Predictive and Preventive Maintenance of Mobile Mining Equipment Using Vibration Data

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This thesis is dedicated to my wife Jacqueline
Abstract

PREDICTIVE AND PREVENTIVE MAINTENANCE OF MOBILE MINING EQUIPMENT USING VIBRATION DATA

John H. Burrows

This thesis discusses traditional and more advanced approaches, procedures and techniques to evaluate the health of mining machinery, based on monitored vibration data. Such methods have shown to be useful for evaluating mobile equipment component health while it is off-line, provided the data is properly acquired and an expert is available to interpret the data. The thesis objective, however, was to develop a means to determine machine health, while operating on-line, without reference to an expert. This approach is based on processing acquired vibration data with artificial neural networks (ANN’s), to enable immediate and meaningful results to be obtained. A case study, based on data obtained from the monitoring of locomotives at the Iron Ore Company (IOCC). The case study is presented, analysed and discussed. Real time data patterns, profiles and trends, obtained by processing vibration signals acquired from various points on locomotives, were used to test the developed technique. The results indicate that observed patterns and trends can be classified into distinct categories that can reliably indicate the mechanical state of the equipment, using ANN’s. An implemented system, based on this approach, will assist maintenance personnel at this mine to accurately identify the trends of a developing component problem in advance of catastrophic failure. In addition to simply predicting the eventual failure of a component, the same system will eventually be able to statistically predict its remaining life prior to catastrophic failure. Thus, a machine could be reliably and safely operated until just prior to failure of a component, rather than undergo a premature change out.

The thesis work is a sub-component of a larger project at IOCC, to implement a mine-wide predictive/preventative maintenance program for pumps, locomotives, trucks.
shovels and drills at their open-pit mine in Labrador City, Newfoundland. This larger system will use intermittent on- and off-line, condition monitoring of this equipment based on ANNs and expert systems (ES). A functional overview of this system is discussed, where the output from on-board monitoring systems, would be available on a timely basis to the maintenance engineer via a dedicated radio link or dispatch system. The data would identify in clear and concise terms exactly where and what is the particular machine alarm condition. Once fully implemented, such an approach would allow improved fault detection of machine components on a timely basis, especially in mines where trained personnel are not readily available to make such decisions.
Résumé

Cette thèse aborde les approches traditionnelles et plus avancées, méthodes et techniques basées sur les mesures de vibration pour évaluer la condition mécanique des machines utilisées dans les mines. Ces méthodes se sont avérées utiles pour évaluer l'état des composantes de l'équipement mobile, à condition que les bonnes données soient prises et qu'un système expert soit disponible pour interpréter les données. Le but de la thèse, cependant, est de développer une façon rapide d'évaluer la condition des machines durant l'opération. Cette approche sera basée sur le traitement des lectures de vibration à l'aide de réseaux de neurones artificiels (RNAs) afin d'obtenir des résultats fiables en temps réel. Une étude de cas est présentée, basée sur des données recueillies sur les locomotives à IRON ORE du CANADA (IOCC), et les résultats sont analysés et discutés. Les données en temps réel, comprenant des signatures et tendances des signaux vibratoires mesurés à divers emplacements sur les locomotives, furent utilisées pour développer la technique. Les résultats indiquent que les signatures et tendances observées peuvent être classées en diverses catégories servant à déterminer précisément la condition mécanique de l'équipement par l'utilisation de RNAs. Un tel système de détection et de diagnostic assistera le personnel de maintenance de la mine à identifier de façon précoce les composantes défectueuses et ainsi prévenir les bris catastrophiques. En plus, de pouvoir prédire les bris potentiels à l'avance, le même système peut déterminer de façon statistique la vie résiduelle des composantes endommagées, ce qui permettra d'utiliser la pièce d'équipement au maximum au lieu d'effectuer une réparation trop précoce.

Les travaux de cette thèse font partie d'un plus grand projet à la mine à ciel ouvert de IOCC Labrador City, consistant à implanter un système de maintenance prédictive/préventive à l'échelle de la mine toute entière couvrant les locomotives, pompes, camions, pelles mécaniques et les foreuses. Ce système utilisera la surveillance intermittente et permanente de l'équipement basé sur les réseaux de neurones artificielles (RNAs) et les systèmes experts (ES). Une description globale de ce système sera donnée, où les résultats des dispositifs de surveillance seront régulièrement mis à la
disposition des ingénieurs de maintenance via des liens radios ou autres systèmes de communication. Les données transmises indiqueront clairement quelle machine est en trouble et la nature exacte de la faute détectée. Une fois implantée, cette approche permettra une détection plus efficace des fautes, plus particulièrement dans les mines où le personnel qualifié pour effectuer le diagnostic n’est pas toujours disponible.
Acknowledgments

The author is deeply indebted to the President of Iron Ore Company of Canada, Mr. Derek Rance, together with the Maintenance Engineering Department of the mine, for the opportunity and encouragement given throughout the course of this investigation. The author would like to express a deep appreciation to Mr. Ron Doucet, the Maintenance Engineering Superintendent, who proposed the project, and to Mr. Bruce Vienneau, the technologist who did most of the routine measurements.

Thanks are also due to Dr. Jon Peck and Dr. Laeeque Daneshmand, the project supervisors, for their guidance and constructive criticism during the preparation of this thesis, and to Mr. Graham Braun for his help in preparing the manuscript for publication.

The author would also like to recognize the contribution made by Mr. Mike Boos, who built and tested the Machine Health Monitoring equipment; and finally Mr. René Archambault for many hours of discussion over a period of eight years on the topic of machine vibration.
Note on the used Units of Measurements

Throughout this thesis, imperial units are used. Where appropriate and possible however, the S.I. metric equivalent have been provided. The reason for adopting imperial units is justified by the following:

1. The majority of vibration monitoring equipment used in the mining industry uses imperial units.

2. Manufacturers only recently started to use metric units.

On this basis it was decided to maintain imperial units for all subsequent data presentations where the source of the data or information was imperial.

Table of Conversion: Imperial to Metric

<table>
<thead>
<tr>
<th>Imperial</th>
<th>x factor</th>
<th>Metric</th>
</tr>
</thead>
<tbody>
<tr>
<td>ft</td>
<td>0.3048</td>
<td>m</td>
</tr>
<tr>
<td>in</td>
<td>25.4</td>
<td>mm</td>
</tr>
<tr>
<td>lb mass</td>
<td>0.4536</td>
<td>kg</td>
</tr>
<tr>
<td>rpm</td>
<td>0.1047</td>
<td>rd/s</td>
</tr>
<tr>
<td>ft-lb</td>
<td>1.36</td>
<td>nm</td>
</tr>
<tr>
<td>c.y</td>
<td>1.3078</td>
<td>m³</td>
</tr>
</tbody>
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## Nomenclature

### Symbols and Abbreviations

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta )</td>
<td>difference</td>
</tr>
<tr>
<td>( x_i )</td>
<td>input</td>
</tr>
<tr>
<td>( \Delta_i )</td>
<td>the correction associated with the input ( x_i )</td>
</tr>
<tr>
<td>( \omega_i(n) )</td>
<td>the value of the weight ( i ) before adjustment</td>
</tr>
<tr>
<td>( \delta_{q,k} )</td>
<td>the value of the weight ( \delta ) for neuron ( q ) in the output layer ( K )</td>
</tr>
<tr>
<td>( \text{OUT}_{pj} )</td>
<td>the value of ( \text{OUT} ) for neuron ( p ) in the hidden layer ( j ). Subscripts ( p ) and ( q ) refer to a specific neuron. Subscripts ( j ) and ( k ) refer to a layer</td>
</tr>
<tr>
<td>( O_j )</td>
<td>the output vector of layer ( j )</td>
</tr>
<tr>
<td>( (i) )</td>
<td>previous layer</td>
</tr>
<tr>
<td>( (j) )</td>
<td>hidden layer</td>
</tr>
<tr>
<td>( (k) )</td>
<td>output layer</td>
</tr>
<tr>
<td>( $ )</td>
<td>operator defined to indicate component-by-component multiplication of the two vectors</td>
</tr>
<tr>
<td>( \Sigma_q )</td>
<td>Summation of weights at neuron ( q )</td>
</tr>
<tr>
<td>( \beta )</td>
<td>a constant which controls the shape of the curve.</td>
</tr>
<tr>
<td>( \lambda(t) )</td>
<td>the failure rate characteristic</td>
</tr>
<tr>
<td>( \eta )</td>
<td>a scaling constant which stretches the distribution along the time axis i.e. the characteristic life</td>
</tr>
<tr>
<td>( t_0 )</td>
<td>the time datum i.e. the starting point of the distribution.</td>
</tr>
<tr>
<td>Symbol</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>-------------</td>
</tr>
<tr>
<td>A(t)</td>
<td>Availability. Probability of being available</td>
</tr>
<tr>
<td>M(t)</td>
<td>Maintainability. Repair time probability</td>
</tr>
<tr>
<td>R(t)</td>
<td>Reliability. Probability of being in good working order</td>
</tr>
<tr>
<td>F(t)</td>
<td>Cumulative failure distribution function</td>
</tr>
<tr>
<td>CF</td>
<td>Crest Factor</td>
</tr>
<tr>
<td>c.y.</td>
<td>cubic yard (1 c.y = 1.3078 m³)</td>
</tr>
<tr>
<td>dB</td>
<td>decibel</td>
</tr>
<tr>
<td>°C</td>
<td>degrees Celsius</td>
</tr>
<tr>
<td>°F</td>
<td>degrees Fahrenheit</td>
</tr>
<tr>
<td>g</td>
<td>acceleration due to gravity (9.81 ms⁻²)</td>
</tr>
<tr>
<td>kb</td>
<td>kilobytes</td>
</tr>
<tr>
<td>kg</td>
<td>kilograms</td>
</tr>
<tr>
<td>in.</td>
<td>inch (1 inch = 2.54 x 10⁻² meters)</td>
</tr>
<tr>
<td>kHz</td>
<td>kilohertz</td>
</tr>
<tr>
<td>km</td>
<td>kilometers (i.e. 1 km = 1 m x 10³)</td>
</tr>
<tr>
<td>kW</td>
<td>kilowatts</td>
</tr>
<tr>
<td>lb. in.</td>
<td>pound inch</td>
</tr>
<tr>
<td>m</td>
<td>meter</td>
</tr>
<tr>
<td>mm</td>
<td>millimeter (i.e. 1 mm = 1 m x 10⁻³)</td>
</tr>
<tr>
<td>ms⁻²</td>
<td>meter per second squared</td>
</tr>
<tr>
<td>MTBF</td>
<td>mean time before failure</td>
</tr>
<tr>
<td>MTTR</td>
<td>mean time to repair</td>
</tr>
<tr>
<td>Symbol</td>
<td>Definition</td>
</tr>
<tr>
<td>--------</td>
<td>------------</td>
</tr>
<tr>
<td>mV/mil</td>
<td>millivolt per thousandths of an inch</td>
</tr>
<tr>
<td>pc/ ms²</td>
<td>pico-coulomb per meter per second squared</td>
</tr>
<tr>
<td>RMS</td>
<td>root mean square</td>
</tr>
<tr>
<td>RPM</td>
<td>revolutions per minute</td>
</tr>
<tr>
<td>s</td>
<td>seconds</td>
</tr>
<tr>
<td>T</td>
<td>tonnes</td>
</tr>
<tr>
<td>tonne</td>
<td>metric mass measurement equal to 1000 kilograms</td>
</tr>
<tr>
<td>V</td>
<td>volts</td>
</tr>
</tbody>
</table>
1. INTRODUCTION TO THE APPLICATION OF MONITORED VIBRATION DATA FOR PREDICTIVE AND PREVENTIVE MAINTENANCE PURPOSES IN THE MINING INDUSTRY

1.1 Introduction

Machine condition monitoring of equipment in the Canadian mining industry has always been of major importance as a significant portion of the operating budget of a mine is apportioned for equipment maintenance. At the Iron Ore Company of Canada (IOCC), more than 50 percent of the operating budget is allocated to maintenance functions. The profit that a mine makes is directly proportional to the availability of the drills, shovels, trucks and locomotives used to obtain the ore. The emergence of higher grade and lower cost mines in many other countries together with the increased operating costs of mines in Canada, requires that the latter become more efficient in order to survive in the highly competitive global economy. Canadian mines have been forced to achieve increased productivity and lower costs per tonne while reducing the numbers of equipment operators and maintenance personnel. This has meant that equipment size has increased to handle the larger quantities of ore mined and transported and as a consequence of this, the equipment used has become more expensive to both purchase and operate. As a result, the importance of the adverse effects of any equipment failure or equipment downtime has also increased.

In a typical open pit mine facility there exists a number of different departments, for example engineering, production, sales, maintenance, finance and personnel. It is the function of management to coordinate the activities of these various and diverse departments to the benefit of the employees and shareholders alike. However the functions of two of these departments, namely production and maintenance, sometimes appear to be mutually exclusive and independent. To management it may appear that
when production targets are being met it is because of "good" production techniques and when they are not it is because of "poor" maintenance techniques. To the finance department, the production department is viewed as a "profit" centre and the maintenance department is viewed as a "cost" centre. To the production department, the maintenance department appears not to be keeping the equipment in good repair and conversely the production department appears to the maintenance department to be overdriving and abusing the equipment. It would appear that a good policy for the mine to adopt would be to combine the maintenance and production departments into one single fiscal and operational entity and thereby ensure that maintenance is considered to be an integral part of production.

By using data that has already been routinely collected and stored on suitable instruments, together with maintenance strategies tailored to suit different components, machines and groups of machines, it is possible, by turning the data into information, to improve the productivity and profitability of the mine. When this information is related to costs, then the maintenance department will be perceived as a "profit" centre rather than a "cost" centre. This will in turn lead to the perception that:

*quality and profitable production is the result of good maintenance strategies and techniques.*

### 1.2 Objective

The objective of this thesis is to describe new maintenance strategies and techniques and determine how these may be selected and implemented on specific mobile mine equipment in an open pit mine. The techniques and equipment that have been developed during the course of the study can be used to check the quality of maintenance procedures undertaken by lower skilled operators or even those responsible for program implementation.

