used or verified, as different signatures do not reach their alarm levels at the same time. Establishing alarm levels for all the signatures monitored and predicting the residual life based on signatures with different alarm levels is an interesting and practical statistical problem. This again would require a large database.

As stated earlier, the failure of a rotating machinery could often be due to anomalies other than vibration-related. Predictive maintenance analysis systems, currently available in the industry, often ignore this fact and very little attention is given to monitoring a physical degradation parameter, such as motor insulation characteristics. It is suggested to monitor this using "virtual trending" of internal parameters. The determination of root causes of degradation is thus very important for a successful machinery prognosis program.

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APPENDICES

APPENDIX A

SYMMETRICAL COMPONENTS OF CURRENTS

The three phase currents of motors, namely I_a, I_b, and I_c are complex numbers. Each of them can be resolved into the positive sequence component, the negative sequence component, and the zero sequence component in the following way

$$I_a = I_{a1} + I_{a2} + I_{a0}$$

$$I_b = I_{b1} + I_{b2} + I_{b0}$$

$$I_c = I_{c1} + I_{c2} + I_{c0}$$

where I_{a1} is the positive sequence component, I_{a2} is the negative sequence component and I_{a0} is the zero sequence component of the current I_a. The relationships between the components in each sequence are :

$$I_{a0} = I_{b0} = I_{c0}$$

$$I_{b1} = e^{-j120}\, I_{a1}, \;\; I_{c1} = e^{+j120}\, I_{a1}$$

$$I_{b2} = e^{+j120}\, I_{a2}, \;\; I_{c2} = e^{-j120}\, I_{a2}$$

The term e^{+j120} is commonly denoted by 'a'. Thus $a^2 + a + 1 = 0$. The sequence components for phase a can now be expressed as

$$I_{a0} = (I_a + I_b + I_c)/3$$

$$I_{a1} = (I_a + aI_b + a^2I_c)/3$$

$$I_{a2} = (I_a + a^2I_b + aI_c)/3$$

It is evident that for a balanced system, the positive and negative sequence components of current do not exist.

