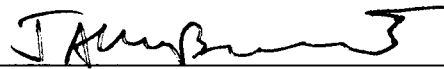


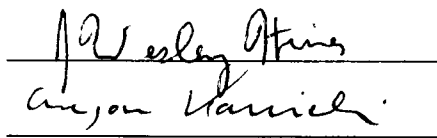
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I am submitting herewith a thesis written by Mark William Slemple entitled "An Expert System Utilizing Time Waveform Data For Machinery Diagnostics." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Mechanical Engineering.



J. A. M. Boulet, Major Professor

We have read this thesis and
recommend its acceptance:



Accepted for the Council:



Associate Vice Chancellor and
Dean of the Graduate School

**AN EXPERT SYSTEM UTILIZING TIME WAVEFORM DATA FOR
FAULT DIAGNOSIS OF ROTATING MACHINERY**

A Thesis

Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Mark William Slempp

August 1997

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ABSTRACT

The study presented in this thesis provides an alternative to the current methods which are used to analyze large quantities of vibration data. This system is designed to perform diagnostics on the rotating machinery that are commonly found in industrial production facilities. Current automated techniques generally analyze only spectral data, but the approach presented herein utilizes a machine's time waveform vibration signature. The algorithms that are presented calculate a number of waveform parameters that characterize certain visible fault patterns that are associated with defects in rotating machinery. A set of diagnostic rules was developed that use the calculated parameters as inputs. The calculation of the waveform parameters and their subsequent input into the diagnostic rules results in a diagnosis as to whether or not the machine from which data was taken is operating within acceptable limits. The diagnostic system does not formulate a precise diagnosis, but simply tells the user if a given machine requires further analysis. Thus, the waveform diagnostic system serves as a screening tool for a vibration analyst when examining a large volume of vibration data. The results of using this technique to analyze data that was collected on over one hundred machines for each of six routine measurement surveys was found to have a potential to reduce an analyst's diagnostic and reporting time by a factor of one-half. This would potentially allow an analyst skilled in the use of this diagnostic system to monitor twice the number of machines that was previously included in a condition monitoring program.

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LIST OF ABBREVIATIONS

ARMS	Absolute Average
CMMS	Computerized Maintenance Management System
FFT	Fast Fourier Transform
RBM	Reliability-Based Maintenance
RCFA	Root Cause Failure Analysis
RMS	Root-mean-square

CHAPTER 1

INTRODUCTION

In industry today, striving to increase operating efficiency is a goal that is shared by any progressive company. This can be seen in the optimization efforts that are driving facilities to trim operating costs while at the same time maximize production output. In order to achieve the goal of peak performance, there are many components which must be optimized individually before their integrated output will result in the most efficient production. The component that might be the most obvious when one thinks of production variables is personnel, since human hands commonly affect most manufacturing processes at one point or another. Also among the variables that must be examined by business managers and production supervisors is the machinery that is used to produce a given product. Managers must consider the amount of money that should be invested in fixed machinery assets, as well as the degree to automate a given process. The reliability of the machinery must also be carefully examined.

Addressing the necessity of machinery reliability for production optimization is the thesis, and more specifically, how machine condition monitoring and evaluation can be used to enhance the reliability of a facility's fixed machinery assets. One reason machinery must be reliable is that many production processes can be crippled by the failure of a single piece of equipment that is responsible for only a small part of the overall production process. One issue that might be raised at this point is the need for pieces of reserve equipment which are in place in order to prevent disruptions in production. However, the

investment required for this reserve equipment is needless in many cases, if one can assume that the reliability of first-line machinery can be optimized. This concept of reliability optimization focuses on the prevention of unscheduled outages along with the maximization of machinery component life.

The goal of preventing unscheduled machinery outages may seem impractical. Yet modern technology allows the collection of different types of data that present a comprehensive picture of the operating condition of a piece of machinery, with the majority of this data collection performed while the machine is in normal operation. The collected data can include a machine's vibration signature, lubricant samples, thermographic images, and ultrasonic measurements. Of these different types of operational data that may be used to evaluate a machine's operating condition, the vibration signature, if one can assume that it is properly collected, often gives the most comprehensive look at a machine's operational characteristics. It is also perhaps the most efficient in terms of the total data collection and analytical time that is required to formulate a diagnosis, as well as the cost of the hardware required to collect the data. The diagnostic technique that is presented in this thesis utilizes a machine's vibration signature to determine if a significant fault is present.

If comprehensive vibration data is taken at the proper time intervals, then with proper data analysis, an accurate assessment of the machine's operating condition is quite feasible. Routine vibration surveys of rotating machinery allow a trained analyst to evaluate the operating state of machinery as it changes over time. This condition evaluation is an essential part of the predictive maintenance strategy, because two of the

goals are to prevent machinery failures and to identify necessary maintenance actions. The prevention of the unexpected machinery failures allows production to continue uninterrupted, where outages can result in significant profit losses. Knowing what maintenance actions are required while a machine is still in service allows efficient scheduling of the corrective procedures during planned outages. In emergencies, machinery can be individually shut down to perform the necessary maintenance procedures. This methodology also maximizes the service life of the individual machinery components, since each component is generally kept in service until it presents a danger to the continued operation of the machine.

Most companies that have not begun to implement a predictive maintenance philosophy are performing their maintenance based on the preventive strategy, unless they are simply allowing machinery to operate until it fails in service. Preventive maintenance involves establishing a regular schedule to perform maintenance actions, where this schedule is designed for a worst-case scenario that is based on manufacturers' general service life estimates for machinery components. However, when maintenance procedures are scheduled at designated time intervals, many actions, such as bearing replacement or alignment procedures, may not be necessary. This preventive maintenance philosophy does not sufficiently account for the possibility of the premature failure of machinery components. These unexpected failures result in repair expenditures many times higher than if the machine would have simply been removed from service before the failure occurred. It can also be argued that the closer that a machine operates on a day to day basis relative to its optimum vibration levels, the less energy will be used in producing a

given product. In addition, this optimization reduces the use of natural resources, while also possibly improving the quality of the final product.

The key to the success of a predictive maintenance program involving the vibration analysis of a plant's rotating machinery is the accurate and efficient analysis of properly collected vibration data. Human experience and heuristic knowledge are ultimately the basis for final opinions regarding the operating state of any given piece of machinery. In addition to a human expert's personal knowledge, he requires a method of collecting, storing, and displaying the vibration data in order to evaluate a machine's operating condition. Modern vibration data collection is performed most commonly with digital data collectors which record vibration data measured by accelerometers, velocity sensors, or displacement probes. However, before a data collection survey can actually be performed, the specifics of the survey must be defined. For any significant number of machines, this is done using commercially available software. Using this software, a database can be created that includes entries that represent the machinery that is to be monitored by the vibration program. For each of these machines, the analyst defines the location and type of the data that he will collect, where a machine is defined as a driving unit (motor, turbine), its driven unit (fan, pump, generator, compressor), and possibly a gearbox, which can further complicate the configuration.

In order to present the clearest picture to the analyst, vibration data is most commonly taken at each bearing location, which usually results in readings being taken at two locations per shaft, termed inboard and outboard. At each location, three measurement points are defined at which readings are to taken in the horizontal, vertical,

and axial directions. An analyst may also collect additional test data such as phase readings or orbit plots. This additional information is often used to determine precisely a fault that is present on a machine, but it is rarely necessary to determine simply if a machine is operating normally or if a fault is present. Once the database is constructed for the machines which are to be included in the measurement survey, an analyst can transfer a data collection "route" from his personal computer to his portable data collector. He can then proceed to collect the vibration data as outlined by the route definition. When data collection is complete, the vibration data is transferred to a personal computer. Each piece of collected vibration data retains the date and time that it was collected, as well as the parameters that were used in its collection.

Once data collection and storage are complete, the data should then be analyzed. An analyst's personal experience and intuition are essential for accurate analysis of vibration data. The most common and also most conservative method of vibration analysis involves manually displaying a plot of each data set collected. This process includes displaying the data in the frequency domain, where the displayed spectrum represents the vibration signal after having a fast Fourier transform (FFT) performed. An analyst also commonly uses the time waveform data. The time waveform represents the output of the measurement sensor, since the time waveform displays vibration amplitude as a function of time. Both of these types of data display techniques have advantages as well as disadvantages. The spectral (frequency domain) data has the advantage of displaying separate peaks, where these peaks represent the individual frequency components of the vibration signal. Each peak has a certain amplitude that is present at its

frequency of oscillation. The frequency of a given peak can be associated with certain faults that would be expected to occur at that frequency for a given machinery configuration. The amplitude value for a peak can then be used to determine the severity of a diagnosed fault. The main disadvantage of spectral data is also the clearest advantage of time waveform data. Transient events such as impacts are not as evident in spectral data partially due to the technique which is used to average several spectra into a composite signal that represents the steady-state operation of a machine. Since transient events do not commonly occur at a fixed frequency, the FFT also tends to diminish their visibility in the individual spectra that are averaged.

The algorithmic analysis of time waveform data is the focal point of this thesis. There are several machinery faults which have characteristic patterns in the time domain, such as imbalance, misalignment, and rotating element bearing defects. The waveform also commonly reveals if a fault is orderly (nonrandom) or if it exhibits a high degree of randomness, which could indicate looseness or a possible degradation of bearing components. The fact that the time waveform data is most commonly displayed in units of acceleration gives an analyst an idea of how much force is actually being generated by a given vibration that is present in a machine. This evaluation is possible since the analyst has a relative idea of a machine's mass after having taken the data. Displaying a vibration signal in units that an analyst can relate to in this manner helps in determining the severity of a given machinery fault. The inclusion of both spectral and time waveform data in the analysis process allows an analyst to make the most informed decision when determining the operating condition of a machine.

Now that the significance of the two types of data that are commonly collected has been established, consider the number of spectral and time waveform plots that an analyst individually displays for a facility with several hundred or thousand machines being routinely monitored, recalling that there are between ten and twenty measurements associated with each machine. This can be an overwhelming amount of data to analyze. This time consuming characteristic of the vibration analysis process is addressed by the algorithmic implementation of the waveform diagnostic technique presented in this thesis. Presently, the main alternative to viewing each individual data set manually is the use of an expert system, or automated fault diagnostic system. Such systems attempt to analyze machinery as would a human expert, formulating a diagnosis for further review. However, this type of an analysis technique when performed on an entire database often generates additional work for an analyst, since a high percentage of false alarms is commonly associated with the use of expert systems. For a number of reasons, including the one mentioned previously, the use of this type of software to analyze large amounts of data is not widely accepted. Another reason, which may be more of a limitation of today's expert systems, is the fact that they generally perform a detailed analysis of only spectral data, and not the time waveform, in their examination of a machine's vibration signature.