In order to illustrate the proposed approach, reference will be made in Chapters 1.0 and 2.0 to theoretical studies and procedures currently used as well as some that were
used in the past as part of a maintenance program. A practical demonstration of the strategies and techniques proposed in this thesis is based on data acquired from monitoring locomotives operating at the IOCC mine located near Labrador City, Newfoundland, Canada.

The first component of the work is a description in Chapters 1.0 and 2.0 of the maintenance strategies, techniques and instruments that are currently available to the maintenance engineer. Secondly the mine operation as well as the case study that was performed on the locomotives at IOCC will be described in detail in Chapter 3.0. Finally a summary of what contributions were made and what are the future plans at the IOCC facility in order to build on the tangible results obtained during the course of this study.

1.3 Goal

The ultimate goal at IOCC, which will build upon the results of this thesis, is to design, construct, test and implement an advanced maintenance monitoring system for mobile equipment at this site with the following specific objectives:

1. The mobile equipment mechanical condition is to be monitored using a variety of transducers, signal conditioning and advanced analysis techniques.

2. The performance monitoring is to be an integral function of the system such that the signals related to the mechanical condition of the components can be discriminated from those obtained from the operation of the machine (i.e. digging, drilling etc.). The system will be integrated to existing systems at the IOCC mine, for example, programmable logic controllers on drills and/or shovels and the existing dispatch system, to avoid duplication of sensors, and operator interfaces.

3. The equipment mechanical condition and performance deterioration assessment is to be done through the use of advanced signal processing and pattern recognition techniques. The system will exceed standard methods by
providing information for immediate use by the mine, rather than simply data. The bulk of the processing will be accomplished on-board the mobile equipment in order to reduce the need for data storage and transmission.

4. High equipment productivity is to be achieved through the basic system design and through a variety of small improvements that will add up to significant gains.

5. The response effectiveness is to be maximized by having the system automatically "detect" anomalies and send an alarm to the maintenance group via the dispatch system. Information only will be transmitted and this will provide the maintenance department with specific details on which component is failing, together with the nature of the fault. Once an alarm is sent, the monitoring system on the equipment will go into a data acquisition mode in order to record data locally from the sensors for the purposes of fault "diagnosis". Such a system was recently installed on an electric cable shovel at this site (Peck, 1995) pers. comm.

6. An instrument will be designed in the future that can be mounted onto equipment, for example a locomotive, and used as a permanent machine-condition monitor, however, it will also be portable, so that it can be used as a stand alone instrument for quality control purposes [1].
2. REVIEW OF MAINTENANCE STRATEGIES AND TECHNIQUES FOR IMPROVING THE DECISION MAKING PROCESS OF MINE MAINTENANCE

2.1 General

Depending on the type of equipment and its utilization, different strategies can be adopted in order to have optimal availability of equipment in the mine. The following sections describe the maintenance strategies and techniques currently used at IOCC to determine equipment and component condition usage.

2.2 Maintenance Strategies

There are currently three popular maintenance strategies: Breakdown Maintenance, Time Based Preventive Maintenance and Predictive or Condition Based Maintenance. These maintenance strategies are shown in figure 2.0 [2, 3].

All three strategies described have a place in the maintenance philosophy of a mine. However, when, where and how these strategies are applied can be determined by...
applying statistical and modeling techniques to the failure data of the various components, machines and groups of machines that has been previously collected over a period of time. This approach will ensure that the optimal maintenance strategy is selected and performed as indicated in figure 2.1.

![Figure 2.1 - Optimal Maintenance](image)

2.2.1 Breakdown Maintenance

Breakdown maintenance is when the machine or equipment is allowed to run to failure, an option that can be used when there is spare capacity or when failure has little or no effect on production and repairs can be effected, or equipment replaced, quickly. Generally this approach requires spare components and skilled personnel to be on hand.

2.2.2 Time Based Preventive Maintenance

Time based preventive maintenance is feasible when machines deteriorate at fixed rates on a consistent basis. The machines must be rated conservatively and when maintenance is performed, good parts are often scrapped and replaced in order to guarantee operation between the shutdown periods. However, there is always a chance that faults will be introduced during the overhaul.
2.2.3 Predictive or Condition Based Maintenance

Predictive or condition based maintenance requires regular systematic checks of key performance parameters, e.g. vibration, temperature, pressure and oil analysis. The signals from the transducers are measured, stored and trended to predetermined warning and alarm levels before remedial action is taken. The warning and alarm levels are obtained from statistical data derived from a population of machines functioning correctly, or in the case of new types of equipment, from standards related to the size and horsepower of the machine.

2.2.4 Modeling

The complete-life failure characteristic of a hypothetical machine is shown in figure 2.2. This figure shows the general form of the “bath-tub” curve with its three distinct failure phases. The curve describes the general trends of failure over time, depending on factors which created the failure at each phase.

![Bath Tub Curve](image)

**Figure 2.2 - Bath Tub Curve [5]**
2.2.4.1 Infant Mortality, Quality Related Failure

During the early life of a population of similar equipment there is a decreasing failure rate. The failures during this phase are normally quality related and are caused by incorrect specification, manufacturing defects, improper installation, transportation or improper storage problems.

2.2.4.2 Maturity, Stress Related Failure

The operating life phase is associated with a substantially constant failure rate and the random stress related failures are caused by high dynamic stresses due to incorrect operation, poor maintenance, incorrect lubrication, incorrect installation or human errors.

2.2.4.3 Aging, Wear Related Failure

The end of life phase is associated with an increasing failure rate. Increased wear-out failures are caused by the accumulation of all of the previous effects. This causes aging, wear, fatigue, corrosion and the exceeding the design mean time before failure (MTBF).

2.2.5 Weibull Distribution

The three phases of failure are modeled separately using the Weibull distribution because there is no model for the complete curve, see figure 2.3.
The data can be represented by the following equations:

\[ \lambda(t) = \frac{\beta}{\eta} \left( \frac{t-t_0}{\eta} \right)^{\beta-1} \]  \hspace{1cm} 2.1

and,

\[ F(t) = 1 - e^{-\left( \frac{t-t_0}{\eta} \right)^\beta} \]  \hspace{1cm} 2.2

Where \( \lambda(t) \) is the failure rate characteristic and \( F(t) \) is the cumulative failure distribution function.

The constants \( t_0, \beta \) and \( \eta \) appearing in the Weibull function can be given physical meaning, where,

\( t_0 \) is the time datum i.e. the starting point of the distribution.
\( \eta \) is a scaling constant which stretches the distribution along the time axis i.e. the characteristic life.

\( \beta \) is a constant which controls the shape of the curve.

When

\( \beta < 1 \), the shape resembles infant mortality or early life.

\( \beta = 1 \), the shape resembles maturity or random.

\( \beta > 1 \), the shape resembles aging or wear-out.

In this way, groups of components and machines can be modeled and chi-square tests used to validate the model for a given confidence level.

Once these models are derived, decisions can be made relative to the type of maintenance that should be used. A cost analysis can be performed, where all the factors contributing to the costs must be factored into the equation e.g. cost of materials, loss of production, cost of labour, overhead etc. The cost analysis also needs to be based on the availability of the equipment or machine. Availability is defined as the probability that equipment will be available when required or the total time it is available for use. The maintainability is a function of the mean time to repair and the reliability is a function of the mean time between failures. Availability, as shown in figure 2.4, may be calculated as follows for simple machines like electrical motors and generators.

\[
\text{AVAILABILITY} = \frac{\text{MTBF}}{(\text{MTBF} + \text{MTTR})}
\]

Where MTBF is the mean time before failure and MTTR is the mean time to repair.
Other techniques like, ABC, Pareto and Multi-dimensional classification charts, could be used to classify the data and determine which type of faults are the most disruptive. Higher level probabilistic models based on Partial Likelihood, Proportional Hazards and Regression Analysis, have been developed for other disciplines e.g. medical and actuarial. These models should be investigated as they could be applied to good effect, in the field of machine condition monitoring, to optimize the maintenance procedures [3, 4, 5, 6, 7].

However, one of the simplest tools that is available to the maintenance engineer to determine component or equipment condition is the historical data. This data should contain information about the machine, design, usage, its importance in the process, hours in use, failure dates, repair times as well as the nature of the faults and their cause.

This data can then be processed into classification charts such as Pareto diagrams as shown in figure 2.5. Three types of Pareto diagrams, n, t and n.t, where n is the number of failures and t the average repair time, can be generated in order to establish priorities based on the various aspects of availability, reliability or maintainability. The graphs in figure 2.5, show a sample Pareto analysis carried out on electric motor failures, the graphs identify which types of fault are most disruptive.
Figure 2.5 - Pareto Analysis [4]

Another very useful representation is obtained through ABC analysis, which can be used to classify the elements which represent the most important fraction of a studied parameter by indicating their percentage according to a given criteria. Using the same data as in the previous example, the ABC curve, shown in figure 2.6, indicates that 10 percent of the failures are responsible for 55 percent of the repair costs.
2.2.6 Mine Maintenance Strategies

Modern mine operational strategies are not necessarily aimed at maximum availability but rather at optimal availability required to achieve minimum operating cost (including idle time due to the nature of the operation). For a production chain consisting of several elements, the availability will depend on the type of chain being considered as well as the logistics behind the adopted maintenance policy.

Therefore, knowing the failure rate and the mean time to repair can help define the maintenance strategy. Failure rate curves can usually be extracted from the historical data of the machines or from reliability studies. A model can also be fit to the data to approximate the failure rate as a function of age or usage.

A statistical knowledge about the reliability characteristics of machinery can provide useful guidelines for the selection of a maintenance or operational policy. For instance if the time between failure follows a Log-Normal distribution and the standard
deviation of the MTBF is reasonably small, time-based preventive maintenance would be much more effective than if the standard deviation was large.

A probabilistic model for the failure rate of a group of machines can be derived by estimating the number of failures for each period of the life of the machines and then fitting an analytical function through the data. Many parametric failure time models have been proposed to describe the behaviour of machines, such as the Poisson (discrete model), exponential, and Log-Normal distributions, but the Weibull model is probably one of the most popular because it can accommodate several types of behaviour such as infant mortality and various aging effects on machinery [7].

2.3 Maintenance Techniques

There are a number of parameters that can be monitored, e.g. oil debris analysis, temperature etc., to determine the condition of the machine. However, one of the most powerful parameters which can be used to monitor rotating machinery is vibration as may be seen in table 2.0. There is a large amount of information contained in the vibration signals that are obtained by monitoring at the various key points of a machine. These signals, however, can be very complex and even with today’s state-of-the-art measurement techniques, there is still much to learn in order to be able to measure, display, and utilize the vibration data to its fullest potential for predictive maintenance purposes.
Often, the unsuccessful use of vibration measurements to assess machine condition in a given situation is not a result of this signal not carrying the proper information but rather due to a lack of understanding of machine dynamics and signal processing techniques. The measurement of vibration is still a very effective tool to determine machine condition, especially since it can detect abnormal operating conditions long before there is any permanent damage to the machine. This feature is often not possible when other more traditional techniques are used.

The emergence of more powerful data acquisition and processing instrumentation has greatly contributed to an increase in acceptance of on-condition maintenance programmes. The continuing development and availability of more effective instrumentation is intimately related to the development of better maintenance
philosophies and predictive maintenance programmes as well as better instruments and analytical techniques [8].

2.3.1 Evolution of Monitoring Instrumentation

The earliest machine-condition monitoring techniques used by maintenance personnel were based on using their eyes, ears and experience. Observing certain parameters with their eyes, for example oil leaks, temperature, pressure, speed etc., is still an integral part of a machine inspector’s maintenance procedure. However, the technique of listening to a key measurement point via the handle of a screwdriver pressed against the ear of an experienced millwright or maintenance engineer, in order to determine the machine’s condition, is being replaced by modern instrumentation that enables the vibration signal, at the same key point, to be accurately measured and analysed. Therefore, less experienced maintenance personnel can now be used to collect information and more consistent objective judgments of machine condition can be performed. However, the ear is still a valuable detection tool when used by an experienced maintenance operator because the brain can still detect subtle variations better than instruments.

Some of the first instruments used to measure the vibration signal were instruments based on sound level meter technology, since many of the pertinent vibration signals are generally located in the audio frequency range. The Canadian Navy and many other navies around the world used instruments that were based on sound level meters, and this approach became a principal component of their maintenance programmes. One of the advantages of this method was that there were suitable instruments commercially available to obtain peak and overall level, as well as octave and one-third octave constant percentage band (CPB) frequency spectra for sound measurements. In addition these instruments were readily adaptable for vibration signal analysis by simply using an accelerometer and a charge amplifier instead of a microphone transducer and a voltage amplifier.
Two papers by C.A.W. Glew in the early 70's describe the results obtained by the Canadian Navy using a portable octave CPB analyser for predictive maintenance. Vibration in general, and octave CPB analysis in particular, still ranks as one of the best techniques for fault detection and it is fundamental to the machine-condition monitoring approach described in this thesis [9, 10].

As vibration measurements gained more widespread acceptance in industry, especially in the pulp and paper, chemical, petrochemical and mining industries, dedicated instruments were developed. These included simple portable vibration meters measuring only the overall level of acceleration which is a force indicator, as well as manually swept filter vibration analysers for finer resolution of the various frequency components contained in the vibration signal. Dedicated vibration monitors, using proximity probes for measuring displacement, which is a stress indicator, and velocity transducers, which are fatigue indicators, were also developed for permanent monitoring of critical machines.

In the late 1970's and early 1980's, the development of small low cost microcomputers became a reality due to Large Scale Integration devices and other technological advances in the electronics and computer industry. These advances enabled the large databases, necessary for storing, trending and analysing, to be handled with relative ease.

The emergence of more powerful diagnostic instruments, for example, vibration analysers, incorporating recursive digital filters and Fast Fourier Transform (FFT) techniques, with advanced features like cepstrum, envelope analysis and CPB spectrum comparison using log-log scales, enabled diagnosis to be made more scientifically and reliably. However, these instruments were usually fairly bulky, making it difficult to carry them in the field for extensive periods of time. They were also relatively complex to operate by the maintenance personnel.