APPENDIX B

COMPUTER CODE FOR DYNAMIC NONLINEAR SIMULATIONS OF MOTOR PERFORMANCE IN SIMNON

```
"PROGRAM NAME : PHIMB.T ( PHaseIMBalance )
"THIS PROGRAM IN SIMNON SIMULATES THE DYNAMIC BEHAVIOR OF
"AN INDUCTION MOTOR WITH ADDITIONAL RESISTANCE IN 1 PHASE


CONTINUOUS SYSTEM phimb
"----- STEADY-STATE REFERENCE FRAME D-Q MODEL OF
"----- AN INDUCTION MACHINE IN TERMS OF CURRENT

OUTPUT ia ib ic lm te
STATE iqs ids i0s iqr idr w
DER diqs dids di0s diqr didr dw
TIME t
pi = 3.14159265
p2 = pi*2
sqr3 = sqrt(3)
spd =(60*w)/(pole*pi)
p = 2*ras/3+rs/3
q = ras/3+2*rs/3
g = sqrt(2)*(ras-rs)/3
A = wb*wb/D

"------------ VOLTAGE INPUTS
va=vl*sin(wb*t)
vb=vl*sin(wb*t-(2.0*pi)/3.0)
vc=vl*sin(wb*t+(2.0*pi)/3.0)

"------------ STATE EQUATIONS
diqs = A*(lr*vqs-lr*p*iqs-lmm*w*ids-lr*g*i0s+lmr*iqr-lrm*w*idr)
dids = A*(lr*vds+lmm*w*iqs-lr*rs*ids+lrm*w*iqr+lmr*idr)
di0s = (v0s-g*iqs-q*i0s)/(ls-lm)
diqr = A*(-lm*vqs+lm*p*iqs+lsm*w*ids+lm*g*i0s-lsrr*iqr+lsr*w*idr)
didr = A*(-lm*vds-lsm*w*iqs+lms*ids-lsr*w*iqr-lsrr*idr)
dw = (te-tl)/(j*(2/pole))
```

```
"----- VOLTAGE TRANSFORMATIONS
vqs = va
vds = (vc-vb)/sqr3
v0s = sqrt(2/3)*0.7072*(va+vb+vc)
te = 0.75*pole*lm*(idr*iqs-iqr*ids)
ls = (xm+xs)/wb
ls1=(xm+1.3)/wb
lr = (xm+xr)/wb
lm = xm/wb
lrm = lr*lm
lsm = ls*lm
lsr = ls*lr
lmm = lm*lm
lmr = lm*rr
lsrr = ls*rr
lms = lm*rs
D = (xm+xs)*(xm+xr)-(xm*xm)

"CURRENT TRANSFORMATIONS and THREE PHASE CURRENTS
ia = iqs+i0s/sqrt(2)
ib = -(0.5*iqs)-(0.5*sqr3*ids)+i0s/sqrt(2)
ic = -(0.5*iqs)+(0.5*sqr3*ids)+i0s/sqrt(2)

"INTRODUCING LOAD TORQUE AT 1 SEC
tl= if(t<1) then 0.0 else 7.8

"INTRODUCING PHASE IMBALANCE AT 4 SEC
ras=if (0.0 < t and t < 4)then 2.1 else 4.2


"--------- PARAMETERS OF A 2 HP MOTOR
vl:188.0
wb:377
rs:2.1
rr:0.9
xr:1.495
xs:1.495
xm:48.15
rm:1.33112
j:0.06
pole:4
END
```

```
"*****************************************************************

"                          NOTE :

"1.  FOR THE BALANCED CASE, WE HAVE ras = rs and

"2.  IN ORDER TO ADD HARMONICS TO THE SUPPLY VOLTAGE,
"    WE MODIFY THE ABOVE EQUATIONS FOR VOLTAGE INPUTS
"    IN THE FOLLOWING MANNER:

"       For 5% third harmonics, we have
"       va=vl*sin(wb*t)+0.05*vl*sin(3wb*t)
"       vb=vl*sin(wb*t-(2.0*pi)/3.0)+0.05*vl*sin(3wb*t-(2.0*pi)/3.0)
"       vc=vl*sin(wb*t+(2.0*pi)/3.0)+0.05*vl*sin(3wb*t+(2.0*pi)/3.0)


"       For 5% third harmonics AND 1% fifth harmonics, we have
"       va=vl*sin(wb*t)+0.05*vl*sin(3wb*t)+0.01*vl*sin(5wb*t)
"       vb=vl*sin(wb*t-(2.0*pi)/3.0)+0.05*vl*sin(3wb*t-(2.0*pi)/3.0)
"                                   +0.01*vl*sin(5wb*t-(2.0*pi)/3.0)
"       vc=vl*sin(wb*t+(2.0*pi)/3.0)+0.05*vl*sin(3wb*t+(2.0*pi)/3.0)
"                                   +0.01*vl*sin(5wb*t+(2.0*pi)/3.0)

"*****************************************************************
```

APPENDIX C

MATLAB CODES

1. CODES FOR GENERATING SYNTHETIC DATA

```
************************************************************************
%       PROGRAM NAME : THBIAS.M
%       FUNCTION        : GENERATES SYNTHETIC DATA WITH DIFFERENT
                            LEVELS OF BIAS DEGRADATION

rand('normal');
rand('seed',1027);
Z=rand(200,1);
MEAN(Z);
(STD(Z))^2;
b1=[Z;Z+2;Z+2;Z+2;Z+2];
b2=[Z;Z+4;Z+4;Z+4;Z+4];
b3=[Z;Z+8;Z+8;Z+8;Z+8];
axis([0 1000 -3 12]);
plot(b1)
grid
pause
meta thbias1
plot(b2)
grid
pause
meta thbias2
plot(b3)
grid
pause
meta thbias3

************************************************************************
%       PROGRAM NAME : THNOISE.M
%       FUNCTION        : GENERATES SYNTHETIC DATA WITH DIFFERENT LEVELS OF
                          NOISE DEGRADATION

rand('normal');
rand('seed',1027);
Z=rand(200,1);
MEAN(Z);
(STD(Z))^2;
n1=[Z;Z*2;Z*2;Z*2;Z*2];
n2=[Z;Z*4;Z*4;Z*4;Z*4];
n3=[Z;Z*8;Z*8;Z*8;Z*8];
axis([0 1000 -25 25]);
plot(n1)
grid
```

```
pause
meta thns1
plot(n2)
grid
pause
meta thns2
plot(n3)
grid
pause
meta thns3
```

****

```
%       PROGRAM NAME : THRAMP.M
%       FUNCTION     : GENERATES SYNTHETIC DATA WITH GRADUALLY INCREASING
                       BIAS

rand('normal');
rand('seed',1027);
Z=rand(200,1);
MEAN(Z);
(STD(Z))^2;
b4=[Z;1.005*Z;1.005*Z+1;1.005*Z+2;1.005*Z+3];
plot(b4)
axis([0 1000 -3 6])
grid
pause
meta thramp
```