The algorithmic analysis of time waveform data that is presented in this thesis is performed by calculating a number of parameters that attempt to characterize fault patterns that may be present in a vibration signal. The analysis of this signal is generally quite abstract, and associating a pattern that may be visually recognizable in a time waveform with a specific type of machinery fault can be difficult. However, a quick look

at the appearance of a time waveform gives an analyst an idea of the operating condition of a machine from which the data was taken. Additional study often does not reveal a significant amount of additional information regarding the machine's condition. This is a rather distinct difference between spectral and time waveform data analysis, since spectral data is often examined in detail by associating individual peaks with fault frequencies that would be expected for a given machinery configuration. Such detailed spectral analysis often reveals additional information that is not realized by the analyst at first glance. The algorithmic analysis technique of time waveform data that is described in this thesis uses several simple mathematical algorithms to calculate parameters which can be used to determine if a machine potentially has a fault present. The technique does not perform extensive analysis on the signal, as do expert systems which examine spectral data. It attempts to perform an evaluation as to whether or not a significant problem exists in a machine which is being analyzed, or if the vibration levels seem to be within reasonable limits. This technique does not necessarily attempt to determine the precise nature of the faults, their severity, or their root cause. It is designed to serve as a screening tool, allowing the analyst to concentrate his efforts on machines that require further attention.

The algorithms themselves use each piece of time waveform data individually, calculating eight parameters that are used to identify machines which should be examined more closely. Three of these parameters describe the degree and type of impact present in the signal. The impact parameters are designed to identify different stages of bearing defects, looseness, gear defects, and cavitation. There are also two pairs of parameters that describe the sinusoidal characteristics of the signal. The sinusoidal parameters are

designed to identify rotor imbalance, misalignment, belt defects, resonance conditions, and coupling problems. An additional parameter measures the repeatability of a time waveform. Electrical motor defects can be identified conjunctively using the impact detection parameters, the sinusoidal detection parameters, and the repeatability parameter. It should be kept in mind that the present goal of this analysis technique is not to identify which of these defects is present nor to what degree. The goal is only to determine if characteristics of any of the aforementioned faults are present at levels that are potentially damaging to the machine. Taken together, the algorithms are to serve only as a screening tool, with the purpose of identifying machines which require a more detailed, comprehensive analysis before a final evaluation of the operational state can be determined by a trained vibration analyst.

Using the algorithmic time waveform analysis technique presented in this thesis as a screening tool will be shown to significantly affect the amount of data that must be manually analyzed while maintaining the analyst's previous level of accuracy. The system of algorithms will also be compared against a commercially available expert system, where both systems are used as a diagnostic screening tool, so that an analyst need only look more closely at the machines identified. Ultimately, the proposed time waveform analysis technique will serve a similar role to that for which today's existing expert systems were intended. By examining data in the time domain, this technique takes a markedly unusual approach. Eventually, a combination of the two diagnostic approaches utilizing time waveform and spectral data will likely be the most effective tool for an automated analysis of vibration data.

CHAPTER 2

MAINTENANCE OVERVIEW

2.1 Industrial Maintenance Considerations

In industry today, business managers are realizing that industrial maintenance commonly involves high level business decisions. As a result, many business managers are also realizing that the responsibility for the maintenance decisions that must be made should not be placed entirely upon the repair personnel. Depending on the specific industry, maintenance costs can vary from 4% to 14% of the total cost to manufacture a specific product, and these cost figures are being noticed more than ever by business managers [PAR-1]. These high maintenance expenditures are seen by some as perhaps the largest controllable cost in the entire production process, and this targets them as a production element where intense optimization efforts should be focused [PAR-1]. One of the results of successful maintenance optimization is higher production capacity, and this leads to fewer interruptions in production, improved quality, and an overall increase in profits. With machinery reliability and maximum production capacity in mind, progressive manufacturers are altering their maintenance philosophy from simply reacting to machinery breakdowns to focusing on the elimination of these unscheduled outages. The implementation of this change in attitude has a direct effect in helping to hold down maintenance costs while at the same time minimizing production disruptions. This

progressive approach to optimizing industrial maintenance is termed Reliability-Based Maintenance (RBM).

2.2 Reactive Maintenance

The acceptance of progressive approaches to practicing maintenance is gradually growing in the country's industrial environment, which has a long history of purely reactive, or breakdown, maintenance. From the time that machinery was first used in production processes until the early 1970's, managers and maintenance personnel simply allowed machinery to remain in service until it failed. Reactive maintenance is inefficient, as well as expensive, due to production losses from unscheduled machinery outages as well as damage to the machinery caused by sudden failures. For this type of maintenance, the procedures performed by maintenance personnel are commonly limited to periodic lubrication. The main advantage to this type of maintenance is the low investment cost that is required to set up and operate the program, since the training required for the maintenance personnel is minimal and essentially no test equipment is needed [EMM-11]. However, reactive maintenance does require a large spare parts inventory, so that when a machine fails, it may be repaired or replaced as quickly as possible. However, the manner in which breakdown failures generally occur almost always results in higher total downtime than if the machine had been removed from service, before its failure.

2.3 Preventive Maintenance

Recently, many companies have implemented a periodic preventive maintenance

strategy. To aid in the successful implementation of this approach, maintenance scheduling software is often used to track and then appropriately schedule periodic maintenance tasks. This scheduling is intended to reduce machinery breakdowns and unanticipated expenses, which helps control plant output and increase profits. Today, preventive maintenance is by far the most widely accepted maintenance philosophy and is proven to extend equipment life and improve reliability [EMM-12]. Preventive maintenance provides the first level of control beyond the reactive level, and studies have shown that a successful program can provide a 30% decrease in maintenance costs compared to costs that would have been incurred in a purely reactive mode [PAR-1]. However, preventive maintenance will not always prevent machinery breakdowns, and there are disadvantages to the implementation of this type of maintenance philosophy. One such drawback is that by design, preventive maintenance has a labor intensive structure that often leads to excessive maintenance actions being performed. The practice of this maintenance philosophy also assumes that there is a strong relationship between operating age and component reliability. This is commonly an invalid assumption, except in cases where product elements are in contact with production equipment, causing wear, fatigue, and corrosion [PAR-3]. This allows for the possibility that if interval-based maintenance is practiced for an entire industrial facility, a large number of unnecessary maintenance actions will be performed in an attempt to insure that no machine is allowed to fail while in service. As a result, preventive maintenance programs incur costs associated with repairs regardless of the operating condition of the equipment when it is removed from service [WAT-109]. These unnecessary repairs also allow for the

possibility of maintenance personnel introducing previously nonexistent problems when corrective actions are performed.

The maintenance scheduling software that was previously mentioned plays a critical role in preventive maintenance programs. Such software is referred to as a computerized maintenance management system (CMMS). The system administers the maintenance work orders that are scheduled for the department, and it also serves as the maintenance department's 52-week business plan, budget, and the basis for its daily actions [PAR-3]. While a CMMS administers the normal maintenance work orders, it can also track their associated cost. In addition, a CMMS can track a spare parts inventory and machine history information, while also performing maintenance expense analysis. The types of work order that are generally delegated by a CMMS are operator inspections, lubrication, cleaning, calibration tests, filter changes, and other minor operational machinery adjustments.

2.4 Predictive Maintenance

In the late 1980's, technological advances provided instruments that allowed readings to be taken from which the operating condition of a piece of machinery could be determined. This knowledge allows the predicting of maintenance requirements while the machine is still in service. The implementation of this technology in the maintenance industry is termed condition based maintenance or predictive maintenance. As does preventive maintenance, predictive maintenance aims to prevent unscheduled machinery failures. In addition to eliminating machinery failures, predictive maintenance utilizes

technology to identify the problems present in a piece of equipment, which allows the accurate prediction of when specific corrective maintenance actions should be performed. The practice of predictive maintenance is based on the fact that machinery components often give warning of an impending failure. Typical signals include excessive vibration, heat, thickness decrease, and wear particles present in lubricants. Predictive maintenance also provides the ability to isolate and correct inherent design flaws in machinery, as well as problems with a machine's installation and operation [MOB-83b].

There are a number of benefits that can be derived from successfully implementing a predictive maintenance program. The first advantage is that the condition of a facility's machinery is known at any time. This permits repairs to be optimally scheduled and performed with minimal production interruption, resulting in increases in production availability of 2% to 10% [PAR-4]. Another advantage to the implementation of the predictive maintenance methodology is the anticipation of required maintenance actions. This can reduce a plant's emergency work orders, as well as reducing the amount of maintenance personnel's overtime labor. This allows the efficient planning of maintenance procedures with regard to the availability of manpower, parts, and repair equipment. The improvement of product quality is also a benefit, since product quality can be affected by degraded components in production equipment [MOB-43]. In many cases this is not realized until a significant number of defective products has been produced. Predictive maintenance allows the identification of problems that threaten the final quality of a product so that repairs can be scheduled and performed before quality is compromised. Safety is also enhanced by eliminating unnecessary preventive maintenance actions, and

also by eliminating the need for emergency maintenance actions, when time constraints may be severe. In addition, the labor required to repair machinery due to catastrophic failures can be virtually eliminated. Substantial benefits can also be realized in energy savings that are brought about by the effective implementation of a predictive maintenance program. When a machine vibrates due to a fault condition, such as misalignment, looseness, or imbalance, the energy leaving the system in the form of machinery vibration is not being used to produce a product. Yet the manufacturer must still pay for this wasted energy. Some studies have shown that the power consumption can of a machine be reduced considerably if sources of high vibration are removed by performing necessary maintenance actions [PAR-4].

2.5 Proactive Maintenance

In the past several years, a more advanced maintenance approach is beginning to gain acceptance among the maintenance community. This technique is termed proactive maintenance. This approach to performing maintenance has the potential to enhance preventive and predictive maintenance programs that are already in place. Proactive maintenance attempts to reduce the total maintenance required. The ideal goal of this maintenance philosophy is to eliminate all failures of machinery components in a plant, which is also the goal of predictive maintenance. However, maximizing the life of machinery through the systematic removal of the sources of fault conditions and failures distinguishes this maintenance approach from others [EMM-12]. This systematic removal of underlying causes of machinery problems is possible by applying advanced investigative

and corrective technologies. The benefits that can be seen from the successful implementation of proactive maintenance technologies include the reduction of repetitive problems that shorten a machinery component's life, since these problems can be identified and removed through design enhancements. The quality of new and rebuilt equipment is ensured by performance verification procedures, since machinery is occasionally installed with defects that can shorten a component's life [PAR-5]. These procedures often involve the component suppliers so that they must insure that their products meet the required specifications. The proactive maintenance philosophy also supports precision installation and rework of machinery so that optimal component life is realized.

The removal of repetitive machinery failures, termed root cause failure analysis (RCFA), which was previously mentioned as one of the components of proactive maintenance technologies, is an important concept that has been overlooked by maintenance personnel for many decades. An example would be a machine's outboard fan bearing that has failed every four months, for as long as the maintenance personnel can recall. For this example, there is most likely an underlying cause for the bearings premature failure, such as a rotor imbalance or shaft misalignment. Other faults that commonly recur if the root cause is not identified and corrected include frequent seal failure and structural degradation, such as cracking of the grouting or foundation. These faults are actually symptoms of the underlying machinery fault condition. However, for many decades maintenance personnel have simply fixed the symptomatic problem and accepted the frequently required repairs as normal for the machine. RCFA includes an advanced set of analytical tools and engineering logic directed at identifying and correcting

the underlying problem, and this approach often results in significant savings to a plant [PAR-5].