In the 1980's, the advent of affordable portable measuring instruments with built-in memory, commonly called data-loggers or collectors, had a significant impact on
machine-condition vibration monitoring. These data-loggers were light, they could be carried around the plant all day, and removed the burden of writing down the results in adverse environmental conditions. Thus, the task of collecting data by a machine inspector during his daily inspection routine was greatly simplified. Since data-loggers were very easy and practical to use, the routine inspections were carried out more regularly and systematically by less specialized personnel. By using the software that normally accompanied such instruments, reports could be generated quickly for distribution to those who plan the maintenance schedules. Only a few seconds per measurement point were required to acquire the necessary data, and therefore several hundred points could be covered in a single day by relatively low skilled personnel.

2.3.2 Time Based Vibration Analysis Techniques

The following is a description of the time based analysis techniques currently available to the maintenance engineer for vibration analysis [11, 12].

2.3.2.1 Overall Level Measurements

Overall level measurements using root mean square (RMS) are the most common vibration measurement in use. It is important that the instrument measures true RMS and not the mean, but calibrated assuming a sinusoidal waveform, because a vibration signal is rarely a sinusoid. However, it is a simple and inexpensive type of measurement to take and there are charts available which indicate the levels deemed acceptable, for example VDI 2056 shown in figure 2.7. The greatest limitation of this approach is the lack of sensitivity and information available in the data. Unless a problem is severe, the overall level measurements may not change significantly. Using different types of transducers, typically accelerometers, velocity and displacement probes, it is possible to determine whether the increase in vibration is high or low frequency in nature. Unfortunately people have relied too heavily in the past on these measurements alone, and they have been surprised to see machines fail, seemingly, without warning [13].
2.3.2.2 Peak Level Detection

As an alternative to overall level, the peak level of the signal can be used. This is particularly useful for monitoring the change in the amount of impulsiveness, possibly due to increased bearing damage. However, on its own this method is not reliable, as other effects can also increase the peak level of a signal, but in conjunction with overall level measurements it is a useful technique to identify bearing faults. A useful way of showing the data is shown in figure 2.8.
2.3.2.3 Crest Factor

The time waveform of a bearing in good health is mostly random. As bearing damage increases, the waveform becomes far more impulsive, with higher peak levels. The crest factor (CF), sometimes called the impact index, is the ratio of the peak level to the RMS overall level. A useful chart for showing developing faults is shown in figure 2.9. The chart can also be used for showing the distribution of a population of similar bearings.

Figure 2.8 - Trending Overall and Peak Level Acceleration for Bearing Fault Detection [13]
2.3.2.4 Shock Pulse

The shock pulse method detects development of a mechanical shock wave caused by increasing bearing damage. It is actually a measure of the level at the bearing resonance 32kHz. This method has been widely used in the past. However, caution must be taken when used, since the shock pulse reading can decrease in later stages of bearing damage, due to a reduction in impulsiveness. However, other conditions, such as turbulence and cavitation in pumps, can give false readings.
2.3.2.5 Spike Energy

Spike energy is based on high frequency peak acceleration. It uses a circuit to reject vibration due to low frequency sources, thus highlighting the peak level due to the excitation of machine resonances. This measurement, patented by IRD Mechanalysis Inc., is now available in electronic meters from other manufacturers.

2.3.2.6 Kurtosis

Kurtosis is a statistical parameter, derived from the fourth statistical moment about the mean of the probability distribution function of the vibration signal and it is an indicator of the peakedness of that function. The Kurtosis technique has the major advantage that the calculated value is independent of load or speed variations. This method has been adopted by at least one instrument manufacturer[14] [15].

2.3.2.7 Envelope Detection

One major problem in attempting to monitor bearing damage is that more dominant low frequency signals can effectively mask the bearing frequencies. The aim of this method is to filter out those low frequency signals. This technique is called envelope detection and it is achieved by first passing the signal through a high pass filter, typically 5kHz and then rectifying the signal so that it may be analysed using a spectrum analyser. This method has been found to be a reliable technique for identifying bearing faults [16].

2.3.2.8 Time Waveform

Using an instrument as simple as an oscilloscope, it is possible to view the waveform of the vibration. It is difficult to use this information in isolation, however it can be a very helpful tool in combination with others. For example, it can be very useful in detecting a rub between the rotor and stator on an electric motor or generator.
2.3.2.9 Orbits

Orbits have been in use for a number of years, and are particularly useful in the analysis of journal bearing systems. They can be taken using a simple two channel oscilloscope connected to proximity probes. More recently they have been derived from a pair of frequency spectra. The major benefit is that they show the relative motion of the dominant vibration. Therefore it is possible to discern unbalance, such as that due to a misalignment.

2.3.3 Frequency Based Vibration Analysis

The following is a description of frequency based vibration analysis techniques available to the vibration analyst. Typical frequencies associated with common faults are shown in the “Illustrated Diagnostic Chart” to be found in the appendix of this thesis [12, 17].

2.3.3.1 Spectrum Analysis

A spectrum is derived from the vibration waveform by performing a Fast Fourier Transform (FFT) or a Constant Percentage Band (CPB) filtering function. Given that the running speed of the machine is directly proportional to the frequency measured, it is possible to relate peaks in the spectrum to machine components. The direct analysis of the spectrum, and of indices derived from it, have been found to be the best vibration based indicators of machine condition.

2.3.3.2 Waterfall Plot

A waterfall plot, also known as spectral map and cascade plot, is a three dimensional representation of a spectra, usually with time as the third dimension. The advantage of this format over single or overlaid spectrum displays, is that changes over time can be identified by eye.
2.3.3.3 Cepstrum Analysis

The cepstrum is the spectrum of the logarithm of the power spectrum. It is used to highlight periodicities in the spectrum, in the same way that the spectrum is used to highlight periodicities in the time waveform. Thus, harmonics in the spectrum are summed into one peak in the cepstrum, allowing simplified identification and trending of specific fault frequencies. It has been found to be useful in bearing and gearbox analysis [18].

2.3.3.4 Spectrum Comparison

By mathematically subtracting the absolute overall levels of two CPB spectra, changes in level are easily identified. Fault frequency analysis can then be performed to relate the frequencies to the machine components. However, this method does not cope well with large running speed changes.

2.3.3.5 Trend of Spectral Difference

Trending the relative levels, that is the difference between the current spectrum and the baseline spectrum, was found to be a good indicator of many problems, including unbalance and misalignment when lower frequency bands were trended, and growing bearing damage when higher frequency bands were trended. The difference between the current spectrum and previous spectrums using RMS levels was also a good indicator of oncoming problems. The use of logarithmic scaling for the amplitudes was found to be very useful.

2.3.4 Vibration Measurement, Detection and Diagnosis

The two main objectives of vibration measurements are fault detection and fault diagnosis. Fault detection is mainly concerned with detecting abnormal conditions in running machines. It is a sort of screening process which will seek, out of a population of machines, only those exhibiting abnormal behavior relatively quickly. Fault diagnosis is
the process of analysing the data in order to determine precisely what is wrong with a
particular machine. Once a fault has been detected, and confirm that an actual fault exists;
however, this process generally takes more time.

This distinction between detection and diagnosis is very important, as out of the
many analysis techniques available to the vibration analyst today, some are well adapted
for diagnosis but not for fault detection, and vice-versa. Inadvertent use of inadequate
measurement techniques could result in unreliable results, precious time being wasted by
stopping a machine that does not have a fault, or even worse the complete failure to
detect an important fault. This partly explains why many vibration analysis programmes
in the past have failed or fallen short of meeting the expectations of those who
implemented them, and this has considerably slowed down the acceptance of vibration
measurement in many industries.

Measurement techniques for fault detection are especially important because the
results obtained will often be the determining factor in important decisions that can affect
not only maintenance costs but also the operational capabilities and production savings of
a given plant or mine. For instance, early detection of faults can be crucial on complex
equipment such as compressors, shovels and drills etc., if one is to allow enough time to
plan for the corrective action to take place during a regular scheduled shutdown. The
reliability of the prediction of the lead time to failure is also very important, as a wrong
prediction could have serious consequences in these situations. Fault detection

Although there has been a trend in the last few years to increase the diagnostic
capabilities of data-loggers, principally by using FFT analysis, the use of more powerful
detection techniques in commercially available instrumentation has been somewhat
overlooked. For instance many data-loggers detect faults based solely on a change of the
overall level. Since some machine faults do not necessarily result in an increase of the overall level thresholds, a strong vibration component from another source can mask the change and the machine could very well fail long before the instrument can detect the fault. Therefore it is highly desirable to compare and trend the vibration data to a baseline spectrum. A baseline spectrum is derived by measuring the vibration levels on a new, or a correctly operating machine. Faults can be detected, and identified by trending, over equal intervals of time variations. However, with a population of machines, a statistical variation of baseline spectrums will occur and each machine should preferably have it's own reference baseline. In the absence of reference data, initial settings can be derived statistically from a population of similar machines. Spectrum comparison is especially useful in the case of gearboxes, as several gearbox failures have been witnessed in which there was no appreciable change in the overall vibration level as shown in figure 2.10 (R. Archambault, 1994) pers. comm.
2.3.5 FFT Versus CPB

There are two main techniques available today to obtain a frequency spectrum:
Fast Fourier Transform and Constant Percentage Band analysis. The FFT method gives a
constant bandwidth based on a linear frequency scale. The CPB method gives a constant
percentage bandwidth based on a logarithmic frequency scale. The centre frequency of
the octave CPB doubles for each octave increment e.g. 8, 16, 64, 125, 250, 500, 1000,
2000, 4000 and 8000 Hz, the upper and lower frequencies of the octave CPB are located
at \( \sqrt{2} \) and \( 1/\sqrt{2} \) times the centre frequency. Sometimes a decade may be referred to when
logarithmic scales are used. In this case the frequency or as is more usual the amplitude
increases by multiples of ten (e.g. 10, 100, 1000 etc.) with each increment being called a
decade. The FFT spectrum is more suited to analysis and diagnosis, as it shows more
clearly the harmonics and the side-band patterns in the signal. The CPB spectrum is
more suited to trending and detection, as it covers a larger frequency range, as may be
seen from figure 2.11, and it is easier to use for comparison purposes, especially if there
is a small speed variation.

Figure 2.11 A linear FFT is synthesized to form part of a logarithmic CPB
spectrum [8]

The amplitude ranges that can occur are in excess of 1000 to 1 and therefore a
logarithmic scale is preferable. For this purpose a decibel (dB) scale is used where the
value in dB is determined from $20\log_{10}(\text{Signal Voltage Ratio})$ [19].

In order to detect most machine faults, a broad frequency range must be used to
include low frequency components such as a sub-harmonic of shaft speed and oil whirl,
and high frequency components, i.e. harmonics of tooth mesh and structural resonances
excited by rolling element defects. Experience by the author has shown that at least 80
dB of amplitude range and three decades of frequency information are required to display all the essential information in a vibration spectrum obtained with a good quality correctly mounted accelerometer. Baseline spectral comparison by taking the difference between two spectra is not very easily accomplished using FFT spectra, as may be seen in figure 2.12. FFT spectra are always computed with a linear frequency scale and unless a very large number of lines are used, only one decade of frequency can be adequately displayed on the base-band spectrum. A quick calculation of how many lines would be required on an FFT analyser to maintain a 3 percent resolution at 10Hz and still maintain a full scale frequency of 10kHz would yield over 30,000 lines, which is beyond the capability of most current analysers.
A special case of a CPB spectrum analysis is the octave band analysis. One of the main advantages of this approach is that the filters have been standardized to the ANSI S1.11-1966 class II specifications [29] in order to ensure reproducibility of filter characteristics. Octave CPB velocity spectrum comparison is recommended for the following reasons:
1. Since the bands are quite wide, the amount of data is kept to a minimum, although there is still enough information to detect and identify unbalance, misalignment or gear and bearing faults.

2. Time averaged octave CPB spectrum data can be trended much more easily than FFT data.

3. Small changes in running speed do not affect the results substantially.

4. More reliable spectral estimates can be obtained in the presence of random, impulsive and non-stationary signals.

The use of standardized frequency bands generates more universal statistics and simplifies the preliminary diagnosis of machine faults by less skilled personnel. Octave CPB Spectrum Comparison is an effective fault detection technique, allowing the separation of gearmeshing components from the signal change caused by a damaged bearing or an unbalanced condition. A wide frequency range is required to detect all types of faults as may be seen in figure 2.13.
Figure 2.13 - A wide vibration frequency range is required to detect all types of fault [8]

2.3.6 Trending and Machine Profiling using Octave CPB Velocity Spectra

Trending is the graphical display of the vibration amplitude for each individual band at each individual point. The vibration data is collected at regular intervals, typically every three to four weeks, depending on the equipment and its criticality. The vibration data may be collected from each point in three dimensions, namely horizontal, vertical and axial, but experience and intimate knowledge of the machine may indicate that not all of the points and directions are necessary for monitoring the condition of the machine.

Profiling is the simultaneous graphical display and comparison of all the points associated with the machine or combinations of machines e.g. electric motor and generator or an electric motor, gearbox and pump. The reasonable amount of data produced by octave CPB analysis allows more meaningful data to be represented on the
same graph, thereby simplifying the detection, diagnosis and trending of faults. This is
the technique that was key to the development of a new type of data collector and
procedures for machine-condition monitoring by the author. The instrument is described
in Section 2.5.3 of this thesis and its use is described in the case study in section 3.5.

Because Octave CPB data also lends itself very well to the generation of machine
profiles, the machine inspector now has a better representation of the vibration data and
can now obtain a better overall view of the vibration severity of a machine, as each band
or group of bands represents different categories of faults. Changes in the machine’s
profile are also very useful representations to the vibration analyst and are key to the
techniques used and described in this thesis.