2. CODE FOR THE SEQUENTIAL PROBABILITY RATIO TEST

```
**********************************************************************************************
% PROGRAM NAME : SPRT
% FUNCTION     : THIS PROGRAM ASKS FOR THE DATA FILE NAME AND OTHER
                 VARIABLES AND COMPUTES THE LIKELIHOOD RATIO OF FAILURE
**********************************************************************************************

disp('Note : Your data file must have extension DAT ')
disp('for example, " name.dat " ')
fname=input('Enter your data file name : ','s');
eval(['load ',fname]);
x=abs(fname);
[ar ac]=size(x);
D=eval(setstr(x(1,1:ac-4)));
[m]=size(D);
it1=[1:47];
D=[it1',D2(:,2)];
i=D(:,1);
data(i)=D(:,2);
axis([1 50 0 3.5]);
plot(i,data)
grid
title('TEST DATA, MAXIMUM DIFFERENCE IN CURRENTS, MOTOR # 4')
xlabel('Data Points')
ylabel('RMS Current in Amps')
pause

ndp    = input('Number of Data Points:   ');
iskp   = input('Number of Data Points to be Skipped from the beginning :  ');
skp    = input('Number of Data Points to be Skipped throughout data : ');
alfa   = input('alfa (False Alarm probability) :   ');
beta   = input('beta (Missed Alarm probability) :    ');
disp(' ')

%**        COMPUTATION OF LIMITS        **

disp('The Computed Lower and Upper Limits are:')
A = log(beta/(1-alfa))
B = log((1-beta)/alfa)
disp(' ')
axis([iskp ndp A B]);
subplot(111)

%**           MEAN AND VARIANCE           **

disp('** Option for the mean and variance of the normal data  **')
disp('(you can either enter them or they can be calculated)')
disp(' ')
disp('1. If you want mean and variance to be calculated')
disp(' ')
```

```
disp('2. If you want to enter the mean and variance')
disp(' ')
option=input('Enter your option ( 1 or 2) :   ');
if isempty(option)
option=1;
elseif option == 2
  mean0=input('Enter the mean :');
  var0=input('Enter the variance :');
elseif option == 1
  lrn = input('Number of Data Points to be used for learning:');
  mean0=mean(D(1:lrn,2));
  var0=(std(D(1:lrn,2)))^2;
else
  disp('NOT A VALID OPTION ! ')
  break
end

%***          TYPE OF DEGRADATION             ***

disp('These are your Options for the type of Degradation:')
disp(' ')
disp('1. Both Bias and Noise degradation ')
disp(' ')
disp('2. Bias Degradation only ')
disp(' ')
disp('3. Noise Degradation only ')
disp(' ')
disp('Default is Number 1')
disp(' ')
option=input('Enter your Option ( 1 or 2 or 3 ) :')
if isempty(option)
  option=1;

%**   B I A S   D E G R A D A T I O N     **

elseif option == 2
  mean1=input('Maximum allowable variation of mean from nominal mean : ');
        lamda(1)=0;
        j=1;
        x1(1)=0;
              if iskp==0
                i=1;
              elseif iskp>0
                i=iskp;
              end
              upcnt=0;
              locnt=0;
              while i<ndp
              j=j+1;
              lamda(j)=lamda(j-1)+(mean1/var0)*(data(i)-mean0-(mean1/2));
              dat1(j)=lamda(j);
```

```
ref(j)=0.0;
        if lamda(j)<A
          dat1(j)=A;
          lamda(j)=0;
          locnt=locnt+1;
        elseif lamda(j)>B
          dat1(j)=B;
          lamda(j)=0;
          upcnt=upcnt+1;
        end
%     if i<=lrn;
        i=i+1;
%     elseif i>lrn;
%       i=i+skp;
%     end
   end
  plot(dat1,'g-')
    title('TRAJECTORY OF THE LIKELIHOOD RATIO')
    xlabel('DATA POINTS')
    ylabel('LIKELIHOOD RATIO LAMDA')
    grid
    hold on
    plot(ref)
    hold off
    pause
    locnt
    upcnt

%**     N O I S E   D E G R A D A T I O N      **

elseif option == 3;
    disp('** Options for the allowable variation of VARIANCE **')
    disp('**         from nominal variance              **')
    disp(' ')
    disp('Option is 1 if you want to enter the factor')
    disp('by which variance should change')
    disp(' ')
disp('Option is 2 if you want to enter the actual allowable variance ')
    disp(' ')
    option=input('Enter your option ( 1 or 2 ) :  ');
    if isempty(option)
        option=1;
    elseif option == 2;
        var1 = input('New  Variance (options: 2 to 3) : ');
    elseif option ==1;
        factor=input('Factor by which variance should change : ');
        var1=var0*factor;
    else
        disp('!!  NOT A VALID OPTION  !!')
        break
    end
```

```
%** Now that we know what var1 is, we can proceed to  **
%** calculate lamda for noise degradation             **

          lamda(1)=0;
          j=1;
          x2(1)=0;
               if iskp==0
                 i=1;
               elseif iskp>0
                 i=iskp;
               end
               locnt=0;
               upcnt=0;
               while i<ndp
               j=j+1;
lamda(j)=lamda(j-1)+0.5*((1/var0)-(1/var1))*(data(i)-mean0)^2
                                                  +log(sqrt(var0/var1));
               dat2(j)=lamda(j);
               ref(j)=0.0;
                      if lamda(j)<A
                        dat2(j)=A;
                        lamda(j)=0;
                        locnt=locnt+1;
                      elseif lamda(j)>B
                        dat2(j)=B;
                        lamda(j)=0;
                        upcnt=upcnt+1;
                      end

                 if i<=lm;
                   i=i+1;
                 elseif i>lm;
               i=i+skp;
                 end
            end
            plot(dat2,'g-')
               title('TRAJECTORY OF THE LIKELIHOOD RATIO')
               xlabel('DATA POINTS')
               ylabel('LIKELIHOOD RATIO LAMDA')
               grid
               hold on
               plot(ref)
               hold off
               pause
               locnt
               upcnt
```

```
%** B O T H   B I A S   A N D  N O I S E   D E G R A D A T I O N **

elseif option == 1;

   mean1=input('Maximum allowable variation of mean from nominal mean :');

%* options for new variance *

         disp('** Options for the allowable variation of VARIANCE **')
         disp('**           from nominal variance                **')
         disp(' ')
         disp('Option is 1 if you want to enter the factor')
         disp('by which variance should change')
         disp(' ')
disp('Option is 2 if you want to enter the actual allowable variance ')
         disp(' ')
         option=input('Enter your option ( 1 or 2 ) :  ');
         if isempty(option)
                 option=1;
         elseif option == 2;
                 var1 = input('New  Variance (options: 2 to 3): ');
         elseif option == 1;
                 factor=input('Factor by which variance should change:');
                 var1=var*factor;
         else
                 disp('!!  NOT A VALID OPTION  !!')
                 break
         end

%** Now that we know mean1 and var1, we can proceed to  **
%** compute lamda for both bias and noise degradations  **

           lamda(1)=0;
           j=1;
           x3(1)=0;
                 if iskp==0
                   i=1;
                 elseif iskp>0
                   i=iskp;
                 end
                 locnt=0;
                 upcnt=0;
                 while i<ndp
                 j=j+1;

lamda1(j)=lamda(j-1)+0.5*((1/var0)-(1/var1))*(data(i)-mean0)^2+log(sqrt(var0/var1));
lamda2(j)=(mean1/var1-mean0/var0)*(data(i)-mean0) + 0.5*(mean0^2/var0-mean1^2/var1);
lamda(j)=lamda1(j)+lamda2(j);

                 dat3(j)=lamda(j);
                 ref(j)=0.0;
```

```
                    if lamda(j) < A
                       dat3(j)=A;
                       lamda(j)=0;
                       locnt=locnt+1;
                    elseif lamda(j) > B
                       dat3(j)=B;
                       lamda(j)=0;
                       upcnt=upcnt+1;
                    end
                 if i< =lrn;
                    i=i+1;
                 elseif i>lrn;
                i=i+skp;
                 end
             end
          plot(dat3,'g-')
             title('TRAJECTORY OF THE LIKELIHOOD RATIO')
             xlabel('DATA POINTS')
             ylabel('LIKELIHOOD RATIO LAMDA')
             grid
             hold on
             plot(ref)
             hold off
             pause
             locnt
             upcnt
      else
             disp ('NOT A VALID OPTION !')
             break
      end
end
clear
```