The practice of proactive maintenance also includes the precision rebuilding and installation of machinery, and this technique has also proven to extend significantly the service life of installed machinery. The most common rework and installation specifications that are poorly performed, or not performed at all in some cases, are rotor balance and shaft alignment. If the effort is spent to perform these actions with a relatively high degree of precision, the service life of a machine can be easily doubled [PAR-5], more than paying for the initial investment required to perform the maintenance action. Requiring performance specifications for newly purchased and rebuilt equipment is also a component of proactive maintenance, and this ensures that the supplier is held responsible for providing machinery that meets the standards which are included in the purchase specification. Vibration readings are commonly taken to identify mechanical conditions that should not be present in a new piece of equipment. Rebuild actions that are performed should also adhere to standards that ensure that when equipment is reinstalled, it has no pre-existing condition that will shorten its service life.

2.6 Integrated Reliability-Based Maintenance

The three progressive maintenance strategies previously discussed, preventive, predictive, and proactive, each play an important role in the successful implementation of a unified reliability-based maintenance philosophy. These three maintenance approaches must be combined so that they are properly balanced in an effort to achieve a plant's

maximum reliable production capacity. The accurate machinery condition information given by predictive maintenance often makes the need for preventive and proactive maintenance actions clear, and this helps to reduce the excessive performance of maintenance actions which are present in a purely preventive program. In a reliability-based maintenance program, predictive maintenance provides an excellent short-term return on the initial investment, and it also lays the groundwork for the introduction of other reliability-based strategies. This gradual implementation of different strategies is quite common, since startup resources are often limited. However, once initial successes can be reported, support and funding for a reliability-based maintenance program is generally given so that the individual maintenance technologies that comprise the program are allowed to expand as needed to cover comprehensively a plant's machinery with preventive, predictive, and proactive maintenance technologies [PAR-6].

There are three distinct stages in the development of a reliability-based maintenance program. These are the startup period, the proactive expansion phase, and the mature RBM program phase. The startup period often involves a difficult shift from a reactive philosophy, or somewhat preventive philosophy, to a more progressive approach towards maintenance. This transition often involves the creation of two groups, and the first is termed the maintenance planning group. This group may already exist to some extent in a preventive capacity, but its focus must shift to integrating preventive maintenance actions with machinery condition information. The planning done by this group must also include downtime minimization for required actions, complete planning and coordination of required actions, work order tracking, and machine history tracking and analysis. Another

group that must be set up during the initial stages of a reliability-based maintenance program is the reliability improvement group. Their initial focus is the implementation of predictive maintenance in the plant. Proper training of this group is critical, especially as their focus shifts towards proactive maintenance considerations.

The second stage in the development of a reliability-based maintenance program is the expansion of initial predictive maintenance efforts and the introduction of proactive techniques. If initial predictive efforts include only periodic vibration analysis, other technologies that may be implemented are on-line vibration analysis, oil analysis, thermography, motor current analysis, and ultrasonic testing. The proactive maintenance operations that may be introduced include precision alignment, balancing, and root cause failure analysis. During this stage of the program, the focus begins to shift from the analysis of single events to bottom-line plant improvement [PAR-7]. Mature reliability-based maintenance programs can often be recognized by an attitude change that occurs in plant management, as well as the maintenance personnel. The plant personnel in a mature program often have a rather aggressive attitude towards the implementation of reliability based maintenance, and the focus is often on the entire elimination of machinery breakdowns, permanent improvement of product quality, and achieving maximum possible production capacity. At this stage, a reliability program rarely performs single event analysis, and concentrates on overall improvements. The successful implementation of this type of reliability program provides significant increases in a plant's bottom-line profits, as well as other benefits such as customer satisfaction. There is also commonly an increase in personal pride held by maintenance personnel, since in a reliability-based

maintenance program, personnel can individually make a significant contribution to the overall improvement of their plant's production process.

CHAPTER 3

CONDITION MONITORING PROGRAM OPTIMIZATION

3.1 Condition Monitoring Program Effectiveness

In many cases, the most important step towards the successful implementation of reliability-based maintenance is to establish a solid foundation consisting of an efficient predictive maintenance, or condition monitoring, program. It is important to have a measure of the effectiveness of such a program, since in its initial stages, there is often a need for the justification of continued funding. Having an accurate measure of the current effectiveness of a predictive maintenance program is also essential for the continual optimization of machine performance and reliability. The accurate evaluation of a plant's predictive maintenance program first requires the establishment of performance standards [MOB-41]. An accurate measure of a program's current performance levels is also necessary for comparison to a baseline performance standard. However, the universal definition of concise performance standards and performance levels for all maintenance programs is difficult, since each such program can have goals specific to the production environment in which it operates. These goals range from the reduction of specific machinery outages, to the overall improvement of plant productivity, or even the reduction of a plant's spare parts inventory. However, the success of a condition monitoring program can generally be evaluated by defining a measure of overall program performance and also a measure of the effectiveness for the personnel that perform the

condition monitoring [MOB-41].

3.2 Condition Monitoring Program Performance Standards

Program performance standards are needed to measure the improvements in overall plant performance that can be attributed to the condition monitoring program. The standards for a given plant depend on the original goal defined for the predictive maintenance program. If a program is established for the sole purpose of eliminating catastrophic machine failures, then the measure of performance would be based on the number of machine failures that occur each year. Programs with goals such as improving machinery reliability, overall production capacity, product quality, and lowering operating costs would have measures of performance determined by several criteria [MOB-41].

Unscheduled delays and overtime expenditures are also undesirable in a plant's production environment. The key to defining performance standards for individual programs is that the set of defined criteria must reflect the previously defined goals of the predictive maintenance program. Several of the most common measures of program performance will be discussed.

Plant maintenance costs should be noticeably reduced with the implementation of a condition monitoring program. Determining a measure for this reduction in maintenance costs includes examining the change in labor and material costs which are incurred in performing plant maintenance. The short term benefits in this area will be seen as a reduction in overtime wages and material costs, because these costs are generally inflated by unscheduled machinery failures. Another performance standard that may be adopted is

the reduction in spare parts inventory. A reduction in the frequency and number of corrective maintenance actions performed in a plant will directly affect the cost of purchased materials required to complete the maintenance actions. In addition, successful predictive maintenance programs can significantly reduce the number of spare machines and machinery components that would ordinarily be kept readily available in a plant. An effective condition monitoring program should reduce a plant's spare parts inventory by about 50 percent in its first three to five years [MOB-41]. In addition, condition monitoring also provides lead time that may be utilized in the procurement of replacement components. The time interval between problem detection and the need for the replacement part may be months, which allows ample time to procure the replacement component in the most cost-effective manner.

Production capacity is also a measurable standard for the performance of a predictive maintenance program, and this is perhaps the area where predictive maintenance produces the most notable improvements. There is generally significant room in a plant to optimize its production capacity, mainly because most plants operate far below their capacity. A low level of operational production capacity is commonly the result of poor equipment reliability and poor operating condition [MOB-42]. A successful condition monitoring program will significantly resolve most equipment reliability issues, while noticeably increasing production time. Any deviation from optimal operating condition should be identified by the condition monitoring program, allowing corrective procedures to be scheduled efficiently. Considering the crippling effect of the failure of a single critical piece of equipment, the optimization of program performance can increase

production capacity by as much as fifty percent. Product quality can also be used as a measure of the effectiveness of a predictive maintenance program. Rejected and reworked parts result in significant expenditures for many manufacturing facilities, and this is an area that can be significantly affected by a successful condition monitoring program. These standards provide a framework that may be customized to individual plant production environments, providing a set of standards by which the performance of the program may be determined.

3.3 Condition Monitoring Team Performance Standards

In addition to establishing overall performance standards for a predictive maintenance program, standards for the performance for the condition monitoring are also required. This set of standards complements those applied to the program as a whole by examining the human element involved in the program. This provides a measure of performance for the program's personnel so that the techniques used to conduct the condition monitoring program may be further optimized. Despite the necessity for these standards, they are often more difficult to establish accurately than are the performance criteria that apply to the program as a whole. The implementation of such performance standards is even prevented in some cases by the work culture that is present in some manufacturing facilities. This is especially true in facilities where hourly or union labor is in place, since agreements can be present that prevent the measurement of performance criteria of individual plant personnel. However, the successful implementation of a predictive maintenance program requires monitoring personnel to be responsible and

accountable [MOB-43]. Condition monitoring programs should have teams dedicated to specific areas of the plant, and in some cases, to individual machines or production lines. These individual teams are then given the responsibility for successfully implementing and maintaining a condition monitoring program for their designated group of machines. For optimum performance, these condition monitoring teams are also held accountable for the performance and reliability of their assigned machines.

One measure of performance that may be measured is the adherence of monitoring personnel to fixed monitoring intervals. This data collection frequency depends on the impact that a sudden failure would have on production capacity, but common intervals vary from weekly to monthly. The importance of adhering to these regular intervals is due to the fact that machine reliability evaluation depends on the trending (examining changes over time) of certain parameters that are calculated from the collected vibration data [MOB-35c]. The trending of a given parameter can be displayed on a plot where its amplitude is displayed as a function of time. Another measure of condition monitoring team performance is the effectiveness of data acquisition. This measure of data acquisition efficiency represents the number of vibration readings, infrared scans, and oil samples that an analyst collects in a given length of time. For a given data collector, this number can give a measure of his data collection performance compared to a standard that has been applied to the whole team. It is also important that the collected data be accurate. If a person collecting vibration data is not attentive, his vibration sensor may not be firmly attached to the data collection surface, which results in a poor transmission path from the machine to the sensor. This problem of data validity is difficult to recognize during the

data analysis phase of a condition monitoring program, and it can also mislead an analyst as to the condition of the machine from which the data originated.

Perhaps the most fundamental measure of monitoring team performance is its diagnostic accuracy. This is due to the fact that a monitoring team's goal is to identify accurately problems that require or will eventually require corrective maintenance actions. For a measure of analytical accuracy to be determined, each fault diagnosis should be as clear as possible. If an analyst's report is vague, discussing several possible problems, then it is difficult to judge its accuracy. This inexactness also makes it difficult to decide whether the machine needs to be removed from service. It is more efficient for sufficient resources be invested by a condition monitoring team so that it is able to come to a clear diagnosis, than it is for the team to provide an imprecise course of recommended action. It can be argued that if a vague diagnosis is the final word given by the condition monitoring team, then that was an inefficient use of the plant's resources. A feedback loop between the analyst and repair personnel can be quite effective, since a repair is performed based on a report generated by the analyst. The individual responsible for the corrective action performed on the piece of equipment can either confirm or deny the diagnosis given by the analyst, and this feedback also allows the condition monitoring team to insure that the required maintenance actions are performed.