2.3.7 Synthesis of CPB Spectra From FFT Data

The synthesis of a CPB spectrum from FFT data does not always yield reliable
results, since many factors render the operation difficult. The various types of vibration
data from machinery consist of deterministic, random, impulsive and non-stationary
signals. The FFT handles deterministic data very well, but for the other types, extra care
must be taken by using special time windows, long averaging times, special integrating
cursors and sometimes elaborate triggering techniques. Measurement of non-stationary
signals requires extreme precautions, otherwise results could easily be in error by more
than 10 dB. One can be led into a false sense of security when measuring what appears to
be a stable machine, as the introduction of certain types of faults will often create
impulsive signals which, at a high sampling rate of the FFT analyser, will appear as non­
steady signals. The limitations of FFT techniques when dealing with these non-steady
signals comes from the fact that by its very nature, it operates on blocks of samples,
instead of continuously processing the signal in the manner of analog or recursive digital
filters, and one must insure, by judicious choice of windows and sampling rates, that
there are no gaps in the data between the various blocks, otherwise important information
could be lost. At high sampling rates, however, FFT analysers included in current
data-loggers introduce very large gaps. As the speed of the processor is not able to cope with the high flow of incoming data.

Because CPB data covers a wide frequency range, and therefore requires high sampling rates, its measurement is not easily achieved with FFT techniques. Attempts to simulate octave CPB data from FFT data can introduce significant errors due to windowing, asymmetry, non-standard slopes and ripple in the pass and stop bands. In order to obtain sufficient resolution at low frequency while still maintaining high frequency information, a very large number of lines would be required, as previously stated, or several analyses must be performed, with the consequent introduction of gaps in the data and potential for errors. In either case, if sufficient averaging is to be performed to obtain repeatable data (minimum Bandwidth - Time (BT) product = 10 with stationary data and a much larger BT product if the data is non-stationary), the synthesis of a CPB spectrum using FFT techniques will be much slower than standard filtering techniques, with the potential risk of large errors.

2.3.8 Transducers

The use of a transducer is required to change the mechanical energy associated with machine vibration into an electrical signal. There are three basic transducers that can be used to do this, an accelerometer, a velocity transducer and a displacement transducer. An accelerometer gives a greater dynamic amplitude and frequency range compared to velocity and displacement transducers as may be seen in figure 2.14.

The parameters peak velocity and RMS velocity can be obtained by integrating the output signal from the accelerometer after signal conditioning with a charge amplifier if it is of the piezoelectric variety. The parameter peak to peak displacement can be obtained by double integrating the signal conditioned output from the accelerometer. However if absolute displacement is required an eddy current displacement probe is preferable and if a very low frequency is involved, i.e. below 5 Hz, it is also preferable to use a special displacement probe. For the majority of applications an accelerometer will
suffice but as may be seen from figures 2.15 it is essential to have proper coupling between the vibrating surface and the accelerometer to obtain accurate and reproducible results. Figure 2.15 clearly shows that the high frequency response is impaired by hand-held probes and this could lead to missed failure indicators for components like bearings, but the use of permanently mounted transducers is prohibitively expensive for small and non-critical machines. By using a strong magnet to intermittently attach the accelerometer to various parts on a machine, a reasonable compromise can be made as far as cost, accuracy and speed of measurement are concerned. When using a magnet to attach the transducer it is essential to ensure that a clean flat surface be cemented to the point that is to be measured. This may entail both grinding the surface prior to mounting and using a removable plastic cover to ensure the surface remains clean between monitoring intervals. For the purposes of this study some of the measurements were taken with permanently mounted transducers and others were taken using a magnet to attach the transducer [20, 21].
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Figure 2.14 - Comparison of dynamic amplitude and frequency ranges of three types of transducers [8]

Figure 2.15 (a)
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Figure 2.15 (e)

Figure 2.15 (f)

Figure 2.15 (g)
As was previously stated, if the accelerometer output signal is integrated, the output parameter is changed to velocity. The advantage of using velocity as a parameter for monitoring is that the frequency characteristic is substantially flat across the band. This means that higher frequency outputs are not given a higher weighting compared to lower frequencies as would be the case with acceleration, as may be seen in figure 2.16. This means a bearing fault would not be given a higher weighting than an unbalanced fault.

Figure 2.16 - Comparison of Vibration Spectra [8]

Since vibration impedance paths may vary for similar machines by as much as 60 dB (1000 to 1) due to the variation of mobility from machine to machine, it is recommended that relative rather than absolute values be used for trending and profiling.
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the logarithmic decibel unit being ideal for this purpose as may be seen in figures 2.16 and 2.17 [8].

\[ \text{Mobility} = \text{Vibration} \times \text{Freq.} \]

Figure 2.17 - The Measured Vibration as a Product of Force times Mobility [8]

2.3.9 Recommended Approach For Vibration Analysis as Part of a Maintenance Program

Since fault detection and diagnosis impose such conflicting requirements on the instrumentation, the approach recommended in this thesis is to divide the maintenance procedure into two separate parts, namely:

a) Detection with CPB's, and

b) Diagnosis with FFT's.
With complex and critical machinery, the use of more advanced diagnostic
techniques such as cepstrum and envelope analysis, gating techniques, intensity and
operational deflection shapes is often warranted, since regular FFT analysis does not
always provide enough information to diagnose a fault. With this approach, equipment
and personnel can be used more effectively and less skilled personnel can be brought into
the process.

2.4 Knowledge Based Tools

The use of knowledge based tools in order to use less experienced personnel for
assessing the condition of the machine or the quality of a repair enables the mine
management to use production personnel to check their work. There are two fundamental
approaches as follows:

a) A Rule Based Expert System

b) An Artificial Neural Network

The rule based expert system requires an inference engine and a knowledge base
as well as a data or a fact base. It is a computerized system that uses knowledge about the
system to arrive at a solution to the problem. The solution can be algorithmic or
heuristic. Algorithms are step by step techniques that have been obtained from experts in
the field. Heuristics are rule-of-thumb techniques that do not necessarily follow a logical
sequence but they are nevertheless obtained from personnel experienced in the field.

There are many commercial software packages that are available to the
maintenance personnel for fault diagnosis using vibration data. Companies like IRD,
CSI, Entek, Palomar, B&K, DataSignal, Design Maintenance Systems and TEC have
software packages that are knowledge based expert systems. A common theme that is to
be found in expert systems is the problem solving process. The steps in this problem
solving process are:
a) Current vibration data is examined and noted for frequency and amplitude values.

b) A series of proven rules are applied to the data to search for causes for each change.

c) All rule violations are combined to give a probability that the diagnosis is correct.

Therefore in summary it can be said that this approach gives the probability of a particular fault based on the vibration data. However this is not the approach that has been adopted for this thesis.

The approach that has been taken is one that uses Artificial Neural Networks (ANN) to recognize patterns associated with various faults based on vibration data in the form of peak and RMS acceleration and velocity octave CPB's in the form of a machine profile.

2.4.1 Artificial Neural Networks (ANN)

ANN's are massively parallel, extremely fast, intrinsically fault tolerant, can learn from experience, generalize from examples and extract essential characteristics from noisy data. An ANN is made up of a number of processing elements which are connected by synapses to form layers of neurons. Each neuron is a simple mathematical processing unit with no intelligence of its own see figure 2.18. However, when many neurons are interconnected, an extremely complex structure is produced, and this, after training, can provide the necessary functionality for intelligent processing [22].

Processing of a single neuron is achieved by successively multiplying input values associated with each input synapse and summing the results. The final value is subjected to a transfer function, typically sigmoidal, and this output is then fed as an input to many other neurons. In a multi-layer network, output signals from all neurons eventually
propagate their effect across the entire network to the final layer where results are output to the real world. The functionality and power of the network is primarily dependent upon the number of neurons in the network; the interconnectivity patterns or topology, and the value of the weights assigned to each synapse, which is a function of the learning algorithm during training.

Training is performed by showing the ANN example input patterns and adjusting the synaptic weight until the desired outputs are activated. The process is then repeated, perhaps several thousand times, until all of the network outputs respond in a specified manner. The example patterns are held in FACT files, these files are created during training, when the facts or data are presented at the input of the network and the corresponding output is tested and verified by the training process. The learning algorithm then analyses the contribution and the magnitude of errors at the various nodes in the network, working back from the output. The weights are then adjusted and the process is repeated until all the errors are below a specified minimum. A useful approach is to split the FACT files into two sets and use one group for training and the other for testing and validation [23].

2.4.2 Network Configuration

The neuron, as shown in figure 2.18, is used as a fundamental building block for backpropagation networks. A set of inputs is applied either from the outside or from a previous layer. Each of these is multiplied by a weight, and the products are summed. This summation of products is termed NET and it must be calculated for each neuron in the network. After NET is calculated, an activation function F is applied to modify it, thereby producing the signal OUT.

\[ \text{OUT} = \frac{1}{1 + e^{-\text{NET}}} \]
The activation function usually used for backpropagation is shown in figure 2.19. This function, called a sigmoid (Equation 2.4), is desirable because it has a simple derivative, a fact that is used when implementing the backpropagation algorithm.

\[
\frac{\delta \text{OUT}}{\delta \text{NET}} = \text{OUT}(1 - \text{OUT})
\]

\[
\text{OUT} = \frac{1}{1 + e^{-\text{NET}}}
\]

\[
F'(\text{NET}) = \frac{\delta \text{OUT}}{\delta \text{NET}} = \text{OUT}(1 - \text{OUT})
\]

Sometimes called a logistic, or simply a squashing function, the sigmoid compresses the range of NET so that OUT lies between zero and one. Multilayer
networks have greater representational power than single-layer networks only if a nonlinearity is introduced. The squashing function produces the needed nonlinearity.

There are many functions that might be used; the backpropagation algorithm requires only that the function be everywhere differentiable, and the sigmoid satisfies this requirement. It has the additional advantage of providing a form of automatic gain control. For small signals (NET near zero) the slope of the input/output curve is steep, producing high gain. As the magnitude of the signal becomes greater, the gain decreases. In this way large signals can be accommodated by the network without saturation, while small signals are allowed to pass through without excessive attenuation [22].

2.4.3 The Multilayer Network

A multilayer network suitable for training with backpropagation is shown in Figure 2.20. The figure has been simplified for clarity. The first set of neurons, connecting to the inputs, serve only as distribution points; they perform no input summation. The input signal is simply passed through to the weights on their outputs. Each neuron in subsequent layers produces NET and OUT signals as described above.

![Figure 2.20 - Three Layer Backpropagation Network](image)
The network consists of three layers: an input layer, a hidden layer, and an output layer. The input or distribution layer is designated layer i. Each neuron in the hidden layer is associated with a set of weights that are connected to the outputs from the input layer. The outputs of the hidden layer j are associated with a set of weights that terminate on the neurons of output layer k.

Backpropagation can be applied to networks with any number of layers; however, only two layers of weights were used for the project at IOCC as will be discussed in the case study in section 3.5.

2.4.4 Training of an ANN

The objective of training the network is to adjust the weights so that application of a set of inputs produces the desired set of outputs. For reasons of brevity, these input-output sets can be referred to as vectors. Training assumes that each input vector is paired with a target vector representing the desired output; together these are called a training pair. Usually, a network is trained over a number of training pairs. For example, the input part of a training pair might consist of a pattern of ones and zeroes representing a binary image of a number. As may be seen in figure 2.21, a set of inputs for the number eight is drawn on a grid. The output could be a binary code or a seven segment display.
Figure 2.21 - Number Recognition

If a square is shaded, the corresponding neuron's input is one; otherwise, that neuron's input is zero. The output might be the number 8, or perhaps another set of ones and zeroes that could be used to produce a binary output pattern equivalent to 8, i.e., 1000. It is possible to train the network so as to recognize the numbers from 0 to 9, therefore a minimum of 10 training pairs would be required. However some of the squares may be incorrect, this would correspond to the data being noisy but it would still constitute a valid training pair, many of these pairs could be used in addition to the original 10. A group of training pairs is called a training set.

Before starting the training process, all of the weights are initialized to small random numbers. This ensures that the network is not saturated by large values of the weights. For example, if the weights all start at equal values and the desired performance requires unequal values, the network will not learn.

Training the backpropagation network requires the following steps:

1. Selecting the next training pair from the training set and applying the input vector to the network input.
2. Calculating the output of the network.

3. Calculating the error between the network output and the desired output (the target vector from the training pair).

4. Adjusting the weights of the network in a way that minimizes the error.

5. Repeating steps 1 through 4 for each vector in the training set until the error for the entire set is acceptably low.

The operations required in steps 1 and 2 above describe the way in which the trained network is used; that is, an input vector is applied and the resulting output is calculated. Calculations are performed on a layer-by-layer basis. Referring to figure 2.20, first the outputs of the neurons in layer j are calculated; these are then used as inputs to layer k; the layer k neuron outputs are calculated and these constitute the network output vector.

In step 3, each of the network outputs, labeled OUT in figure 2.20, is subtracted from its corresponding component of the target vector to produce an error. This error is used in step 4 to adjust the weights of the network, where the polarity and magnitude of the weight changes are determined by the training algorithm.

After enough repetitions of these four steps, the error between actual outputs and target outputs should be reduced to an acceptable value, and the network is said to be trained. At this point, the network is used for recognition and weights are not changed.

It may be seen that steps 1 and 2 constitute a “forward pass” in that the signal propagates from the network input to its output. Steps 3 and 4 are a “reverse pass”; here, the calculated error signal propagates backward through the network where it is used to adjust weights. These two passes are now expanded and expressed in a somewhat more mathematical form [22].
2.4.5 Forward Pass

Steps 1 and 2 can be expressed in vector form as follows: an input vector $X$ is applied and an output vector $Y$ is produced. The input target vector pair $X$ and $T$ comes from the training set. The calculation is performed on $X$ to produce the output vector $Y$.

Calculation in multilayer networks is done layer by layer, starting at the layer nearest to the inputs. The NET value of each neuron in the first layer is calculated as the weighted sum of its neuron's inputs. The activation function $F$ then "squashes" NET to produce the OUT value for each neuron in that layer. Once the set of outputs for a layer is found, it serves as input to the next layer. The process is repeated, layer by layer, until the final set of network outputs is produced.