3. CODE FOR ADAPTIVE REGRESSION ANALYSIS

```
%************************************************************************************
% PROGRAM NAME : ADA.M
% FUNCTION   : This program takes processed data to perform multivariate linear regression analysis.
               The data file contains the matrix A that consists of 9 columns of numerical values.

%* The following menu defines each column of the data file.
%* 1. column 1 = Number of data points.
%* 2. column 2 = overall lifetime of a component.
%* 3. column 3 = coefficient of the constant parameter (b0) in the regression model.
%* 4. column 4 = values of the first variable i(t)=it8-it7
%* 5. column 5 = i(t-1)
%* 6. column 6 = i(t-2)
%* 7. column 7 = i(t-3)
%* 8. column 8 = i(t-4)
%* 9. column 9 = i(t)*i(t-1)
%************************************************************************************

disp('THE SIZE OF DESIGN MATRIX "B"  IS: ')
[mm,nn] = size(A);
m1 = mm-1;
n1 = nn-2;
disp([m1,n1])
j=input('Enter the STARTING row number for the regression model ');
i=input('Enter the ENDING row number for the regression model ') ;

if i>m1
i=m1;
elseif j>=i
disp('WRONG numbers try again')
clear;
eval('xxx');
end

disp('These are your options for trending data using linear')
disp('regression models :')
disp(' ')
disp('1. Simple Regression Model using just i(t)' )
disp(' ')
disp('2. Multiple Regression Model using i(t) & i(t-1)')
disp(' ')
disp('3. Multiple Regression Model using i(t), i(t-1) & i(t-2)')
disp(' ')
disp('4. Multiple Regression Model using i(t), i(t-1), i(t-2) & i(t-3)')
disp(' ')
disp('5. Multiple Regression Model using i(t),i(t-1),i(t-2),i(t-3)&i(t-4)')
disp(' ')
disp('DEFAULT IS NUMBER 1.')
disp(' ')
```

```
option = input('Enter your option (an integer number)  ')
if isempty(option)
        option=1;
elseif option == 2
        R=A(j:i,3:5);
        k=5;
elseif option == 3
        R=A(j:i,3:6);
        k=6;
elseif option == 4
        R=A(j:i,3:7);
        k=7;
elseif option == 5
        R=A(j:i,3:8);
        k=8;
else
        R=A(j:i,3:4);
        k=4;
end
disp (R)

Y=A(j:i,2);
%B=(inv(R'*R))*R'*Y;
B=R\Y;
disp (Y)
disp('The coefficients of the multivariate regression model are;')
disp('B')
disp(B)
pause

Ybar=R*B;
E=Y-Ybar;
q=i-1;
%rp=A(j:q,3:6)
%al=A(47,3:6)
Rpred=A(40:47,3:6)
Ypred=Rpred*B
Yact=A(40:47,2)
E1=Yact-Ypred

plot(A(:,4),A(:,2),'-.')
%title('Prediction of Residual Life using Adaptive Modeling')
hold on
plot(A(j:i,4),Y,'-',A(j:i,4),Ybar,'--',A(j:i,4),E,'*')
text(0.07,13,'window used to')
text(0.07,10,'estimate')
text(0.07,7,'parameters')
hold on
plot(A(40:47,4),Yact,'-',A(40:47,4),Ypred,'--',A(40:47,4),E1,'*')
text(2.5,69,'actual life')
text(2.9,40,'predicted')
```

```
text(2.9,37,'life using')
text(2.9,34,'estimated')
text(2.9,31,'parameters')
text(2.3,12,'error in prediction')
hold off
xlabel('Current Difference (Amps.)')
ylabel('Life (hr*10)')
grid
pause
meta temp

plot(A(40:47,4),Yact,'r',A(40:47,4),Ypred,'w--')
xlabel('Current Difference (Amps.)')
ylabel('Life (hr*10)')
grid
pause
plot(A(40:47,4),E1,'g--')
xlabel('Current Difference (Amps.)')
ylabel('Error (Amps)')
grid
pause

answer=input('Do you want to make another run? (Y/N)[Y]: ','s');
if isempty(answer)
answer='Y';
end

if answer == 'Y'
clear;
%eval('xxx');
elseif answer == 'N'
disp('Good bye')
exit
else
clear;
%eval('xxx');
end
```