Another measure of condition monitoring team performance again involves diagnostics and reporting, but in this case it is a measure of the elapsed time between data collection and final diagnostic report generation. This time interval should be kept to around two to three days, since longer periods can severely limit the effectiveness of a

condition monitoring program [MOB-44]. This measure of team performance can then be compared to a standard that has been set for the allowable time between data collection and final reporting. It should be noted that in most programs there will be separate standards that are applied to specific emergencies, which should have diagnosis performed the same day that the data is collected. Some condition monitoring programs require the immediate notification of the maintenance manager if a machine is identified as having a high probability of failure. The time waveform analysis techniques presented in this thesis will be shown to be quite effective in helping the analyst conform to these imposed time constraints. These analytical techniques significantly reduce the time required to analyze large amounts of vibration data, and vibration data often accounts for the majority of the data that is analyzed in a routine condition monitoring program. The final measure of condition monitoring team performance that will be discussed is the performance level of the group of machines that is the responsibility of the monitoring personnel. The specification of this performance measure involves defining a baseline standard that reflects the condition of the machinery at the time of the implementation of the condition monitoring program. This baseline standard should characterize the performance of the machine over the past two to three years [MOB-44]. The long-term improvement in machine production availability, product quality, and machinery capacity can be examined, and the degree of improvement will reflect the performance of the team that is responsible for the reliability of these machines.

CHAPTER 4

CONDITION MONITORING PROGRAM IMPLEMENTATION

4.1 Scope of a Condition Monitoring Program

A predictive maintenance program prescribes structure, responsibility, and documentation for the monitoring and analysis of selected rotating equipment. Selecting the group of equipment that is to be included in a predictive maintenance program is a decision that should be made by considering a number of factors. The two main competing factors are the individual measures of criticality of the pieces of equipment and the plant resources that are to be made available to the condition monitoring program. If no limitation were placed on the available resources, then the solution would be to monitor most all plant equipment. However, an unlimited resource base is generally impractical, and this makes the decision of the specific machinery to include in the condition monitoring program more difficult. Individual factors that should be considered include the machine's importance to the safety of plant personnel, production availability, plant reliability, equipment value, insurance costs, and equipment maintenance history [VIG-3]. Difficulties arise in selecting machines to be monitored when there are insufficient resources to monitor all of the equipment that is deemed critical. In this case, the machines that are most visible to plant management are often selected [VIG-3]. The ideal solution in this case is to review failure statistics and use the machines' maintenance history to determine which equipment has the greatest need for condition monitoring.

When determining the machines that are to be monitored, it is helpful to know the approximate number of machines that can be monitored adequately. A machine that does not necessarily produce a product, but is necessary for another machine's operation is referred to as a piece of support equipment. This type of machine is generally the simplest to monitor effectively, and the condition of these support machines can most commonly be evaluated using data taken at ten locations on the machine. These pieces of equipment also tend to be accessible and often run continuously. If a piece of support equipment must be briefly removed from service, then this is generally not a problem. These factors make it possible for a person to collect data on at least fifty support machines in a normal eight hour shift [VIG-3]. The collection of vibration data for complicated production lines, where data collection locations are often not as accessible and not as conventional as the collection locations of support equipment, is somewhat more time consuming. The data collection interval for most machinery is monthly, but highly critical machinery may justify a shorter interval. Until sufficient data has been taken on a given machine so that the trends of vibration levels can be established, it is not recommended that longer than one month be allowed to pass between data collection on any machine [VIG-4]. In addition to the time required for data collection, an equal amount of time needs to be allowed for its analysis, reporting, and database administration. When the program is implemented, there also needs to be time allowed to set up a database, and this initial time required is roughly equal to the data collection time required for the machines to be included in the database.

4.2 Importance of Adequate Documentation

The successful implementation of a vibration monitoring program can be aided by the availability of adequate documentation, and this documentation can often be useful during data collection as well as data analysis and reporting. Floor plans and maps are useful so that data collection personnel can quickly find equipment that is to be monitored. Knowing the relative locations of the equipment being monitored also helps in grouping machines together into data collection routes, which is part of the database setup process. These routes are defined so that an analyst can collect data as quickly and efficiently as possible as he walks through the plant on his collection route. Maps showing the locations of the machinery included in a condition monitoring program are also useful when new personnel become involved with the program. Machine diagrams are also useful during the implementation of a condition monitoring program. The diagrams can be used to construct the database as accurately as possible, specifying the correct data collection locations. These diagrams are also helpful in finding the correct data collection locations on the machines when an analyst is collecting data on his designated route. Data sheets that can be used to record a machine's physical specifications and configuration are also useful documentation. This information is often helpful to an analyst when analyzing the collected vibration data, because an analyst spends most of his analysis time relating the vibration patterns and frequencies that are present in the data to the failure patterns that are expected for specific machinery components.

A schedule for obtaining data that includes each of the machines included in the condition monitoring program is also very useful. The schedule will help to insure that

data is collected on all of the machines at the proper time interval. Contact information for suppliers of equipment and individual machinery components can also be useful when trying to determine information about a machine that could not be obtained otherwise without tearing it down and examining its design and components. Procedures outlining data collection and analysis should also be documented. These procedures include information about the transducers that are used, the transducer mounting technique, the data collection parameters defined in the data collector, and the guidelines used to generate reports. A method for documenting case histories should also be considered so that information compiled at the time of a fault instance can be revisited at a later date. Documented fault information is also useful when attempting to identify the root cause of a machinery failure pattern. The documentation of cost analysis information can also be beneficial to a vibration monitoring program. This documentation provides information about the money saved by removing machines from service which were identified with fault conditions before failure occurred.

4.3 Condition Monitoring Database Setup

The database setup that was previously mentioned is critical to the successful implementation of a condition monitoring program that utilizes predictive maintenance technologies. Proper database structure is necessary for data collection, facilitates later data analysis, and is necessary for identifying trends of vibration data parameters. The structure most commonly used is the hierarchal database, commonly referred to as a tree structure, and most condition monitoring database software packages support this

structure. Figure 4.1 shows a typical hierarchical database. The database places machines that are physically grouped together into the first level of the database, and this division is commonly referred to as the station level. In some cases, stations can represent certain buildings that contain process machinery or production lines. Separate databases can also be created if it is desired to classify further the equipment that is monitored.

Once the machines included in the condition monitoring program are grouped at the database level and then the station level, the individual machines must be defined in the database. This requires specifying general information that can be used to relate the physical machine with the entry in the database. The points at which individual vibration readings are to be taken are then defined, and a collection of measurement points is the next logical layer below the machine level. Data collection is generally performed by taking two perpendicular, radial readings at each bearing location, and a single axial reading per shaft [VIG-6]. This common rule of thumb is derived from the fact that the axial measurement is necessary in identifying alignment problems, and the relationship between the perpendicular radial readings is necessary to identify resonance conditions.

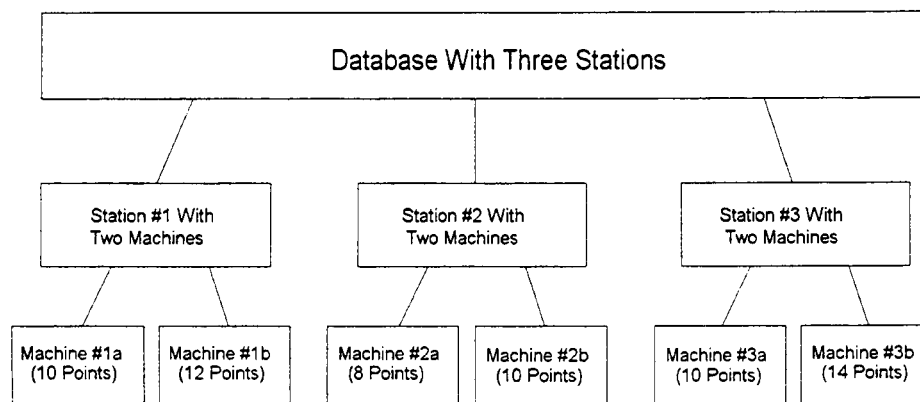


Figure 4.1. Example Hierarchical Database Structure

This convention is valid for most common support equipment. However, in many cases one or more of the ten specified data locations is not accessible due to the location of a coupling guard, for example, or perhaps the absence of a surface that provides good contact for the transducer. Many pieces of equipment also utilize gearboxes to transfer the power from the driving unit to the driven unit, and in many gearbox configurations, the design of the bearing caps on the sides of the gearbox are only conducive to the collection of axial readings. Many other complicated pieces of production equipment also require a high degree of customization when defining the machine at the point level.

It should be noted here that when defining the measurement points that are associated with a machine, it is essential to follow a standard convention when defining the identification codes of the measurement points. The adherence of a standard naming convention will allow information about a measurement point's exact location to be conveyed using only a three character identification code. This involves assigning one character as the component identifier. For example, this allows condition monitoring personnel to define all motor points of a machine with an M as the component character of the measurement point label. The second component identifier that should be defined is the bearing location identifier, which will typically be an O for the outboard bearing and an I for the inboard bearing. The terms inboard and outboard are generally assigned considering a point's location relative to the machine's coupling. A 1 and a 2 could also be defined as the standard inboard and outboard identifiers for the location identification character. The third character of the measurement point label should reflect the orientation of the vibration readings that are to be collected at this measurement point.

The orientation character is generally assigned an H for horizontal readings, a V for vertical readings, and an A for axial readings. There are a number of naming conventions that a given condition monitoring program can adopt, but the key is to be consistent when defining the measurement points for each machine included in the database. This will allow efficient data collection, since from the three digit code, the person collecting the vibration readings will know where on a given machine each reading should be taken. This is an important issue each time an employee is assigned to the condition monitoring program and given the responsibility for the data collection and analysis of a group of machines that is already included in the program.

4.4 Readings Collected at Each Measurement Point

For each measurement point that is defined, a routine monitoring survey will involve taking a vibration reading at the specified location on the machine. The collected readings measure the mechanical response of the machine to the excitations present in the system. The excitations present in the system may be caused by an imbalanced rotating component, misaligned component shafts, rolling element bearing faults, electrical faults, et cetera. In addition other equipment in close physical proximity to the machine on which a reading is taken can transmit energy in the form of a vibration to this machine. The resulting vibration of the machine is measured using a vibration transducer, and this device converts the mechanical energy into an electrical signal. The measured signal represents the behavior of the machine as a function of time, and this representation of the data is referred to as a time waveform. The time waveform often appears complicated. As a

result, it is difficult to extract quickly detailed information about the specific causes of a machine's vibration from this time series data. The algorithmic analysis of time waveform data that is presented in this thesis calculates parameters from this data, such that these parameters characterize the patterns that are present in the data.

Another representation of the data that is collected at a measurement point is its display in the frequency domain. This representation of the data is derived by performing a fast Fourier transform on the measured signal. This technique decomposes the complex time domain signal into its contributing sinusoidal components. The signal can then be represented by plotting the amplitudes of the contributing sinusoidal vibrations at their corresponding frequencies. By determining the frequencies at which vibrations occur in a machine, it is possible to deduce what faults may be present. The third method of viewing collected data is by identifying trends in calculated parameter values. Parameter values can be calculated for certain bands of the frequency domain that are defined by the user to be of significance. These calculated analysis parameter bands represent the energy that is present in the specified region of the frequency spectrum, and the behavior of these values trended over time reveals if there is a pattern of increase in calculated parameter values. Once a fault condition is identified, this representation of the data will often give the clearest indication of whether a machine is operating in a stable condition, or if its condition is rapidly degrading.