The calculation process can be stated in vector notation. The weights between neurons can be considered to be a matrix $W$. For example, the weight from neuron 8 in layer 2 to neuron 5 in layer 3 is designated $w_{8,5}$. Rather than using the summation of products, the NET vector for a layer $N$ may be expressed as the product of $X$ and $W$. In vector notation $N = XW$. Applying the function $F$ to the NET vector $N$, component by component, produces the output vector $O$. Thus, for a given layer, the following expression describes the calculation process.

$$O = F(XW)$$  \hspace{1cm} 2.5

The output vector for one layer is the input vector for the next, so calculating the outputs of the final layer requires the application of Equation 2.5 to each layer, from the network's input to its output.

2.4.6 Reverse Pass

2.4.6.1 Adjusting the Weights of the Output Layer.

Because a target value is available for each neuron in the output layer, adjusting the associated weights is accomplished using a modification of the delta learning rule.
The delta learning rule is a method of adjusting the weights, where $\delta$ is the difference between the target $T$ and the actual output $A$.

$$\delta = (T - A) \quad 2.6$$

The input $x_i$ is multiplied by $\delta$ and a factor called the training rate $\eta$ to control the average size of weight change.

$$\Delta_i = \eta \delta x_i \quad 2.7$$

$$\omega_i(n+1) = \omega_i(n) + \Delta_i \quad 2.8$$

where

- $\Delta_i$ = the correction associated with the $i^{th}$ input $x_i$
- $\omega_i(n+1) = \text{the value of weight } i \text{ after adjustment}$
- $\omega_i(n) = \text{the value of weight } i \text{ before adjustment}$

Interior layers are referred to as "hidden layers", as their outputs have no target values for comparison; hence, training is more complicated.

The training process for a single weight from neuron $p$ in the hidden layer $j$ to neuron $q$ in the output layer $k$ is shown in figure 2.22. The output of a neuron in layer $k$ is subtracted from its target value to produce an ERROR signal. This is multiplied by the derivative of the squashing function $[OUT(1-OUT)]$ calculated for that layer's neuron $k$, thereby producing the $\delta$ value.

$$\delta = OUT(1-OUT)(\text{Target - OUT}) \quad 2.9$$

Then $\delta$ is multiplied by $OUT$ from a neuron $j$, the source neuron for the weight in question. This product is in turn multiplied by a training rate coefficient $\eta$ (typically 0.01 to 1.0) and the result is added to the weight. An identical process is performed for each
weight proceeding from a neuron in the hidden layer to a neuron in the output layer. The following equations illustrate this calculation:

\[
\Delta \omega_{pq,k} = \eta \delta_{q,k} \text{OUT}_{pj}
\]

\[
\omega_{pq,k}(n+1) = \omega_{pq,k}(n) + \Delta \omega_{pq,k}.
\]

where:

\(\omega_{pq,k}(n)\) = the value of a weight from neuron p in the hidden layer to neuron q in the output layer at step n (before adjustment); note that the subscript k indicates that the weight is associated with its destination layer.

\(\omega_{pq,k}(n+1)\) = value of the weight at step n + 1 (after adjustment)

\(\delta_{q,k}\) = the value of \(\delta\) for neuron q in the output layer K

\(\text{OUT}_{pj}\) = the value of \(\text{OUT}\) for neuron p in the hidden layer j.

Subscripts p and q refer to a specific neuron, whereas subscripts j and k refer to a layer.
Figure 2.22 - Training a weight in the Output Layer [22]

2.4.6.2 Adjusting the Weights of the Hidden Layers.

Hidden layers have no target vector, so the training process described above cannot be used. This lack of a training target did, in the past, impede efforts to train multilayer networks, until backpropagation provided a workable algorithm.

Backpropagation trains the hidden layers by propagating the output error back through the network layer by layer, adjusting weights at each layer.
Equations 2.10 and 2.11 are used for all layers, both output and hidden. However, for hidden layers, δ must be generated without the benefit of a target vector, as in figure 2.23. First, δ is calculated for each neuron in the output layer, as in equation 2.9. It is used to adjust the weights feeding into the output layer. It is then propagated back through the same weights to generate a value for δ for each neuron in the first hidden layer. These values of δ are used, in turn, to adjust the weights of the hidden layer and, in a similar way, are propagated back to all preceding layers.

Consider a single neuron in the hidden layer just before the output layer. In the forward pass, this neuron propagates its output value to neurons in the output layer through the interconnecting weights. During training, these weights operate in reverse, passing the value of δ from the output layer back to the hidden layer. Each of these weights is multiplied by the δ value of the neuron to which it connects in the output layer. The value of δ needed for the hidden-layer neuron is produced by summing all such products and multiplying by the derivative of the squashing function.

\[
\delta_{pj} = \text{OUT}_{pj} (1 - \text{OUT}_{pj}) \left\{ \sum_q \delta_{q,k} \omega_{pq,k} \right\}
\]  

2.12
Figure 2.23 - Training a weight in the Hidden Layer [22]

Using the $\delta$ value, the weights feeding the first hidden layer can be adjusted using Equations 2.10 and 2.11, modifying indices to indicate the correct layers.

A $\delta$ must be calculated for each neuron in a hidden layer, and all weights associated with that layer must be adjusted. This is repeated, moving back toward the input layer by layer, until all weights are adjusted.

With vector notation, the operation of propagating the error back can be expressed as follows. Call the set of $\delta$'s at the output layer $D_k$ and the set of weights for the output layer the array $W_k$. To arrive at $D_k$, the $\delta$ vector for the hidden layer use the following the two steps.

1. Multiplying the $\delta$ vector of the output layer $D$, by the transpose of the weight matrix connecting the hidden layer to the output layer $W_k^t$.

2. Multiplying each component of the resulting product by the derivative of the squashing function for the corresponding neuron in the hidden layer.
Symbolically,

\[ D_j = D_k W_k^T S \left[ O_j S (1 - O_j) \right] \]

where the operator $S$ is defined to indicate component-by-component multiplication of the two vectors. $O_j$ is the output vector of layer $j$, and $I$ is a vector, all components of which are 1.

### 2.4.7 Adding a NeuronBias

In many cases, it is desirable to provide each neuron with a trainable bias. This offsets the origin of the logistic function, producing an effect that is similar to adjusting the threshold of the perceptron neuron, thereby permitting more rapid convergence of the training algorithm; a weight connected to $+1$ is added to each neuron. This weight is trainable in the same way as all of the other weights, except that the source is always $+1$ instead of being the output of a neuron in a previous layer.

### 2.4.8 Momentum

Momentum is a method for improving the training time of the backpropagation algorithm while enhancing the stability of the process. This method involves adding a term to the weight adjustment that is proportional to the amount of the previous weight change. Once an adjustment is made, it is “remembered” and serves to modify all subsequent weight adjustments. The adjustment equations are modified to the following:

\[
\Delta \omega_{pq,k}(n + 1) = \eta \delta_{q,k} \text{OUT}_{pq} + \alpha [\Delta \omega_{pq,k}(n)]
\]

\[
\Delta \omega_{pq,k}(n + 1) = \Delta \omega_{pq,k}(n) + \Delta \omega_{pq,k}(n+1)
\]

where $\alpha$, the momentum coefficient, is commonly set to around 0.9 and $n$ is the training-rate coefficient, serving to adjust the size of the average weight change.

Using the momentum method, the network tends to follow the bottom of narrow gullies in the error surface rather than crossing rapidly from side to side.
2.4.9 Advanced Algorithms

A method for improving the speed of convergence of the backpropagation algorithm is referred to as second-order backpropagation, which uses second derivatives to produce a more accurate estimate of the correct weight change. It has been shown that the algorithm is optimal in the sense that using higher-than-second-order derivatives will not improve the estimate.

Another method for improving the training characteristics of backpropagation networks is derived by not using the conventional 0-to-1 dynamic range of inputs and hidden neuron outputs, as this range is not optimum. Since the magnitude of a weight adjustment is proportional to the output level of the neuron from which it originates, \( \text{OUT}_{ij} \), a level of 0 results in no weight modification. With binary input vectors, half the inputs, on the average, will be 0 and the weights they connect to will not train. The network will train if the input range is changed to +/- 1/2 and a bias is added to the squashing function to modify the neuron output range to +/- 1/2. The new squashing function will be as follows:

\[
\text{OUT} = \frac{1}{2} + \frac{1}{(e^{-\text{NET}}+1)}
\]

Convergence times can be reduced by an average of 30 to 50 percent with these easily implemented changes. This is an example of the practical modifications that can bring substantial improvements in the algorithm's performance and thereby impact practical application.

2.4.10 Network Paralysis

As the network trains, the weights can become adjusted to very large values. This can force all or most of the neurons to operate at large values of \( \text{OUT} \), in a region where the derivative of the squashing function is very small. Since the error sent back for training is proportional to this derivative, the training process can come to a virtual
standstill. There is little theoretical understanding of this problem, but it is commonly avoided by reducing the step size \( n \), however this extends the training time.

2.4.11 Local Minima

Backpropagation employs a type of gradient descent, i.e. it follows the slope of the error surface downward, constantly adjusting the weights toward a minimum. The error surface of a complex network is highly convoluted, full of hills, valleys, folds, and gullies in high-dimensional space. The network can get trapped in a local minimum (a shallow valley) when there is a much deeper minimum nearby. From the limited viewpoint of the network, all directions are up, and it has no way to escape, as shown in figure 2.24.

![Objective Function](image)

Figure 2.24 - Local minima [22]

2.4.12 Step Size

Using infinitesimally small weight adjustments implies infinite training time. It is necessary to select a finite step size, and there is very little to guide that decision other than experience. If the step size is too small, convergence can be very slow; if too large, paralysis or continuous instability can result. An adaptive step size algorithm that adjusts that step size automatically as the training process proceeds would be a useful feature.
2.4.13 Temporal Instability

If a network is learning to recognize a number, it does no good to learn 8 if, in so doing, it forgets 7. A process is needed for teaching the network to learn an entire training set without disrupting what it has already learned. This can be achieved by showing the network all vectors in the training set before adjusting any weights. The needed weight changes must be accumulated over the entire set, thereby requiring additional storage. After a number of such training cycles, the weights will converge to a minimal error. This method may not be useful if the network faces a continuously changing environment where it may never see the same input vector twice. In this case, the training process may never converge; it may wander aimlessly or oscillate wildly. In this sense backpropagation fails to mimic biological systems.

2.4.14 Statistical Methods

Statistical methods are useful both for training artificial neural networks and for producing the output from a previously trained network. Statistical training methods offer an important advantage by avoiding local minima in the training process.

2.4.15 Training Applications

The artificial neural network is trained by means of some process that modifies its weights. If the training is successful, application of a set of inputs to the network produces the desired set of outputs. There are two categories of training methods: deterministic and statistical. A deterministic training method follows a step-by-step procedure to adjust the network weights based upon their current values and the values of the inputs, actual outputs, and desired outputs. Statistical training methods make pseudorandom changes in the weight values, retaining those changes that result in improvements.
2.5 Instrumentation

The hardware and software that was designed, developed and used for the machine condition monitoring programme that was used during the course of the case study was based on vibration monitoring equipment that had been developed by the author and has been used over a period of eight years by the maintenance departments of many companies in the primary and secondary industries of Eastern Canada.

An example of how one particular Canadian mining company has benefited from a machine-condition monitoring programme using similar instruments and techniques is described in detail in [10]. Quebec Cartier Mine at Mount Wright, located close to IOCC on the Quebec-Labrador Trough in Northern Canada, was one of the sites where in the late 80's the author developed and tested, in conjunction with Brue & Kjaer, instrumentation and techniques based on trending octave CPB's.

The Quebec Cartier Mine produces some 16 million tonnes of iron ore per year. The Mount Wright mine is an open-pit development 6400m long by 1220m wide that will ultimately sink 300m below ground level. On the DC-electric shovels used for ore excavation, the condition of the motor-generator set and the hoist swing transmission was monitored as well as the hoist's Magnetorque drive. On the haulage trucks used for transporting the ore to the crushing plant, the monitoring programme covered the diesel engine and generator. In the mine's concentrator, the autogeneous mills, pumps and conveyors were monitored, as well as rotary blasthole drills and other ancillary equipment. For more detailed information on this work, the reader is referred to [23].

2.5.1 Vibration Monitoring Equipment, Hardware.

Some of the vibration monitoring instrumentation described below was developed, during the course of this thesis, specifically for the IOCC project for example, the Charge Amplifier Switching Unit - III (CASU-III), the Neural Network (NT506) and the Machine-Health Monitor - IV (MHM-IV), shown in Figure 2.29
The following hardware equipment was used for the study:

a) Machine-Health Monitors, MHM-III & MHM-IV
b) Vibration Signal Conditioning Unit, VSCU-II
c) Charge Amplifier Switching Unit, CASU-III
d) Signal Analyser, Brue & Kjaer 2035
e) Neural Network, Neural Technologies NT5000 & NT506
f) Digital Audio Tape Recorder, Sony TCD10-PRO

2.5.2 Vibration Monitoring Equipment, Software.

The following software was used for the study:

a) Machine-Health Reporter - III, MHR-III
b) Neural Network, Neural Technologies NT5000 & NT506

2.5.3 Vibration Equipment, Equipment Description

The following sections describe in detail the key instruments that were used for this study.

2.5.3.1 Machine-Health Monitor

The Machine-Health Monitor - III (MHM), shown in figure 2.25, is an octave CPB data collector which when used in conjunction with the Machine-Health Reporter - III (MHR) can be used to monitor vibration patterns, trends and profiles as well as calculate statistical alarm and reference limits on populations of machines. The data collector MHM was used over a period of a year to monitor mine equipment at IOCC and collect data at regular intervals on pumps and locomotives. The data was then trended using the MHR software in order to detect and make a provisional diagnosis of the fault.
More detailed analysis was also made using the Vibration Signal Conditioning Unit - II (VSCU), a DAT recorder and a signal analyser.