4. MODIFIED CODE FOR ADAPTIVE REGRESSION ANALYSIS

```
**************************************************************************************
% PROGRAM NAME  : LIN1.M
% FUNCTION :   OFFERS THE CHOICE OF SIMPLE, DYNAMIC LINEAR AND STATIC
               QUADRATIC REGRESSION MODELS AND GIVES PREDICTION PLOTS
% SUBROUTINES : ERRANA.M, QUAD.M
**************************************************************************************

ans5=input('Do you want to see a DEMO? (Y/N): ','s');
if isempty(ans5)
ans5='Y';
end
if (ans5 == 'Y') |(ans5 == 'y')
clear;
demo1;
end

clear;
load filename.dat
AA=filename;
[p1,q1]=size(AA);

for i=1:p1
a1(i)=i;
a2(i)=1;
end

a3(1)=0;
a3(2:p1)=AA(1:p1-1,2);
a4(1)=0;
a4(2)=0;
a4(3:p1)=AA(1:p1-2,2);
a6(1)=0;
a6(2)=0;
a6(3)=0;
a6(4:p1)=AA(1:p1-3,2);
%
%***** Construction of Design Matrix
%***** suitable for dynamic regression models
%***** with one, two or three points back in time.

A=[a1',AA(1:p1,1),a2',AA(1:p1,2), a3', a4',a6'];

plot(A(:,2),A(:,4))
axis([0 max(A(:,2)) min(A(:,4)) max(A(:,4))]);
title('D I S P L A Y   of   D A T A')
xlabel('Time (hrs)')
ylabel('Signature')
grid
pause
```

```
[mm,nn]=size(A);
m1 = mm;
n1 = nn-2;

disp('Regression Modeling OPTIONS')
disp(' ')
disp('1. Adaptive Regression (AR) Models ')
disp('2. Regular Regression Models (default)')
disp(' ')
ans = input('Enter YOUR options: ');
end
if ans==1
ws=input('Enter the NUMBER of DATA points to construct AR models: ');
else
ws=m1-1;
end
%
i=m1;
j=i-ws;
dt = A(i,2)-A(i-1,2);
%
disp('These are your options for trending data using linear')
disp('regression models :')
disp(' ')
disp('1. Simple   Regression Model: < b0+b1*x(t) >' )
disp('2. Dynamic  Regression Model: < b0+b1*x(t)+b2*x(t-1) >')
disp('3. Dynamic  Regression Model: < b0+b1*x(t)+b2*x(t-1)+b3*x(t-2) >')
disp('4. Dynamic  Regression Model: < b0+b1*x(t)+b2*x(t-1)+b3*x(t-2)
                                       +b4*x(t-3) >')
disp('5. Static   Quadratic  Model: < b0+b1*x(t)+b2*(x(t))^2 >')
disp(' ')
disp('Default is Number 1.')
disp(' ')
disp('THE OPTIONS FOR MULTIPLE SIGNATURES WILL BE AVAILABLE')
disp('     IN A LATER VERSION OF THE PROGRAM  !!!!        ')
disp(' ')
%
option = input('Enter your option (an integer number)  ');
if isempty(option)
        option=1;
elseif option == 2
alarm = input('Enter the ALARM LEVEL: ') ;
        R=[A(j:i,3:5)];
        k=5;
elseif option == 3
alarm = input('Enter the ALARM LEVEL: ') ;
        R=[A(j:i,3:6)];
        k=6;
elseif option == 4
alarm = input('Enter the ALARM LEVEL: ') ;
        R=[A(j:i,3:7)];
```

```
        k=7;
elseif option == 5
      quad
        break
else
alarm = input('Enter the ALARM LEVEL: ') ;
        R=A(j:i,3:4);
        k=4;
end
%
Y=A(j:i,2);
%B=(inv(R'*R))*R'*Y;
B=R\Y;
[sizr,sizc]=size(B);
sizb=sizr;
%
Ybar=R*B;
E=Y-Ybar;
[qe,pe]=size(E);
RMS = sum(sqrt((E.^2)))/qe;

errana

co=1;
%********** OUTPUT FILE containing information about the models ********
diary lin1.dat

if k==7
disp('*******************************************************************')
disp('Dynamic Regression Model: < b0+b1*x(t)+b2*x(t-1)+b3*x(t-2)+b4*x(t-3)>')
disp(' ')
disp('Number of Data Points Used in Model Construction:')
disp(i-j)
disp('The coefficients of regression model are:')
disp(' ')
disp('   b0      b1      b2      b3   b4')
disp(B')

elseif k==6
disp('*******************************************************************')
disp('Dynamic Regression Model: < b0+b1*x(t)+b2*x(t-1)+b3*x(t-2) >')
disp(' ')
disp('Number of Data Points Used in Model Construction:')
disp(i-j)
disp('The coefficients of regression model are:')
disp(' ')
disp('   b0      b1      b2      b3')
disp(B')

elseif k==5
disp('*********************************************************')
```

```
disp('Dynamic Regression Model: < b0+b1*x(t)+b2*x(t-1) >')
disp(' ')
disp('Number of Data Points Used in Model Construction:')
disp(i-j)
disp('The coefficients of regression model are:')
disp(' ')
disp('     b0        b1        b2  ')
disp(B')

else
disp('*********************************************************')
disp('Simple Regression Model: < b0+b1*x(t) >')
disp(' ')
disp('The coefficients of regression model are:')
disp(' ')
disp('Number of Data Points Used in Model Construction:')
disp(i-j)
disp('     b0        b1  ')
disp(B')
end

disp('RMS error is')
disp(RMS)
disp('Coefficient of Determination is')
disp(R2)
disp('Coefficient of Variation is')
disp(cv)
pause

  ii=i;
  alarm1=alarm;
  while A(ii,4) < alarm1
          co=co+1;
          A(ii+1,2)=A(i,2)+(ii-i+1)*dt;
    if k==7
   A(ii+1,4)=(A(ii+1,2)-B(1)-B(3)*A(ii,4)-B(4)*A(ii-1,4)-B(5)*A(ii-2,4))/B(2);
    elseif k==6
      A(ii+1,4)=(A(ii+1,2)-B(1)-B(3)*A(ii,4)-B(4)*A(ii-1,4))/B(2);
    elseif k==5
      A(ii+1,4)=(A(ii+1,2)-B(1)-B(3)*A(ii,4) )/B(2);
    else
      A(ii+1,4)=(A(ii+1,2)-B(1))/B(2);
    end

    jj=ii;
    ii=ii+1;
    if co==200
         alarm1=0.0;
         disp('SIGNATURE trend does NOT CONVERGE to the ALARM LEVEL')
         disp('        <Hit Return Key to Continue>')
         pause
```

```
        break
    end
  end
  for ii=1:jj+1
        alar(ii)=alarm;
  end
  ts=A(jj,4);
  if A(jj,4) <= A(i,4)
    disp('The PREDICTION process may NOT be CONVERGING <Hit return key>')
    pause
  else
    A(i:jj,2:4)
    axis([0 1.1*A(jj,2) min(A(:,4)) 1.1*alarm])
    plot(A(j:i,2),A(j:i,4),'r',A(i:jj,2),A(i:jj,4),'--g',A(:,2),alar','*r')
    title('PREDICTION OF ALARM LIFE OF THE MOTOR')
    text(2,1.03*alarm,' - Data Used in the Model,  -- Predicted Values')
    text(2,1.01*alarm,' * Alarm Level')
    xlabel('OVERALL LIFE (HOURS)')
    ylabel('VIBRATION SIGNATURE (INCH/SEC)')
    grid
    meta lin1
    pause
  end

  disp('Predicted overall life is')
  disp(A(jj,2))
  disp('The confidence interval is')
  lb=A(jj,2)-errm;
  ub=A(jj,2)+errm;
  disp(lb)
  disp(ub)

diary off
hold off
answer=input('Do you want to make another run? (Y/N): ','s');
if isempty(answer)
        answer='Y';
end
if (answer == 'Y') |(answer == 'y')
        clear;
        lin1
else
        disp('Good bye')
end
```