It is generally accepted that vibration data that is displayed in the frequency domain should have amplitude units of peak velocity (inches/second) or RMS (root mean square) acceleration [VIG-10]. The presentation of spectral data in displacement tends to

exaggerate the low frequencies and attenuate the high frequencies. Spectral data displayed in acceleration will most clearly show the high frequencies present, but often suppresses the lower frequencies. Velocity data gives the most balanced view of the entire frequency spectrum. Figure 4.2 illustrates the relationship between the different amplitude units in which vibration data can be displayed [BER-2.11]. The severity relationship that exists between amplitude units is a direct result of the integration or differentiation of a given signal from one set of amplitude units to another. The time waveform is generally displayed in RMS acceleration, and it is commonly used to assist in determining the severity of identified faults. This is particularly true of faults involving impacts, because impacts are most often defined in terms of the forces or accelerations involved [BAR-4]. There are a number of additional data collection parameters that must be specified when defining the data that is to be collected at the individual measurement points. These include the maximum frequency of the spectrum ($F_{\max}$). The number of spectral lines of resolution must also be specified, as well as the number of averages that are collected to

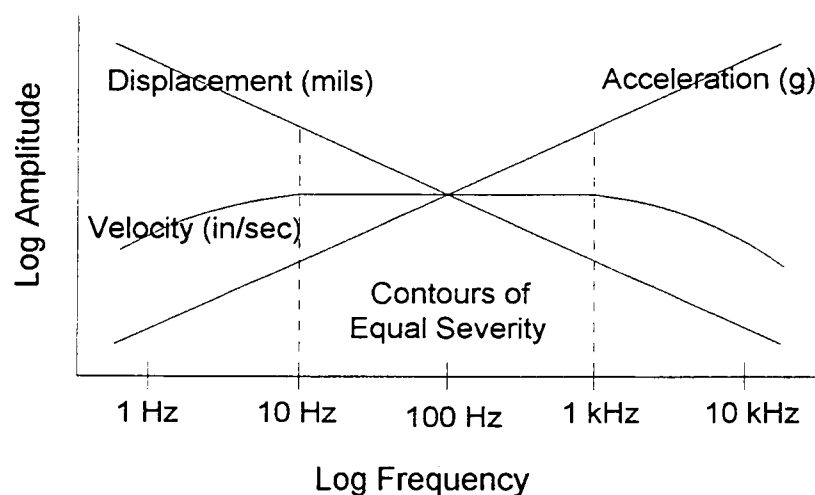


Figure 4.2. Comparison of Vibration Severity in Different Amplitude Units [BER - 2.11]

produce the spectrum that is actually stored in the data collector. A detailed discussion of these variables is beyond the scope of this thesis, but the consistency of these parameters is considered throughout the discussion of the time waveform analysis technique that will be presented.

CHAPTER 5

VIBRATION ANALYSIS

5.1 Introduction to Vibration Analysis

Once condition monitoring personnel have collected and stored vibration data from the machines that are part of a periodic survey, there is still little known about the operating condition of these machines. Even though experienced analysts can perform some analysis at the time of data acquisition using a data collector with a live display, the result of this type of analysis is generally limited to a note that is made so that attention will be drawn to this machine when the data is more carefully analyzed. Analysis that is performed in the field can also lead an analyst to take additional data that might aid in the comprehensive examination of the vibration readings. The analytical process that can be used by different vibration analysts can be as varied as the machinery from which data is taken. It has already been mentioned that most analysts have spectral, time waveform, and trend data available for the present survey as well as previous surveys. This data is available for display at the click of a mouse with modern vibration analysis software. Automated analytical programs are also available, and these programs perform their own analysis on data that has been collected and stored in the database. The more simple programs perform comparisons between spectral peaks or calculated parameter values and limits that are previously defined in the database. More advanced programs are available which extract features from the spectral data and then use these features as the input to a

set of diagnostic rules from which a diagnosis may be generated. These more advanced programs are referred to as automated fault diagnostic systems, and they are a type of expert system [PIE-1]. Modern vibration analysis software provides the analyst with more views of the data than he can practically consider, due to the amount of data that is generally collected during a routine vibration survey. Therefore, an analyst must determine which of the available tools to use in his analysis process.

5.2 Screening Phase of the Analysis Process

There are a number of steps in the vibration analysis process that may or may not be present in an individual analyst's machine condition evaluation technique. Generally, the first step in the analysis of data that is collected during a routine vibration survey is to identify which machines have a potentially significant fault. This step in the analysis process will be referred to as the screening phase. The time waveform analysis technique that is presented in this thesis is intended to be used by an analyst during the screening phase of the analysis process. This phase of the analysis process is not necessarily expected to identify the precise fault that is present or its corresponding severity. The purpose of this phase is to prevent the analyst from having to perform a detailed, time-consuming evaluation of all the collected spectral, time waveform, and trend data, as well as a comparison of current data to historical data that is also commonly stored in the database. The time that must be spent to analyze the data that is collected for each machine is part of the larger problem that one has when deciding which machines and how many to include in a condition monitoring program. If this were the ideal situation, where

there were no constraints limiting manpower or the time allowed for analysis, then looking at all the types of collected and historical data in detail would be the most conservative, comprehensive method. However, this is not a practical approach to analysis in most condition monitoring programs. To help an analyst accurately analyze data from as many machines as possible, there are a number of diagnostic tools and techniques that may be used to automate the screening phase of the analysis process.

5.2.1 Exceptions Analysis Reports

One of the most common techniques that is used to identify machines that potentially have a significant fault is to generate an exceptions analysis report. This type of automated analysis requires calculating values for the different parameter bands that are defined in the analysis parameter set that is tied to the measurement point from which spectral data is being analyzed. In an analysis parameter set, there are generally six to twelve parameters that are defined for specific regions of the frequency range associated with the collected spectral data [BER-7.13]. The calculated parameter values represent the energy that is present in the corresponding frequency bands. These analysis parameter bands generally include one specified for the overall energy in the spectrum, and there is also commonly a band defined to calculate subsynchronous energy, which is located in the frequency range below the turning speed of the machine. Other bands are defined for regions of the spectrum between one and ten times the machine's turning speed. Additional parameter bands may also be defined to calculate the energy of the spectrum in other regions where high levels indicate the presence of specific faults patterns. For each analysis parameter band, there is an associated alarm level. These alarm levels are

generally defined when the database is created and further refined as the program matures. It should be noted that most software allows the specification of up to three or more different types of alarm levels, and these different alarm levels are most commonly referred to as warning, alert, and fault levels. The specified alarm levels for each parameter band serve as limits which are compared to a value calculated from spectral data for that same band.

The output of a spectral exceptions analysis consists of a list of spectral data sets, along with their associated machines and measurement points, where exceptions are found. The degree of the exception is also displayed, and this degree is characterized by the level of the associated alarm. The output generally includes the calculated parameter values for the exceptional spectrum and the alarm levels that are penetrated. This output gives no clear indication of faults that are present, but does serve as a list of machines that require further analysis. It should be noted that this type of analysis generally does not include a comparison to historical data. This can result in the case where a machine has had the same exception in a previous survey, and the analyst has already reviewed the data and made the decision that the level of the exception is not of significance. The method that is used to calculate the spectral analysis parameter levels in an exceptions analysis should also be briefly discussed. The parameter values are calculated by adding all of the energy within the parameter band and not by simply taking the highest spectral peak. This type of power summation is similar to the calculation that is performed when determining the overall RMS vibration level for the entire spectrum. This method of parameter calculation will generate the same parameter value for a single, large peak as is calculated

for a collection of peaks which represent the same amount of energy. However, the severity of a fault condition is more often determined by examining the energy present in the single largest peak that is located within the parameter band than by considering the total energy that is contained within the band.

5.2.2 Automated Fault Diagnostic Systems

During the initial screening phase of the vibration analysis process, another technique that can be used to identify machines that might have a significant fault is the implementation of an automated fault diagnostic system [PIE-2]. These systems can perform their analysis on the entire group of machines for which routine vibration data is collected. Such diagnostic systems perform their analysis first by extracting features from the spectral data. These features include calculated values such as spectral overall amplitude, floor amplitude, subsynchronous energy, and nonsynchronous energy. Values for the synchronous peaks in spectrum are also calculated in many cases. The features extracted from the spectral data sets are then used to construct diagnostic facts that reflect the state of the measurement point at which data was acquired. Certain diagnostic facts serve as the premises for the individual rules of the expert system. If the premises for a given rule are satisfied, then that rule in the knowledge base of the expert system will “fire”, identifying a fault condition that may be present in the machine. The diagnostic facts are created for each measurement point, and as a result, different rules in the knowledge base may fire for each point that is evaluated by the expert system. The individual point diagnostics are then used to formulate a diagnosis for the entire machine. The combination of rules across the entire machine is essential, because in many cases,

data from different orientations and locations is necessary for the accurate diagnosis of certain machinery faults. For example, a machine that has excessive flexibility in the horizontal direction would appear to be imbalanced if only a reading taken in the flexible direction were used to formulate the diagnosis. The horizontal and the vertical readings must be compared to identify the true fault that is present in this case.

The output of most automated fault diagnostic systems will be a list of the machines that were analyzed and the problems that the analysis identified. Additional information about the data used by the system in the formulation of its final diagnosis can be requested. This report often contains more useful information than an exceptions analysis, because it gives the analyst an idea of what might be wrong with the machine and at what locations the specific faults were identified. However, analysts must utilize heuristic knowledge and personal experience in their formulation of a clear and concise machine fault diagnosis. Automated fault diagnostic systems are quite underdeveloped in this area. As a result, expert systems often identify potential faults on almost every machine that they analyze, and they are also generally not concise in their diagnosis, listing several alternatives for each diagnosed fault. This characteristic is often useful to an analyst if the automated diagnostic system is being used in a troubleshooting mode. However, the use of an expert system in this manner is not implemented until a later phase in the analysis process. One reason for the diagnostic imprecision of expert systems is that they must be designed to be conservative in nature. A single instance of a missed diagnosis resulting in a machine failure could severely discourage the further use of the diagnostic system. Iterating upon the designs of the current expert systems that are

applied in the predictive maintenance industry will eventually provide more a effective screening tool that can be used to analyze large amounts of vibration data.