Figure 2.25 - Machine-Health Monitor, MHM-III [30]

The MHM-III is simple to use and only a few minutes are required to learn its basic operation. The liquid crystal display has two lines of 24 characters where all the pertinent information about the measurement is clearly displayed. The first line is used to identify the measurement point (machine, point and transducer orientation) and the second line displays the measurement parameters. Three keys: MEASURE, STORE and NEXT allow the operator to perform measurements, store the data and move to the next route measurement, see figure 2.26. The MENU key displays the various functions available and the numeric keypad can be used to select items in the menu or enter inspection codes and numeric data. To simplify the operation, measurements can be made using the auto-range capability. The MHM-III can be carried by an operator all day without fatigue due to its light weight. A rechargeable battery gives at least 10 hours operation without a recharge.
The analog section has two inputs, a charge amplifier (5-10kHz) which accepts a Bruel & Kjaer Uni-Gain piezoelectric accelerometer with a sensitivity of 1 picocoulomb per meter per second squared (1pc/\text{ms}^2) and a voltage input with a 0 to 1 volt peak input range. The input amplifier has a gain selectable to 0 or 20 dB and is followed by an integrator, two weighting networks, Severity (10-1kHz) and Impact (1kHz-10Hz), 11 octave filters (8 to 8kHz) and the output amplifier with a gain selectable to 0 or 20 dB. Each amplifier stage has its own overload detector that can be switched on and off by a network of switches controlled by the microprocessor. In the auto-range mode, the signal is examined during a period approximately equal to half the selected measurement interval (minimum 4 seconds) and if the signal is lower than 159 dB peak acceleration, the gain of the input amplifier is set to 20 dB. If the output of the filters is smaller than 139 dB peak velocity, then the output amplifier is also set to 20 dB gain. The auto-range facility can also be disabled to allow manual setting of the amplifiers gain. The output amplifier and voltage input are connected to a RMS and two true peak detectors (+ and -) followed by a multi-channel 8 bit analog-to-digital converter as may be seen in figure 2.27.
The digital section consists primarily of a microprocessor, a 24 kilobyte programable read only memory (PROM) where the control programme resides and 96 kilobyte of static CMOS read only memory (RAM) for data storage. The instrument is powered by a 9 volt lead acid rechargeable battery and there is also a back-up lithium battery (with a ten-year capacity) to retain the data stored in the memory when the unit is switched off. The digital section also includes an illuminated liquid crystal display, a keyboard chip, a calendar-clock chip, a switching network and a serial interface RS-232C.

The MHM-III has 7 measurement modes: Acc (acceleration RMS and Maximum Peak), Vel (velocity RMS and Maximum Peak), Oct (octave CPB velocity spectrum from 8 to 8k Hz), Disp (peak-to-peak displacement from 0 to 14 mils via the voltage input assuming a calibration of 200 mv/mil), Volt (voltage measurement from 0 to 1 volt RMS or +DC), Data (any number with five digits from .0001 to 99999 representing a
process variable or a machine inspection code) and TIME (date and time format Date: YY/MM/DD Time:HH:MM). In the Acc and Vel mode, the measurement can be continuous using exponential integration with a 1/4 second time constant and updating the display once per second, over a preset measurement time from 2.4.8,16,32 or 64 seconds (linear integration), and in the Max Hold mode (maximum value on any time interval provided it does not exceed the auto-time out of 10 minutes when it is enabled). In the Oct mode, it is possible to examine a sine frequency or perform an auto-sweep from 8 to 8k Hz.

Up to 99 different types of voltage measurement or numerical data entry can be defined in the Volt and Data mode. Each type is identified with a field containing a label of up to eleven characters to describe the parameter and a three-character field to display the unit. Up to 128 machine inspection codes can be loaded into the instrument and a message of up to 16 characters corresponding to each code can be scrolled on the display. Machine inspection codes such as "Oil leak", "Bearing hot!", etc. are normally used to indicate a particular machine condition.

Three weightings are provided for the measurement of acceleration and velocity: linear (10-10k Hz), impact (1k-10k Hz) and severity (10-1k Hz) as shown in figure 2.28. These ranges are all within the flat region of the frequency response of the transducer to insure higher measurement repeatability. Linear acceleration is used normally in the detection of anti-friction bearing faults. To eliminate unwanted low frequency vibration, impact (1k-10kHz) should be selected. In the velocity mode, severity (10-1k Hz) will allow the measurement of the general condition of machines in accordance with ISO 2372 and 3945. The International Standards Organization (ISO) standards are a general standard used primarily for judging machine condition from casing velocity measured at a specified location at each bearing.
The analog section has two inputs, a charge amplifier (5-10kHz) which accepts a Bruel & Kjaer Uni-Gain piezoelectric accelerometer with a sensitivity of 1 pico-coulomb per meter per second squared (1 picocoulomb/m²) and a voltage input with a 0 to 1 volt peak input range. The input amplifier has a gain selectable to 0 or 20 dB and is followed by an integrator, two weighting networks, Severity (10-1kHz) and Impact (1kHz-10Hz), 11 octave filters (8 to 8kHz) and the output amplifier with a gain selectable to 0 or 20 dB. Each amplifier stage has its own overload detector and where it can be switched on and off by a network of switches controlled by the microprocessor. In the auto-range mode, the signal is examined during a period approximately equal to half the selected measurement interval (minimum 4 seconds) and if the signal is lower than 159 dB peak acceleration, the gain of the input amplifier is set to 20 dB. If the output of the filters is smaller than 139 dB peak velocity, then the output amplifier is also set to 20 dB gain. The auto-range facility can also be disabled to allow manual setting of the amplifiers gain. The output amplifier and voltage input are connected to a RMS and two true peak detectors (+ and −) followed by a multi-channel 8 bit analog-to-digital converter as may be seen in figure 2.27.
The MHM-III can measure simultaneously the Max Peak and the RMS value over time intervals selectable from 2 to 64 seconds. The Max Peak level is much more sensitive to short impulses than the RMS. This results in improved fault detection since there are several types of faults which can be detected by a sudden increase of the Max Peak while the RMS level shows no noticeable change. This usually happens when the fault causes only small shocks inside the machine as it is often the case with small defects in rolling element bearings. The crest factor, which is the difference between the Max Peak and the RMS value, can also be displayed.

In order to increase its fault detection capabilities and provide a preliminary diagnosis of a machine fault, the MHM-III incorporates a special mode for the measurement and the comparison of the octave CPB velocity spectrum from 8 to 8kHz. This capability offers several advantages over most conventional vibration data loggers which use only the overall vibration level for fault detection. As previously stated sometimes, trending of the overall vibration level is not sufficient to detect a machine fault. Even when it does, it may be sometimes very late in the development of the fault (too close to failure) and there is no indication of the cause.

The octave CPB spectrum allows the vibration signal to be represented by 11 values each covering a different region of the frequency spectrum. The regions are evenly distributed on a logarithmic frequency scale thus giving equal emphasis on the low frequencies i.e. the rotational speeds and their first few harmonics and the intermediate frequencies where discrete frequencies which usually contain vibration components from gears or caused by shocks and friction between moving parts. When trending vibration data, the octave CPB spectrum offers a good compromise between overall level and narrow band spectrum. Trending octave CPB data usually provides earlier fault detection and more accurate prediction of time to failure.

The MHM-III can be used with or without the help of a computer. It operates in two modes, the ROUTE mode and the FREE mode. Each of these modes has its own designated memory area. In the ROUTE mode, the user simply follows a route step by
Each of the two routes memory and the FREE mode memory in the MHM-III can store over 1000 measurements in ACC or VEL or at least 650 octave band spectra including reference values. Since an average daily routine inspection would consist of approximately 500 measurement points, there is sufficient memory to store other data in addition to the route data.

Reference values can be stored with the route data to enable comparison to the measurements performed in the field. After a measurement is completed in the acceleration, velocity or octave mode, the values are automatically compared and the status of the measurement is generated in the bottom right-hand corner of the MHM-III display. It indicates whether a significant change has occurred when a baseline value is specified, or if the measurement has exceeded an alarm level. Two global tolerance levels in dB or a ratio can be specified. If the difference between the baseline value and the measurement only exceeds the first tolerance level, the status displayed will be "+" or "-" but if the second tolerance level is also exceeded, then "AL" will be displayed. The comparison may also be done on the peak value or the crest factor thus generating status...
such as "++" or "+-" where the first sign is associated with the RMS value and the second one with the peak value or crest factor. When no significant change is detected, the "OK" message is displayed. Absolute alarm levels can also be specified (including displacement), instead of tolerance levels. The status field is also used to indicate an additional reading or a reading outside the measuring range of the instrument.

The MHM-III was designed to be used in the hostile industrial environments where dust or other chemical pollutants are present and it can also withstand severe handling with regard to shocks and vibration. It has been tested with shocks up to 75 g (735 m/s\(^2\)) and in accordance with military vibration standard MIL-28800C [31]. It is also relatively insensitive to thermal shocks and behaves particularly well in very humid environments such as the ones encountered in paper mills or dusty environments such as mines.

Voltage and charge amplifier inputs are incorporated into the instrument. The charge amplifier input is calibrated for 1 pc/ms\(^2\) uni-gain piezo-electric accelerometers, but a transducer compensation of 0 to 60 dB can be selected when using dB units to enable the use of accelerometers with various sensitivities. The MHM-III has an AC output enabling the inspector to "listen" with headphones to the vibration and therefore to provide a subjective evaluation of the health of the machine based on his personal experience. The MHM-III also has a test oscillator output to facilitate checking the instrument in case measurements are in doubt. It provides a nominal signal of 140 dB (in the acceleration or velocity mode) at 159 Hz and this can be used to test cable integrity in the field.

The transducer used for the testing at IOCC with the MHM-III was a Bruel & Kjaer piezoelectric accelerometer with a sensitivity of 1 pc/ms\(^2\) type 4391 with cable WL-0425 and magnet UA-0642.
2.5.3.2 Vibration Signal Conditioning Unit

The VSCU-II is a two channel, battery operated, vibration signal conditioning unit with which the user may connect electrical charge or voltage vibration signals obtained from accelerometers, microphones or an electrical pulse derived from a tachometer, to a two channel digital-audio tape (DAT) recorder or to a two channel spectrum analyser in order to diagnose vibration problems shown in figure 2.29.
Figure 2.29 - VSCU-II Functional Block Diagram
The vibration signal obtained from an accelerometer is initially scaled to give the equivalent output in either metric or imperial engineering units and then it can be attenuated or amplified, in 10dB increments, over a range of -50 to +50 dB, to give the desired output level for recording or analysing. The vibration signal may be band-limited with the high and low pass 3-pole active filters, using the various user selectable cut-off frequencies that have been incorporated into the unit.

An internal oscillator, whose frequency is 159 Hz, may be selected to obtain a reference signal in order to calibrate the DAT recorder prior to recording a vibration signal. A potentiometer on the unit may then be adjusted to set the playback level equal to the record level.

The vibration signal obtained from the accelerometer or the tape recorder may be integrated once or twice to obtain the velocity or displacement signal. However, the signal attenuation is before, and the amplification after the integration in these particular modes.

The VSCU-II also has an envelope detection circuit, which enables an envelope analysis to be performed on a signal obtained from a roller-element bearing. Envelope analysis is a powerful technique for diagnosing faults in bearings as discussed in previous section. The signal is full wave rectified to obtain the envelope which is similar to the way an amplitude modulated radio signal is detected by a radio receiver in order to obtain the modulating voltage and frequency.

A Noise Reducing Headset and Microphone combination may be selected with the VSCU-II to provide a means whereby operator comments can be stored on one of the two channels, when the DAT recorder is being used in the plant, instead of writing data down in a notepad.

The VSCU-II is microprocessor controlled and uses a backlit liquid crystal display for ease of viewing in adverse light conditions, and a sealed keyboard for operation in adverse environmental conditions. Four light emitting diodes display the
functions; channel one and channel two overload, tachometer active and battery low condition. Inputs and outputs are connected via BNC and/or DIN connectors.

2.5.3.3 Charge Amplifier Switching Unit

The Charge Amplifier Switching Unit (CASU-III) is a signal conditioning unit which consists of eight charge amplifiers with two selectable gains 0 dB and 20 dB whose output voltage is linear over the range 0 to 1 volt. The charge amplifier inputs are obtained from eight permanently mounted piezoelectric accelerometers where the outputs can be selected in parallel or selected by means of a switch one at a time. The unit has a 9 volt battery that is used as the power supply for the amplifiers together with a 110 volt, 1 ampere power ac supply that is used as an input for the battery charger. The unit also has a tachometer input that is signal conditioned for interfacing to a DAT recorder.

2.5.3.4 Neural Network NT 5000

The NT5000 is a complete stand alone, neural network control system with programmable analogue and digital interfaces. It is ideal for dynamic control applications easily replacing or supplementing conventional systems. It offers a fully integrated design, development and execution environment, optimised for integrating with equipment like the MHM-III.

The hardware has a 5 channel input multiplexer, with programmable gain, integral and switchable filters for analogue acquisition. The equipment also has fully programmable digital input/output port as well as a serial port with RS-232 and RS-485 protocols. Other features are a high speed analogue output system with integral audio amplifier and speaker; a range of undedicated linear drivers, relays, opto-isolators, and transistors for general purpose interface.

The high-speed integrated 32 bit digital signal processing neural engine has a performance in excess of 2M interconnects per second with a 128 kbyte non-volatile
memory for extended mode data collection and stand alone execution. The equipment is compatible with the Data Translation DT-Connect communications standard.

The PC software is an enhanced back propagation learning system with fully programmable training parameters, graphical data display, on-screen editor and comprehensive utilities.

Implementation is effected by the following six stages:

1. **Network Design**

   The software automatically generates a network topology with the minimum of information, that is the number of inputs and outputs.

2. **Hardware Setup**

   The hardware is configured to select the required number of inputs, gain, handshake signals, input and output filters and monitoring facilities.

3. **Fact Generation**

   The hardware can capture the signals directly using the data capture option this may then be added to the FACT file on the PC. All that remains is then to specify what the fact represents and add comments to the file. The software also operates on ASCII data, from editors, spreadsheets or databases.