5. SUBROUTINE FOR ERROR ANALYSIS

```
*************************************************************************************
% *** Program Name : ERRANA.M
% *** created on 9/25/94
% *** subroutine for statistical error analysis
*************************************************************************************

ymean=mean(A(j:i,2));
xmean=mean(A(j:i,4));
df=ws-sizb;
s2=(E'*E)/df;
s=sqrt(s2);
cv=s*100/ymean;
R2=(Ybar-ymean)'*(Ybar-ymean)/((Y-ymean)'*(Y-ymean));
sx=A(j:i,4)-xmean;
ims=sx.^2;
sxx=sx'*sx;
sy=s*sqrt(1+(1/ws)+(ims/sxx));
% Inclusion of the T-table to find t corresponding to the
% degree of freedom
T=[    1    6.314
       2    2.92
       3    2.353
       4    2.132
       5    2.015
       6    1.943
       7    1.895
       8    1.86
       9    1.833
       10   1.812
       11   1.796
       12   1.782
       13   1.771
       14   1.761
       15   1.753
       16   1.746
       17   1.740
       18   1.734
       19   1.729
       20   1.725
       21   1.721
       22   1.717
       23   1.714
       24   1.711
       25   1.708
       26   1.706
       27   1.703
       28   1.701
       29   1.699
       30   1.697];
```

```
if df>=31
        tt=1.697-0.001*(df-30);
else
        tt=T(df,2);
end
me=tt*sy;
errm=mean(me)
CIU=Ybar+me;
CIL=Ybar-me;
```