5.2.3 Time Waveform Analysis

Another technique that may be utilized during the screening phase of the vibration analysis process is the examination of the time waveform. For an experienced vibration analyst, a glance at the time waveform data for a given machine can be quite informative. The time waveform gives a record of the machine's vibration for a few shaft revolutions. This allows an analyst to identify periodic or sinusoidal patterns that may be present in the data. In the time waveform, these sinusoidal vibration patterns appear to oscillate above and below the time axis with a fixed frequency than can generally be calculated quickly and accurately. Vibration analysis software often can display lines on a plot that represent the start of each shaft revolution. The presence of these revolution markers on a time waveform plot make the frequency of a strong sinusoidal vibration recognizable without the need for any calculation [BRA-9]. Sinusoidal vibrations often have less prominent, high frequency signal components that are also visible in a time waveform plot. Low-frequency, synchronous peaks in the spectral data can often mislead an analyst into thinking that there is periodic, sinusoidal vibration occurring in the machine. This assumption can mislead an analyst to believe that the problem is most likely imbalance or misalignment. The vibration that appears to be occurring periodically in the spectral data can in fact be a result of impacts that are occurring at these synchronous frequencies [BRA-17]. This misdiagnosis can be potentially dangerous, because the energy that is being released sinusoidally is generally far less damaging than an equal amount of energy

that is released by the system in an impact. This is due to the fact that for an impact, the length of time during which the system releases, and consequently reabsorbs, a fixed amount of energy is only a fraction of the period over which the sinusoidal vibration occurs. Perhaps the most severe set of circumstances is when there are severe impacts present that are superimposed upon a low-frequency sinusoidal vibration pattern, which itself has high oscillatory levels.

The presence of impact phenomena, such as bearing defects, looseness, and rotor rubs, is more distinct in the time waveform data than in the spectral data. One reason is that impacts are relatively random in nature and often slightly variable in frequency. This is important because spectral data is most commonly composed of several spectra that have been averaged together in the data collector at the time that the readings were taken. In the frequency domain, spectral averaging insures that the spectrum is representative of the steady-state vibration of the machine, but this technique filters out distinct transient events, such as impacts. The visual effect in the frequency domain of this averaging process is the smearing of a low-amplitude peaks that represent impacts across a range of frequencies. Another advantage of the time waveform is the intuitive relationship between the data being displayed in acceleration and the severity of any faults that may be present. Since the analyst has an idea of the mass of the machine from which he took a given reading, he has an idea of the force that is being generated by the impacts that are present in the time waveform data. The force that is associated with an impact is what actually damages machinery components. In the frequency domain, the conversion of a spectral peak from the velocity units in which the data is commonly displayed to a measure of

force is a more complicated and less intuitive mental operation. However, it should be noted that in order for a time waveform signal to contain the information that is necessary for accurate diagnostics to be performed, the data must be sampled at a fast enough rate so that the discrete data points accurately represent the continuous signal. Figure 5.1 shows the effect of using six different sampling rates for six different readings at the same measurement point. The labels on the right vertical axis give the $F_{\max}$ of each of the displayed spectra, which along with the number of lines of resolution, determines the sampling rate of the data that is collected. It can be seen that for the continuous signal to be accurately represented by the discrete data points, the $F_{\max}$ of the spectrum needs to be around 2000 Hz in this case.

From the previous discussion, it can be seen that the time waveform generally contains the information that is needed for an analyst to determine whether or not a vibration pattern that is being exhibited by a machine is critical to its continued operation. This is the goal of the first phase of the vibration analysis process. If a machine is not in danger of a catastrophic failure, then in most condition monitoring programs, the analyst's time is more efficiently used to further examine machines that are exhibiting dangerous levels of vibration. This is the case in most vibration analysis programs, because the analyst finds more machines that require corrective action than the production and maintenance personnel are willing to immediately remove from service for repair.

Since the time waveform has the information that is required to determine if a machine is operating with significant risk of failure, some might ask why the previous screening methods focus almost solely on the spectral data. One reason is that the

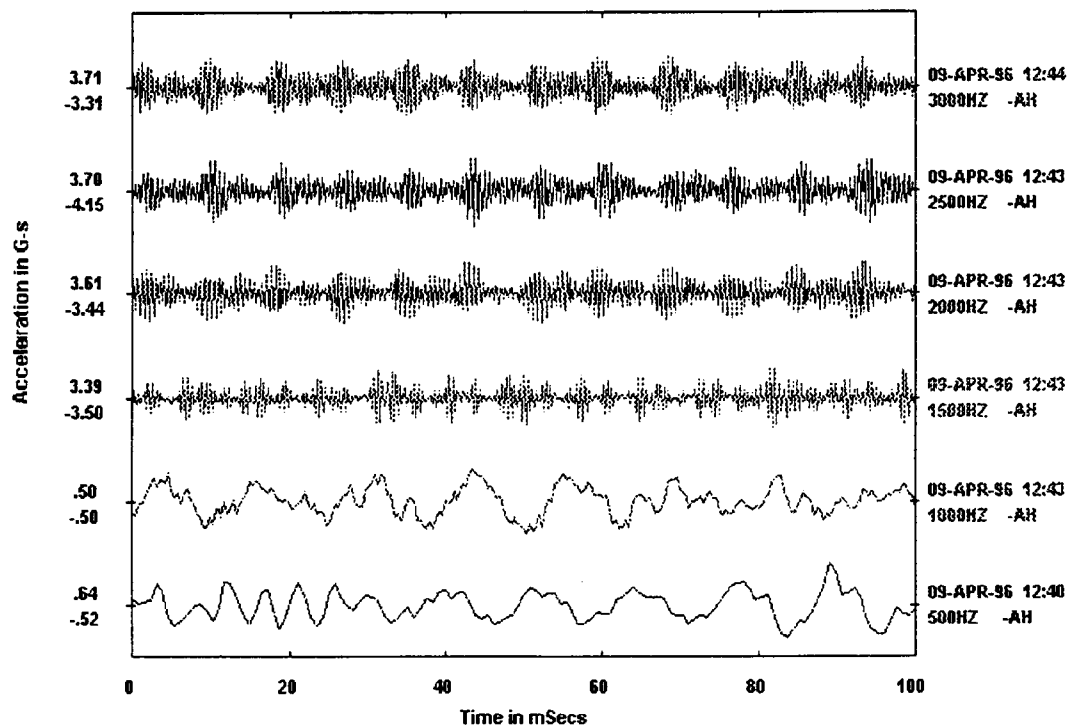


Figure 5.1. Effect of Sampling Rate on Collected Time Waveform Data

information contained in the time waveform is not easily extracted into calculated values with which most vibration analysts are familiar. Extracting a set of parameters from the time waveform data which characterize the fault conditions that commonly occur and for which effective alarm levels can be defined is the goal of this thesis. The parameters that will be calculated from the time waveform data can be compared to the applied limit criteria in order to determine if a given machine requires further examination by the analyst. The degree of automation of this waveform analysis technique is equal to that of the exceptions analysis reporting technique discussed previously. The percentage of machines that are effectively screened, so that no additional analysis is required by the analyst, will be shown to be significantly higher.

5.3 Precise Fault Diagnosis

Once the machines that require further attention by the analyst have been identified, the analyst must determine which machines to remove from service for repair. The analyst must also determine the faults that are present for each machine, as well as a measure of severity for each fault. Estimating the length of time before the machine fails is also part of this phase of the analysis. Determining faults and their corresponding severities is a complex process, and an analyst often relies on a number of diagnostic tools in order to reach a final, definitive diagnosis. Automated fault diagnostic systems are often more effective in this phase of the analysis process than in the screening phase [PIE-2]. Using an expert system as a diagnostic tool gives an analyst an additional, "expert" opinion of the faults that are present in the machine. Once faults have been identified, analysts often

examine how the vibration levels are changing over time in order to estimate the time until failure. Further discussion of the details of the analytical process that leads to a final machine diagnosis is beyond the scope of this thesis.

CHAPTER 6

PARAMETER DETAILS AND IMPLEMENTATION

6.1 Waveform Parameter Overview

The waveform analysis parameters that are defined in this thesis are used to characterize potentially damaging fault patterns that may be evident in time waveform vibration data. Their algorithmic implementation is intended to simulate a human's recognition of the presence of fault conditions in rotating machinery. The parameters themselves are divided into three groups, and these three parameter types are used conjunctively to detect the presence of potentially damaging fault conditions. The first group is designed to detect the presence of impacts in the time waveform data. The presence of impacts is most commonly a symptom of bearing defects or looseness. The next group of parameters characterizes the amount of sinusoidal vibration that is present in the time waveform data. These sinusoidal parameters are effective at detecting potentially damaging sinusoidal vibrations at frequencies below five times the turning speed of a machine. The sinusoidal parameters are most effective at identifying "one times running speed" phenomena, which are commonly an indication of an imbalance or misalignment. The third group of waveform parameters characterize the repeatability of the time waveform data. This is achieved by comparing the energy that is present in certain sections of the time waveform signal. The sections of the time record that are compared to each other correspond to the same relative position of the shaft for each of the

individual revolutions that are represented by the data. The presence of repeatable vibration patterns tends to diminish an analyst's certainty of the presence of random phenomena, such as looseness or later stage bearing defects.

6.2 Division of Time Waveform

One characteristic that is common throughout the definition of the waveform parameters is the fact that the time waveform is first divided into separate intervals that represent individual shaft revolutions. A section of the time waveform data that corresponds to a single shaft revolution is then further subdivided into five equal subintervals for some parameter calculations, and it is also divided into twenty equal subintervals for other calculations. Figure 6.1 shows an example of an individual shaft revolution that has been divided into five equal subintervals. Examination of the time record by dividing it into sections that correspond to individual shaft revolutions is a technique used by vibration analysts to help in the identification of fault conditions that have characteristic vibration patterns that are multiples of the machine's shaft turning speed.

The subdivision of the shaft revolutions is based on the assumption that an analyst can only interpret a finite amount of information at once. It is impractical for a human to consider the significance of each data point in a time waveform. As a result, an analyst must mentally divide the data points of a time waveform into certain regions of interest. This mental division results in the consideration of groups of data points, as opposed to an analyst examining each individual data point. Since there are generally over one thousand