4. **Training**

   The training option is selected from the menu and the software will the fine tune the network over a number of iterations. The training may be viewed by observing the actual/RMS error graph. Training can be stopped, parameters modified and the network continued or restarted at any time. Tolerance can be set to avoid over training.
5. Testing

Once training is complete the performance may be tested on the PC prior to downloading to the hardware. Testing may be done with the training facts as well as a complete set of data the network has not seen before; this allows the robustness of the network to be checked.

6. Operation

Once the network is trained, the configuration is downloaded to the NT5000 unit which can operate in isolation. The inputs and outputs are connected to the analogue or digital ports and the system is ready to operate.

2.5.3.5 Machine Health Monitor - IV

The MHM-IV was designed to acquire the vibration signals from eight accelerometers located at key points on locomotives. The data was collected using a CASU-III and a machine health monitor MHM-IV. The CASU-III has a tachometer input which enables the relative phase to be obtained, by the MHM-IV at the key points, as well as providing a signal that defines the RPM window for data monitoring.

Based on preliminary investigations with ANN’s using the NT5000 it was decided to integrate the previously described MHM-III with a stand alone artificial neural network (NT506). The NT506 hardware and software was designed and manufactured specifically for this project by Neural Technologies. The combination of the circuits from the two instruments is called the MHM-IV and the block diagram is shown in figure 2.29. This unit could be used to capture and store vibration signals as well as being able to detect malfunctioning machines using the previously trained ANN. The data obtained from the aforementioned eight key points was used to generate the machine profile. The profiles obtained when faults occurred were used to train the artificial neural network NT506 to detect various fault patterns.
The MHM-IV enables the detection and preliminary diagnosis of the health of a machine to be performed at remote unattended locations. The instrument can also be used by a relatively unskilled operator to check the quality of a repair or maintenance operation. This device has been used for monitoring the condition of locomotives at IOCC, as will be discussed in section 3.0.

Figure 2.30 - Machine-Health Monitor MHM-IV Block Diagram [26]
3. CASE STUDY - THE IRON ORE COMPANY OF CANADA

3.1 Description of the IOCC Mine and Operations

The Iron Ore Company of Canada operates an open-pit mine, with concentrating and pelletizing plants, in Labrador City, Newfoundland. The mine sends approximately 85,000 tonnes (T) of crude ore to the concentrator each day for processing using the Automatic Train Operation (ATO). At the mine, electric rotary drills are used to drill 15" diameter blast holes. Once a blast is shot, 18 cubic yard shovels are moved into the area to dig the blasted ore and waste rock for loading into 200T haulage trucks. The trucks move the waste to dump areas located outside of the pit limit, while the ore is transported to one of three loading pockets. These pockets are underground storage bins excavated in the waste rock. A feeder at the base of each pocket loads the ore into 95T capacity, side-dump rail cars on the ATO. These trains deliver the ore a distance of 11.25 km to two gyrator cone crushers.

After crushing, conveyors transport the rock to a 300,000T capacity ore storage building. This building provides feed to four grinding mills, two wet and two dry. Once ground, the feed goes to a three-stage spiral process. A secondary gravity separation stage, the Reichert cones, handle a slightly finer feed. The final stage of processing, via magnetic separation, maximizes the recovery of magnetite. The concentrate product is shipped to IOCC dock facilities in Sept-Iles, Quebec or transported by conveyor to the pelletizing plant located adjacent to the concentrator.

The mine has recently set the following goals:

1. to reduce the overall unit cost of production
2. to increase production equipment availability
3. *case study*

3. to improve equipment reliability

All new initiatives undertaken within the company are being directed toward meeting these objectives and to this end this thesis is one of these initiatives.

Traditionally at IOCC, maintenance personnel performed component maintenance and replacement work based upon operating hours accumulated. This resulted in the following:

1. Components being changed out when they had reached their rated useful life (in operating hours) whether they were worn out or not (e.g. truck engine life standardized at 12,000 hours during 1980's, by 1992 was extended to average of 18,000 hours).

2. Unexpected premature failure of some components before they reached the specified useful life (e.g. early failure of bearings in gear cases usually resulted in extensive damage to shafts and gears).

This approach in the past has contributed to unnecessarily high maintenance costs, in excess of 51 percent of total operating costs, and high equipment downtime. The need for improved control of cost and availability necessitated a change in the traditional maintenance philosophy at this site. Internal research indicated that various technologies had been developed which could provide data on equipment and component condition on an ongoing basis. It was determined by mine management that the implementation of these technologies could improve the ability of maintenance personnel to accurately predict component failure and effectively prevent it [25].

### 3.2 Failure Prevention and Prediction

Preventive Maintenance involves actions taken to prolong the operating life of production equipment and to eliminate premature component failure through:

1. effective equipment inspection and service
2. Equipment condition monitoring

These actions can reduce the frequency of unexpected breakdowns and, thereby allow more maintenance work to be planned and scheduled. Additional benefits realized by an effective Predictive/Preventive Maintenance Program (PPMP) include:

1. Reduced equipment downtime resulting in increased production
2. Reduced overtime and more effective utilization of manpower
3. Reduced maintenance costs through early detection of problems

Regular equipment condition monitoring provides maintenance personnel with the ability to effectively detect and diagnose problems at an early stage of development. The appropriate corrective action can then be planned during a scheduled equipment shutdown. This minimizes both maintenance repair cost and equipment downtime.

Equipment inspections include the following:

1. Visual inspection of components and structures.
2. Documentation of current operating characteristics obtained from the equipment operators.
3. Collection of data on equipment condition parameters through such techniques as vibration monitoring of rotating equipment, lubrication oil analysis, infrared thermographic scanning of electrical and mechanical components to identify hot spots and ultrasonic testing to evaluate the integrity of major components and structures.

The results of equipment inspections are closely analyzed by maintenance and inspection personnel. On-going trending of inspection data enables maintenance personnel to forecast when a component will fail. It also provides the opportunity to extend component life by tracking the effect of maintenance or design modifications on the condition trend of the component.
Critical to the success of the PPMP is the assurance of response to maintenance recommendations made by the inspection group. Policies for follow-up are being established prior to the implementation of the program and they are strictly enforced through accountability.

### 3.3 Equipment Condition Monitoring

As discussed in section 2.0 of this thesis, a PPMP must include condition-based monitoring of production equipment. A review conducted during 1992 at IOCC of existing PPMP’s revealed that equipment condition monitoring was being used effectively in some areas at the site. Maintenance departments at IOCC had implemented those techniques commonly associated with the type of equipment maintained in their area (i.e. the production department developed vibration monitoring while the mobile department developed oil analysis). The maintenance engineering department was directed to investigate the potential of the various tools and technologies available for condition monitoring and to apply these in all areas where they could possibly improve equipment reliability. IOCC maintenance departments are responsible for a large variety of production equipment as outlined in Table 3.0.
3.4 Mine Vibration Monitoring and Analysis

The concentrator and pellet plant at IOCC have had vibration monitoring and analysis programs in place since the late 1980's. Some restructuring of the program in the concentrator was required in 1992 to improve its effectiveness. Prior to the changes which took place, the ability to trend and analyze data effectively was limited because data was being collected from too much equipment. There was insufficient time to perform proper analysis and the database had become unmanageable. Techniques for optimizing these procedures were discussed in section 2.0 of this thesis.
The first step in addressing this problem was to identify the critical, life-line equipment in the area. The progress was then modified to ensure that this equipment was given priority for data collection and analysis. The less critical equipment was removed from the program until additional resources were added to support the program. The monitoring team was then able to handle both the data collection and analysis roles effectively.

The response of maintenance personnel to recommendations made by the monitoring team improved, through the establishment of formal procedures for reporting and follow-up. As a consequence of this study the recommended maintenance action is now communicated through the computerized maintenance management system. The monitoring team puts a work request on the system which outlines the required maintenance work. The maintenance planner then reviews the request and plans the maintenance job for the department. The maintenance system allows the monitoring team to track their work requests and therefore monitor the action taken by maintenance personnel. In cases where further discussion is required, meetings are held between the maintenance and vibration groups to assess the need for corrective action and to plan the work.

These two changes have resulted in improved maintenance performance within the concentrator area. The maintenance personnel are now taking more advantage of the vibration monitoring and analysis technology available to them.

The Maintenance Engineering Department during the course of and as a consequence of this study, has expanded the application of this condition monitoring technique to include equipment in other departments. The plant process water and tailings pumps are now being monitored and the vibration data trended. The analysis of this data has led to the following recommendations:

1. Pump impellers had to be properly balanced in the shop prior to installation.
2. Some pump foundations had to be repaired to reduce equipment vibration which could potentially lead to premature failure.

3. Supplier recommended installation and maintenance procedures and precautions were obtained and followed precisely by pump maintenance personnel. During December 1992, the Central Shops balanced pump impellers for the first time. Proper shop balancing, both separately and as an assembly, improved the quality of pump rebuild work and resulted in smoother running machines.

Pump maintenance personnel have developed a plan to make the required pump foundation repairs as units are changed out. This has significantly reduced the previously high vibration readings and as a consequence reduced the pump failure rate.

Pump suppliers were contacted by IOCC to obtain recommended installation and maintenance procedures and operating tolerances. The provision of this information to the tradesmen has resulted in improved maintenance workmanship in both the field and the shop. The vibration technologist provides support as required in this area and performs a vibration check following all installation and repair jobs. The supplier information has also been provided to the IOCC Functional Training Department for incorporation into the appropriate training manuals. The quality of maintenance performed on these pumps has also been improved through the provision of alignment training to the area tradesmen.

Vibration levels on the locomotives in the ATO were the next equipment to be monitored. Problems such as unbalance and misalignment of the drive motor have been successfully identified and corrected before failure of the motor has occurred. Currently, data collection can only be performed when the locomotive is in the shop because many of the data measuring points cannot be accessed with the hood in place. In 1994 eight accelerometers were connected via cables, see figure 3.4 to a charge amplifier switching unit, CASU-III. The unit was located in the cab of locomotive 504, this enabled maintenance personnel to collect data while the locomotive was in an operational mode.
Following the success of this operation the rest of the locomotives will be fitted with accelerometers and a charge amplifier switching unit.

Most of the equipment being monitored for vibration at IOCC rotates at constant speed. Therefore, the concepts, procedures and analysis equipment are well established. However, the Maintenance Engineering Department has implemented a program which involves the monitoring of Mine Production Shovels. In 1995, IOCC approved the provision of capital to purchase data collection and analysis equipment and software required to conduct this study aimed at developing an effective method of gathering, trending and analyzing vibration data from variable speed equipment. This will be the final phase of the project and is due for completion after the submission of this thesis.

Another element of the IOCC research and development project involved the evaluation, extraction and identification of useful patterns and trends in the vibration signals collected with the aim of classifying them into distinct categories which would indicate the mechanical state of mobile equipment. The aim of this activity was to collect sufficient data to train an ANN to accurately and reliably predict potential machine and component failure. A two channel digital audio tape recorder was used to collect real time data at various key points for a number of cycles of operation on one channel. Simultaneously, on the second channel, a tachometer monitored the rotational speed throughout the data collection process. The data was then analyzed on a real time vibration analyzer.

An ANN system does not require an intimate knowledge of the system because ANN's are massively parallel, extremely fast and intrinsically fault tolerant. As shown in section 2.4 ANN's can learn from experience, generalize from examples and extract essential characteristics from noisy data. However, ANN's require a large amount of data for training.

The reasonable amount of data produced by octave CPB analysis allows more meaningful data to be represented on the same graph, thereby simplifying the detection, diagnosis and trending of faults. When monthly overall level measurements were
replaced by monthly measurements of the octave CPB velocity spectrum at IOCC, the reliability of fault detection improved significantly and much earlier warnings were obtained. For example, in the study at IOCC, it was found possible to detect the evolution of a bearing fault on the electric motor and generator of locomotives using octave band CPB’s. The objective was therefore to design an instrument, which contained an ANN, that could be trained to detect and classify a fault or monitor the quality of a repair or maintenance operation [25] [27].

3.5 Locomotive Study

There are 9 locomotives at IOCC and readings of vibration were obtained from all of them but for the purposes of this study only the measurements from locomotives 504 and 505 were used. Each locomotive has the following rotating equipment:-

1. Main Drive Motor

The main drive motor, type A-20-6P, was manufactured by General Motors. The motor has the following specifications, 2300 Volts ac, eight pole single phase, 60 Hz, 900 r.p.m. and 1200 brake horsepower. The motor has two self-aligning double race roller bearings. The outer roller bearing is a Torrington bearing, model number 22324, with 15 rolling elements. The inner roller bearing is a Temkin bearing, model number 95528, with 21 roller elements.

2. Main Generator

The main generator, type D-25-E, was manufactured by General Motors. The generator has the following specifications, maximum output voltage 1000 Volts dc, 1500 Amperes at 900 r.p.m. with 120 rotor bars. The generator has one self-aligning double race roller bearing. The roller bearing is a Torrington bearing, model number 22324, with 15 rolling elements.
The locomotive also has a traction motor with two roller element bearings with a 15 teeth pinion gear on the motor and 62 teeth gear on the wheels. The locomotive wheel bearings are 14 element self-aligning roller bearings. The traction motor was not part of this study because only measurements whilst the locomotive was stationary were made.

The bearing defect frequencies shown on figures 3.0 and 3.1 were calculated using a program called "The Amethyst Bearing Database" [32]. The equations from which the bearing defect frequencies equations were calculated are detailed in [17] and the appendices.

In the following example, a roller bearing was heavily damaged and close to the point of rupture. If the roller bearing had failed and caused an emergency shutdown of locomotive 504 whilst it was on-line heavy production losses would have been incurred. If the roller element failure had caused extensive damage to the motor-generator set, the cost of the repair could have been typically in the order of $90,000, or in the worst case, as much as $150,000. Downtime for locomotives has been estimated by IOCC to be from $500 to $1000 per minute depending on utilisation factors, so the cost of an unexpected failure is considerable. However by detecting the faulty bearing at an early stage and scheduling the repair, the cost was approximately $6000 with 2 hours of downtime. This caused little or no impact on production and therefore the intervention resulted in considerable savings both in equipment and time.