6. SUBROUTINE FOR QUADRATIC REGRESSION MODEL

```
**********************************************************************************************
% *** program name  : quad.m
% *** created on 9/30/94
% *** subroutine for just the static quadratic model
**********************************************************************************************

a5(1:p1)=AA(1:p1,2).^2;

% ***** Design Matrix for Static Quadratic Model *********

A=[a1',AA(1:p1,1),a2',AA(1:p1,2), a3', a4',a6',a5'];

alarm = input('Enter the ALARM LEVEL: ') ;
        R=[A(j:i,3:4),A(j:i,8)];
        k=8;

Y=A(j:i,2);
%B=(inv(R'*R))*R'*Y;
B=R\Y;
[sizr,sizc]=size(B);
sizb=sizr;

Ybar=R*B;
E=Y-Ybar;
[qe,pe]=size(E);
RMS = sum(sqrt((E.^2)))/qe;

errana

disp('**********************************************************')
disp('static quadratic model: <b0+b1*X(t)+b2*X(t)^2>')
disp(' ')
disp('The coefficients of regression model are:')
disp(' ')
disp('Number of Data Points Used in Model Construction:')
disp(i-j)
disp('    b0        b1        b2  ')
```

```
disp(B')
disp('RMS error is')
disp(RMS)
disp('Coefficient of Determination is')
disp(R2)
disp('Coefficient of Variation is')
disp(cv)
pause

  Ap1=B(1)+B(2)*alarm+B(3)*alarm^2;
  disp('Predicted overall life is')
  disp(Ap1)
  disp('The confidence interval is')
  lb=Ap1-errm;
  ub=Ap1+errm;
  disp(lb)
  disp(ub)
  pause

  x=[A(i,4):0.1:1.01*alarm];
  y=B(1)+B(2)*x+B(3)*x.^2;
  yi=1;
  for xax=A(j+1,2):2*Ap1
     alar(yi)=alarm;
     yi=yi+1;
  end
  axis([0 1.1*Ap1 0 1.1*alarm]);
  plot(A(j+1:i,2),A(j+1:i,4),'r',y, x, '--g')
  hold on
  plot (alar','*r')
  grid
  hold off
pause
answer=input('Do you want to make another run? (Y/N): ','s');
if isempty(answer)
        answer='Y';
end
if (answer == 'Y') |(answer == 'y')
        clear;
        lin1
else
        disp('Good bye')
end
```