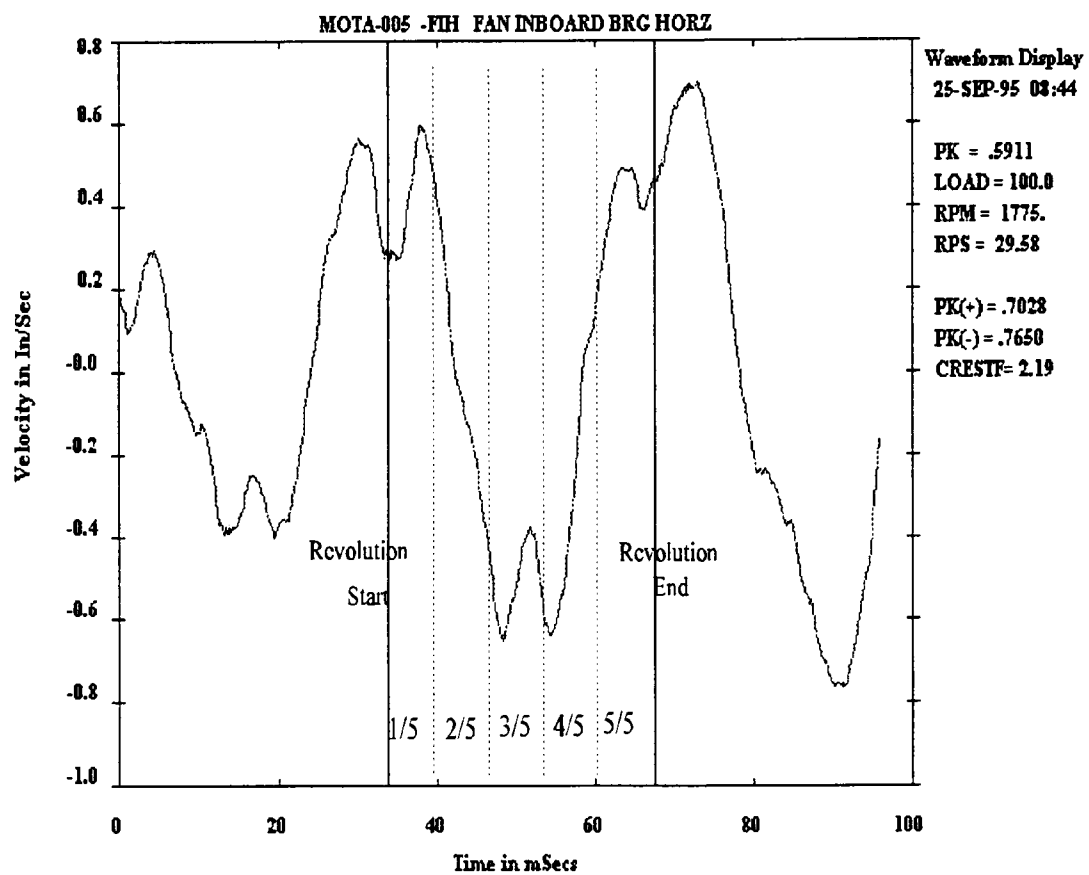


Figure 6.1. Division of Waveform Into Revolution Subintervals

data points in a time waveform signal, this type of organization is essential for an analyst to formulate an opinion regarding the condition of the machine from which a reading is taken. Five revolution subintervals are used to perform a relatively coarse examination of the time waveform, and this simulates an analyst's opinion when first seeing a given time waveform signal. Twenty revolution subintervals are used to calculate parameter values that more closely approximate the true behavior of the time waveform data. The division of the time waveform into intervals and smaller subintervals plays an important role in the calculation and implementation of each of the three parameter types. The significance of this technique as it relates to each of the individual waveform parameters will be discussed when the parameters are presented individually.

6.3 Impact Detection Parameters

The impact detection parameters utilize the revolution division technique by bounding the amplitude of each revolution subinterval at both the positive and negative extremes. The upper bound across the subinterval is defined as the value of the highest positive peak. The most negative peak that is present in each revolution subinterval serves as a lower bound. For calculations that involve dividing the individual shaft revolutions into five intervals, this results in five regions that each have a set of upper and lower bounds. For the calculations involving twenty revolution divisions, each revolution of the time waveform is organized into twenty subintervals, and each of these subintervals has its own pair of upper and lower bounds. Figure 6.2 shows an example of a time waveform where one revolution is divided into twenty subintervals, and the upper and a lower

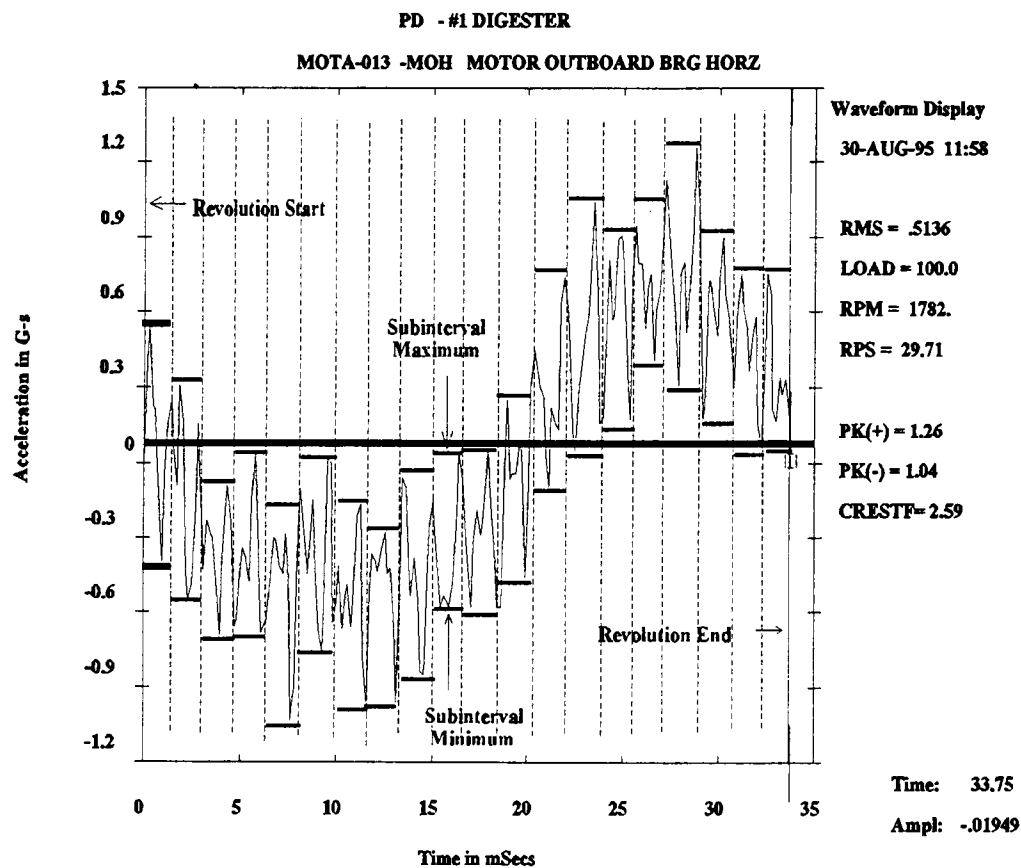


Figure 6.2. Twenty Revolution Subintervals With Upper and Lower Bounds

bounds can also be seen in the figure. The values of the waveform parameters presented in this thesis are generally normalized for an individual shaft revolution. The technique that is used to normalize the individual waveform parameters is presented separately with their definition. Normalization of the parameters is necessary because the number of shaft revolutions that are represented by a stored time waveform signal varies with the data sampling rate. The speed of the machine from which data is collected also directly affects the number of shaft revolutions that are represented by the time waveform data. Since these parameters may vary considerably for different readings that are taken, parameter normalization helps to insure the consistency of the calculated parameter values.

6.3.1 IMPRAT

The first impact parameter that is described will be referred to as IMPRAT. IMPRAT is designed to measure the distinctiveness of an impact relative to the nominal level of vibration of the entire time waveform. This parameter is calculated by taking the largest amplitude difference that is present between the positive and negative bounds of each subinterval. The value of the largest amplitude difference is then divided by the absolute average vibration level (ARMS) that is calculated for the waveform. IMPRAT is defined by

$$\text{where} \quad \text{IMPRAT} = \max (y_{\max_i} - y_{\min_i}) / \text{ARMS} \quad (6.1)$$

$y_{\max_i}$ = maximum value of subinterval i

$y_{\min_i}$ = minimum value of subinterval i

i = subinterval with highest amplitude difference

The ARMS value of a waveform is the average of the absolute value of the amplitude of each of the individual data points present in the time waveform. The maximum amplitude difference is found by examining twenty subintervals per shaft revolution, as opposed to five subintervals. Figure 6.2, presented in the previous section, shows a time waveform where data representing a single shaft revolution has been divided into twenty separate subintervals. IMPRAT can be calculated for this waveform by taking the largest amplitude difference of all the subintervals that are present and then dividing this value by the absolute average of the data points present in the waveform.

IMPRAT is sensitive to changes in the overall energy of the waveform and the size of the impacts that are present. If this parameter is calculated using the root-mean-square (RMS) value of the waveform, instead of the ARMS level, then the calculated values are less sensitive to changes in the overall level of vibration. It should be noted that this calculation will be the most accurate if the maximum peak to peak energy that is released during an impact is captured within a single revolution subdivision. The calculated value of IMPRAT can be misleading if an impact occurs across a revolution subinterval boundary. At present, the algorithm does not attempt to check for this set of circumstances.

IMPRAT most often gives an indication of middle-stage rolling element bearing defects. In a middle-stage bearing defect, the impacts are generally distinct relative to the nominal level of vibration of the time waveform. In this type of machinery fault, the condition of the bearing's components has not degraded significantly. Figure 6.3 is an example of a time waveform with significant, distinct impacts, and for which the calculated

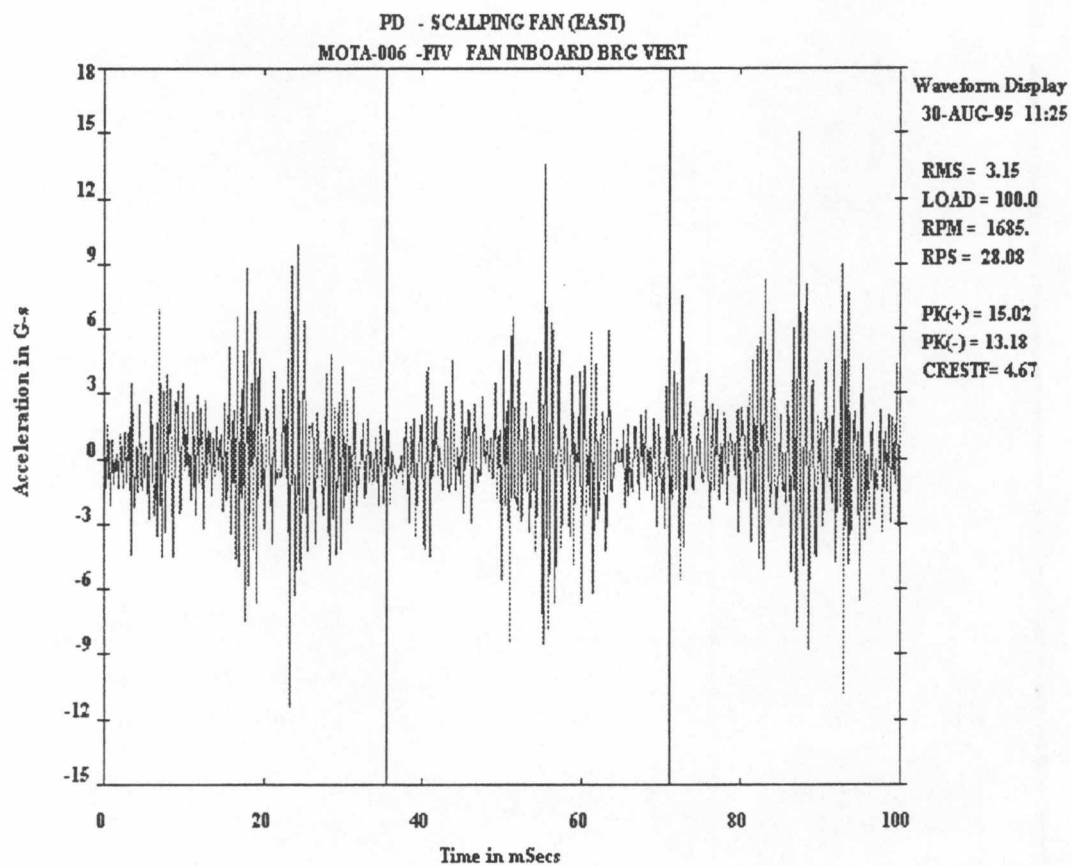


Figure 6.3. Middle-Stage Bearing Defect

value of IMPRAT is 11.0. The largest amplitude difference for all of the subintervals present in the time waveform is 22.75 g's, and the ARMS for the waveform is 0.48 g's.