The trend of the RMS and peak overall velocity revealed no change in the bearing condition. Fortunately, systematic octave CPB Velocity spectrum comparison had been carried out periodically until one day an increase in the higher frequency bands appeared in the spectrum. A FFT spectrum analysis of the signal measured on the defective bearing was also performed to confirm the diagnosis.

In this case, the use of a logarithmic frequency scale allowed the visualization of the component at the RPM of the motor (16 Hz band) as well as the high frequencies (8 kHz band) on the same spectrum. Large increases were found in the 2k, 4k and 8kHz
bands and a bearing fault was subsequently diagnosed. A sudden increase in the 8kHz band indicated that the fault had progressed and that the bearing was getting close to failure, this is shown in figure 3.0.

Figure 3.0 - Octave CPB Vibration Data on Locomotive 504 operating with a faulty bearing

The faulty bearing was changed at the subsequent shutdown, with a corresponding decrease seen in the 500, 1k, 2k, 4k and 8kHz bands, as shown in figure 3.1. This example illustrates the additional information provided by trending the octave CPB data, as well as peak and RMS, this is especially useful when trying to precisely estimate the lead time to failure.
Figure 3.1 - Octave CPB Vibration Data on the Locomotive operating under normal conditions

Octave CPB data also lends itself very well to the generation of machine profiles. This representation of the data enables the machine inspector to get a better overall view of the vibration severity of a machine, as each band represents different categories of faults, as shown in figure 3.2. Changes in the profile are also indicative of specific faults like misalignment, unbalance, faulty bearings etc.
Figure 3.2 - Machine Profile using Absolute Data Locomotive operating under normal conditions

At the beginning of this project, tests were performed using a grid like the one shown in figure 3.3, with ten octave bands and eight 10dB increments of vibration. This allowed the Octave CPB velocity vibration profile, that had been previously collected at regular intervals at IOCC using the MHM-III, to be entered via an optical coupled reader into the NT5000 hardware in order to assess the efficacy of the approach. This was done prior to designing the interface that would allow data to be entered directly from the transducers used to monitor vibration. The MHM-IV incorporated the interface and NT506 neural network hardware as was previously described in section 2.0 of this thesis.
Following the design and manufacture of the MHM-IV, data was collected from transducers located at eight key points on Locomotives 504 and 505 at IOCC. This collection of data is called a machine profile, which in conjunction with the neural network, was trained to recognize four different fault patterns. One of the fault profiles was obtained by incrementally unbalancing the machine by adding weight to the generator rotor. Half of the collected data was used to train the network and the other half was used to test the network. The second fault was a bearing failure that had occurred during the course of normal operations as was the third fault, a broken rotor pulley. The fourth fault was also to be a simulated fault, however, when the motor and generator were mis-aligned by as much as 0.1 inches (0.254mm), no significant change was noticed in the profile. This subsequently has led to a change in a maintenance procedure which took two days to implement. The key monitoring points used during field tests on locomotive 504 and 505 at IOCC are shown in figure 3.4.
### Figure 3.4 - Key Monitoring Points on the Locomotives

The general procedure for machine component fault detection using ANN's is shown in figure 3.5. This figure shows the steps that were followed in order to detect a fault or verify a maintenance procedure, namely monitoring with transducers, signal conditioning and processing, training/testing and finally analysis.

### Figure 3.5 - General procedure for Machine Component Fault Detection using Artificial Neural Networks

The locomotive's generator and motor were intermittently monitored at the points shown in figure 3.4 and the machine profile was obtained using absolute data. The tests
were performed over a period of two days in the locomotive repair shop operating under "normal" operating conditions used for testing the locomotive in the shop. The results are shown in figure 3.2 and the actual data is shown in Table 3. The normal test conditions were with the locomotive stationary and operating under no load.
Table 3.1 - Typical Absolute FACT Files

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<th>INPUT</th>
<th>Normal Operating Conditions</th>
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<tbody>
<tr>
<td>8</td>
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<td>110</td>
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<td>93</td>
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OUTPUT 1000

<table>
<thead>
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OUTPUT 0100

The ANN configuration chosen for this arrangement consisted of 88 neurons in the input layer, 80 in hidden layer and 4 in the output layer. The number of neurons in the hidden layer were obtained empirically by adding neurons using increments of 10 until convergence occurred. Trials were then made using relative data and it was found that the number of neurons required in the hidden layer dropped from 80 to 30 and the number of iterations decreased by a factor of 6. The relative data, that is data which was obtained by taking the difference between a “good” machine and a “faulty” machine, is shown for two faults unbalance and bearing fault in figures 3.6 & 3.7 and table 3.2. A “good” machine condition is represented by zeroes as shown in table 3.2. The data shown are typical of the relative data that was used to train the network for a machine
operating under normal conditions and when operating with an unbalance or a bearing fault. It can be seen that an unbalance fault causes changes in the lower frequency bands and bearing faults causes changes mainly in the higher frequency bands. If a negative value occurred in the results, it could be either entered as a zero or the a baseline could be offset by 10 or 20dB to ensure all values are positive in the table. When a new fault was added, it is important to note that the back propagation ANN had to be retrained with the new as well as the old data set.

Figure 3.6 - Relative Data, Unbalance Fault, Locomotive 505
Figure 3.7 - Relative Data, Bearing Fault, Locomotive 504
### Table 3.2 - Typical Relative FACT Files

#### INPUT: Normal Operating Conditions

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**OUTPUT:** 0100

#### INPUT: Bearing Fault

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**OUTPUT:** 0010
By using octave CPB's specific faults could be identified. The number of input neurons were determined by the number of transducers times the number of frequency bands, i.e. $8 \times 11 = 88$ for this application. The number of neurons in the output layer were determined by the number of different faults that were simulated or had been previously found.

One of the goals of the IOCC Maintenance Engineering Department is to be able to use an artificial neural network interfaced with a data collector to rapidly detect equipment problems. This will insure that there is an efficient and consistent detection and analysis of equipment faults as well as an ability to verify the quality of the mine maintenance procedures. This was done using the prototype MHM-IV that was designed, fabricated and tested during the course of the case study on locomotives. As a consequence of this, a production unit MHM-V will be designed incorporating the various features that proved to be useful and feasible during the course of the project.

Other parameters such as phase and harmonic phase that were proposed as fault indicators but could not be tested during the course of this study due to time restraints will be incorporated into the production unit.
4. CONCLUSIONS

4.1 Summary

This thesis has outlined the importance of maintenance in mines in general and at IOCC in particular. This is due, in part, to the economic considerations that currently exist in the Canadian mining industry. Therefore it has become necessary for Canadian mines to adopt the latest technologies in order to compete in the global marketplace. It is because the last refuge of profitability lies in cost saving, and maintenance is a key parameter in effecting this cost saving, that the strategies and techniques described in this thesis were developed and will continue to be developed.

In chapter 2.0 the three maintenance strategies, namely: breakdown, time based and predictive were described with view to using the mean time to failure and mean time to repair data to select the optimum strategies for maintenance.

The concept of modeling was introduced using the Weibull distribution with Chi testing, as well as various techniques like Pareto and ABC analysis were proposed in order to obtain optimum availability of mine equipment.

Maintenance techniques were outlined and the development of vibration as a maintenance parameter was described in detail. The historical evolution of the instrumentation that led to the approach that was used at IOCC was described. The advantage of the CPB measurement technique compared to the FFT was discussed at length in order to justify the octave CPB Velocity signal processing technique that was adopted for the detection part of the two step process of detection and diagnosis that was advocated in this thesis.
4. Conclusions

A summary of the detection and diagnostic techniques, as well as the various manifestations of faults, was made with a view to establishing the training and testing criteria that would be necessary to identify and classify the machine condition using ANN's. Individual machines and equipment were evaluated in the mine on a global basis, rather than making decisions based on data obtained from individual points alone, that is, the data was gathered simultaneously from a number of key locations on a machine over a period of time. This technique was called machine profiling. The faults were characterized from the historical data that had been accumulated over a two year period at IOCC.

The back propagation ANN network that was used to detect machine faults was described in detail in section 2.4.1 together with the training procedures that used machine profiles. A prototype of the MHM-IV instrument, together with the required software, was developed, built by the author and evaluated during the study. This prototype instrument is now available to the personnel in the maintenance department at IOCC for improving the detection and diagnostic process, especially in remote and critical locations. The instrument will be especially useful where relatively unskilled personnel are used in the decision making process for example, checking the quality of a repair or a maintenance procedure. A production unit is being designed that will incorporate many of the features described in this thesis.

The IOCC mine and mine maintenance operations were described and how vibration data was collected from rotating equipment on locomotives in the case study. The goals of IOCC were outlined and some of the maintenance procedures taken during the course of this study were described. The project involved monitoring of equipment that rotated at constant speed but the techniques will be applied in 1996 to equipment such as shovels and drills that rotate at variable speeds and operate under changing environmental conditions.

Using the MHM-IV data collector that incorporated an ANN, tests were performed on locomotives at IOCC to demonstrate the feasibility of the proposed
approach. The results from these tests are described in section 3.0. The technique based on ANN's was found to be viable and it was found that the various faults tested, for example unbalance and bearing, could be detected and provisionally diagnosed.

One of the key findings was that training neural networks was significantly improved by preprocessing the vibration into discrete CPB's with logarithmic amplitudes. Initial tests on trucks have already indicated that one third octave velocity CPB's will be necessary in order to obtain similar results.

4.2 Future Developments at IOCC

While the current study was in progress a parallel effort was underway between AQUILA Mining Systems (AMS) and the IOCC production department to improve the operational performance of shovels and drills. The system from AMS also used ANN's and monitored signals which can be used by the maintenance monitoring equipment in the future for equipment assessment.

The final phase of the project will start in 1996 and is due to be completed in 1997, this will integrate production and maintenance into a Total Mining System (TMS) that will further improve equipment availability and mine profitability. This will involve all the mine's mobile equipment and the integration of the AMS Advanced Monitoring Platform (AMP) and J.H.Burrows Electronics Inc. (JHB) vibration monitoring equipment.

For the more sophisticated processing of the vibration data required on drills and shovels for maintenance applications, artificial neural network hardware and software will be developed. This software will reside on the AMP designed and manufactured by AMS. The AMP provides a production monitoring and control function, to this system there will be added a fault detection and diagnosis capability. The AMP will also provide an interface to a dispatch system, such that any resulting alarms can be transmitted back to the mine office in real time or on-demand. This effort forms the basis of on-going contractual work with IOCC into 1996.
Once all the mobile equipment have the performance and vibration monitors installed, it will be necessary to link these with the mine management information system in real-time via radio for optimum results. By using this approach, the performance and condition of all the mobile equipment at the mine can be examined and assessed and immediate decisions can be made concerning the scheduling and utilization of the mine equipment.

A basic framework for achieving this capability is already provided by the truck-shovel dispatch systems at IOCC, from Modular Mining Systems. However, real-time transmission of data from multiple mining machines is severely restricted by the amount of data, dispatch system communication hardware and software limitations, topography and cost. In addition, the continuous monitoring of equipment and transmission to the central dispatch computer could result in the collection of massive amounts of data in a short period of time and this would interfere with the truck-shovel dispatching routines [1, 26].

Therefore, to enable real-time monitoring of mobile equipment, a comprehensive and complete real-time monitoring a TMS will be required. The TMS system is currently being designed and it will be installed in several Canadian open-pit mines by AMS to address their current and future needs towards optimizing productivity at minimum cost, through better two-way information flow between each component in the operation. Based on feedback from the monitoring of the overall operation, decision-making will be based on quantitative, on demand information permitting proactive rather than reactive planning to be possible to meet the defined objectives.

The TMS system permits real-time, mine-wide integration of mobile and stationary monitoring systems through the use of broadband (voice, video and data) communication and high resolution, real time Global Positioning Systems (GPS). The transmitted data from equipment monitoring and locating would reside in a centralized database such that it could be readily accessed by maintenance, engineering and management groups. Thus, a facility would exist whereby the status and location of any
component in the mine could be viewed on a graphical user interface by any one of these groups. Using the communication system, the same information could be accessed by mobile terminals (laptops) in the supervisor's trucks anywhere within the pit area. Figure 4.0 provides an overview of the TMS system based on an initial concept from Cleveland Cliffs Inc.

The most apparent benefits of the complete TMS system, would be:

1. the need to manually collect data from the mobile equipment would be eliminated.

2. real-time performance, maintenance and production data is available on a continuous basis from one, several or the entire mobile equipment fleet.

3. alarms, maintenance or operating codes are sent to the mine office or a mobile terminal.

4. two-way communication messages and data can be sent to the mobile equipment from the mine office or a mobile terminal.

In conjunction with Modular Mining Systems and JHB, AMS is evaluating how the Dispatch system at IOCC can be enhanced to permit such capabilities to be achieved at minimum effort and cost [1].
Figure 4.0 - Total Mining System
5. REFERENCES / BIBLIOGRAPHY


5. references / bibliography


[16] Courrech J. & Gaudet M. 1987; Envelope analysis - the key to rolling-element bearing diagnosis, Bruel & Kjaer, Application Note.


5. references / bibliography


[28] Burrows J.H. & Doucet R 1995; Machine Condition Monitoring Using Artificial Neural Networks to Process Vibration Data from Maintenance Monitoring Equipment. COMADEM 95, Queen's University Kingston, Canada.

[29] ANSI S1.11-1966; Constant Percentage Band Filter Specifications.


6. APPENDICES
### APPENDIX A

#### UNIT CONVERSION CHARTS

#### Acceleration

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Ref: $10^{-6}$ m/s$^2$

#### Velocity

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<tr>
<td>dB</td>
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Ref: $10^{-7}$ inch/s

(110 Metric VdB = 102 English VdB)
## SEVERITY CHARTS

### General condition

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Note: These charts are for reference purpose only and should be used with caution, as they may not represent the true health condition of a machine.