7. CODE FOR CALCULATING CORRELATION COEFFICIENT OF TWO SIGNATURES

```
**********************************************************************************************
% PROGRAM NAME : CORCOFF
% FUNCTION       : THIS PROGRAM ASKS FOR TWO DATA FILE NAMES WITH DIFFERENT
                   SIGNATURES AND COMPUTES THE CORRELATION COEFFICIENT
**********************************************************************************************

disp('Enter the first file name when asked')
disp(' ')
!pre
!rename last.dat sign1.dat
!del stg2.dat
load sign1.dat;
disp('Enter the second file name when asked')
disp(' ')
!pre
!rename last.dat sign2.dat
load sign2.dat;
D1=sign1;
D2=sign2;
A=[D1(:,2),D2(:,2)]
ex=A(:,1);
oi=A(:,2);
ex2=ex'*ex;
oi2=oi'*oi;
corcof=(ex'*oi)/sqrt(ex2*oi2);
disp('The Correlation Coefficient between the two Signatures is ')'
disp(corcof)
!del sign1.dat
!del sign2.dat
end
```

VITA

Baishali Ray Chaudhuri was born in 1968 in Ranaghat near Calcutta, India. She went to Mary Immaculate School, Ranaghat and Auxilium Convent, Bandel. She ranked first from her school (Pratt Memorial, Calcutta) in the Indian Certificate of School Examination in 1984. She completed her high school education in Bethune College. Baishali had always dreamt of becoming a professor of Mathematics but fate changed her course of study. She went to Bengal Engineering College in 1986 to study Electrical Engineering. She was recruited by Calcutta Electric Supply Corporation in 1990 and worked there till December 1991 as a trainee engineer. She followed her husband to the U.S. in January 1992. She officially joined the M.S. program in the Nuclear Engineering Department at the University of Tennessee, Knoxville in August 1992. She plans to go back to India after receiving another Master's degree in Electrical Engineering. Her extra-curricular activities include Indian classical dance and music.