6.3.2 IMPAREA

The second impact detection parameter will be referred to as IMPAREA. The calculation of IMPAREA is derived from the fact that when an impact occurs, the level of vibration first reaches a peak and then attenuates. In late-stage rolling element bearing defects, impact attenuation can involve a significant amount of potentially destructive energy. The total amount of energy that can be associated with a given impact and its attenuation is represented by IMPAREA. IMPAREA is calculated by

$$\text{IMPAREA} = \left(\sum_{i=1}^r \sum_{j=1}^n (y_{\max_j} - y_{\min_j}) * \text{width}_j \right) / r \quad (6.2)$$

where

r = number of shaft revolutions represented by waveform

n = number of subintervals per shaft revolution

$y_{\max_j}$ = maximum value in subinterval j

$y_{\min_j}$ = minimum value in subinterval j

width_j = duration of each subinterval

IMPAREA sums the area that is contained between the upper and lower bounds of all of the subintervals that are present in a time waveform. The total calculated area is then divided by the number of shaft revolutions that are represented by the data so that the parameter calculation is consistent for different data sets. The individual subinterval areas

can be seen in Figure 6.2 as the regions that are bounded horizontally by the revolution subinterval designations and vertically by the subinterval's upper and lower bounds.

A significant value calculated for this parameter most commonly indicates a late-stage bearing defect. As a rolling element bearing degrades, more energy will be released during the attenuation process, and it will be released over a longer period of time. This can be attributed to the fact that as the individual rolling elements of a bearing degrade, they lose their geometrical integrity. This degradation results in the internal components having greater clearances than those that were present in the original design. The damaged components no longer roll smoothly along the inner and outer races of the bearing. These characteristics that are associated with bearing degradation result in the resonance of the individual bearing components. This component degradation also results in an inefficient vibration transmission path from the point of an impact to the environment away from the immediate vicinity of the bearing. If the components of a bearing have not severely degraded, then the energy that is released in an impact can be transmitted efficiently away from the location of the impact. This diminishes the amount of time over which attenuation occurs in the localized area of the initial impact, and thus reduces the total amount of energy released to the bearing's components. Figure 6.4 shows an example of a time waveform taken from a machine with a bearing defect where the components have degraded severely, and for which the calculated value of REVAREA is 125.0. This waveform shows impacts where the energy level remains significant as the impact energy attenuates for almost the entire duration of each shaft revolution.

A significant value of IMPAREA can also indicate the presence of certain electrical

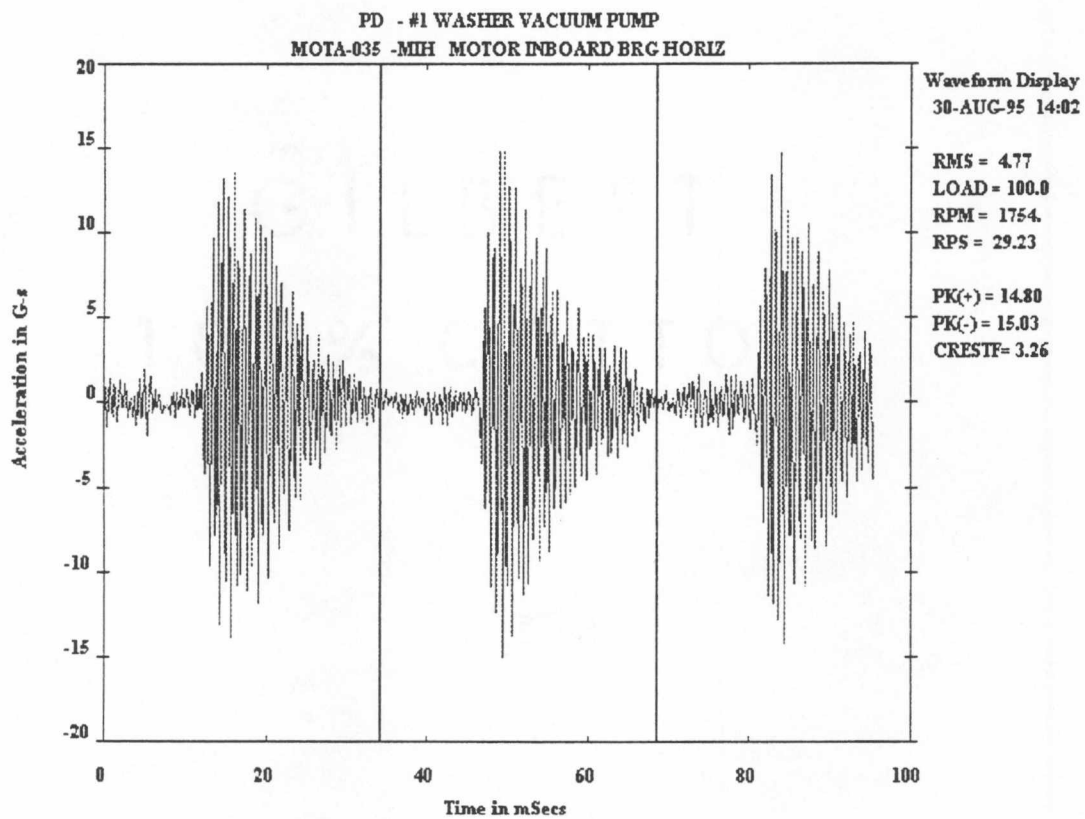


Figure 6.4. Late-Stage Bearing Defect

faults. Figure 6.5 shows a time waveform representing an electrical fault in an AC induction motor. Common electrical faults that may be present in induction motors include eccentric rotors, broken or cracked rotor bars, stator eccentricity, and shorted stator laminations. The energy being released in Figure 6.5 is not exactly in the form of impacts. The vibration that is shown in the figure is a repeatable, high frequency, sinusoidal vibration of significant amplitude. One can imagine that this level of vibration when released consistently at such a high frequency can be quite damaging to a machine. A value of 150.7 was calculated for IMPAREA from the time waveform shown in Figure 6.5.

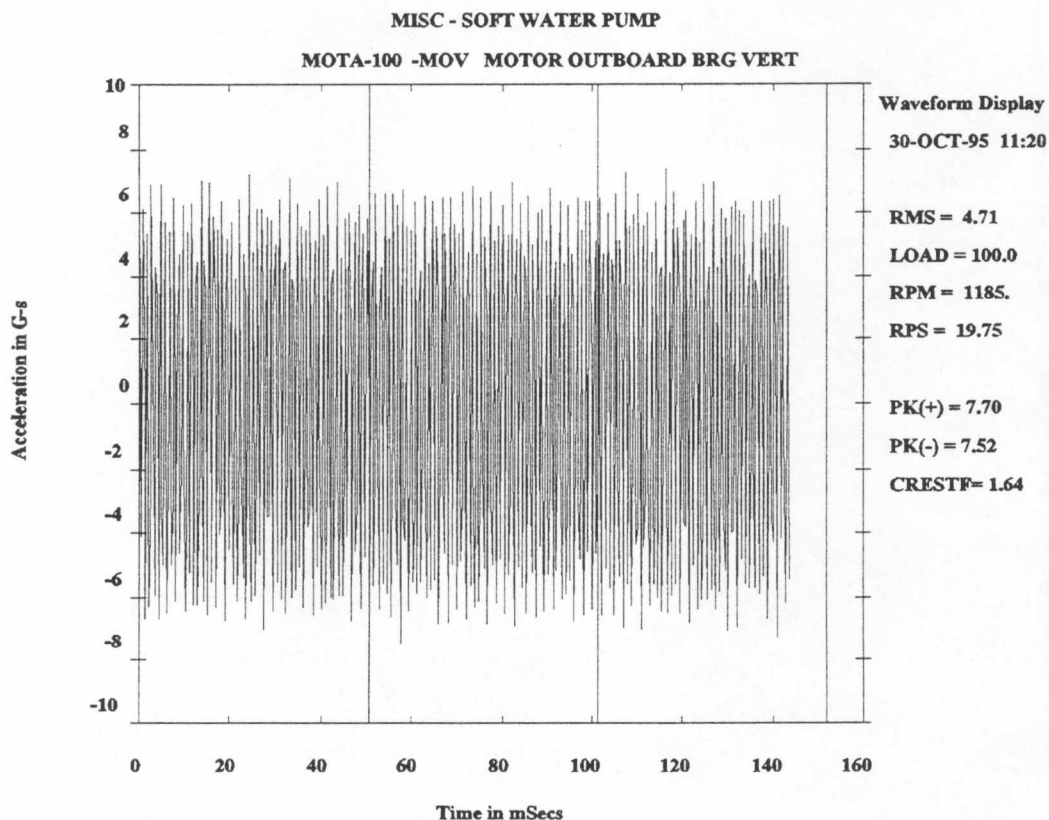


Figure 6.5. Electrical Defect in AC Induction Motor

Looseness conditions can also be suggested by a significant value of IMPAREA. An example of this type of fault condition is a machine that has a loose restraint, such as a bolt. The machine may also have an internal rotating component that no longer fits precisely with a stationary component. No matter the exact type of looseness that is present, this type of fault condition generally involves highly random impacts. When impacts are present at significant levels, they can severely damage a machine, regardless of the exact source of the impact.

6.3.3 IMPRMS

The third impact detection parameter, IMPRMS, is derived from the IMPRAT parameter. It is designed to detect early-stage bearing defects. IMPRMS is calculated by dividing IMPRAT by the overall RMS energy of the waveform. The equation for calculating IMPRMS is

$$\text{IMPRMS} = \text{IMPRAT} / \text{RMS} \quad (6.3)$$

where IMPRAT is calculated by Equation 6.1 and RMS is the root-mean-square energy level of the entire time waveform. IMPRMS is designed to identify a problem when there is a significant value calculated for the IMPRAT parameter and a notably low RMS value. Thus a time waveform from which a significant value of IMPRMS can be calculated contains data representing distinct impacts and a significantly low overall energy level. In a case where this parameter signals a potential problem, there is generally an insignificant value calculated for the IMPAREA parameter.

The presence of a value of IMPRMS greater than about one hundred generally

signals the presence of an early-stage rotating element bearing defect. Figure 6.6 shows an example of such a machinery fault. The figure shows that there is a fault present that involves distinct impacts, yet the overall levels are still relatively low. These low overall levels are not an immediate threat to the operating condition of the machine, but the distinct impacts signal that there is a bearing defect whose condition will degrade. A value of 146.6 was calculated for IMPRMS from the time waveform displayed in Figure 6.6.

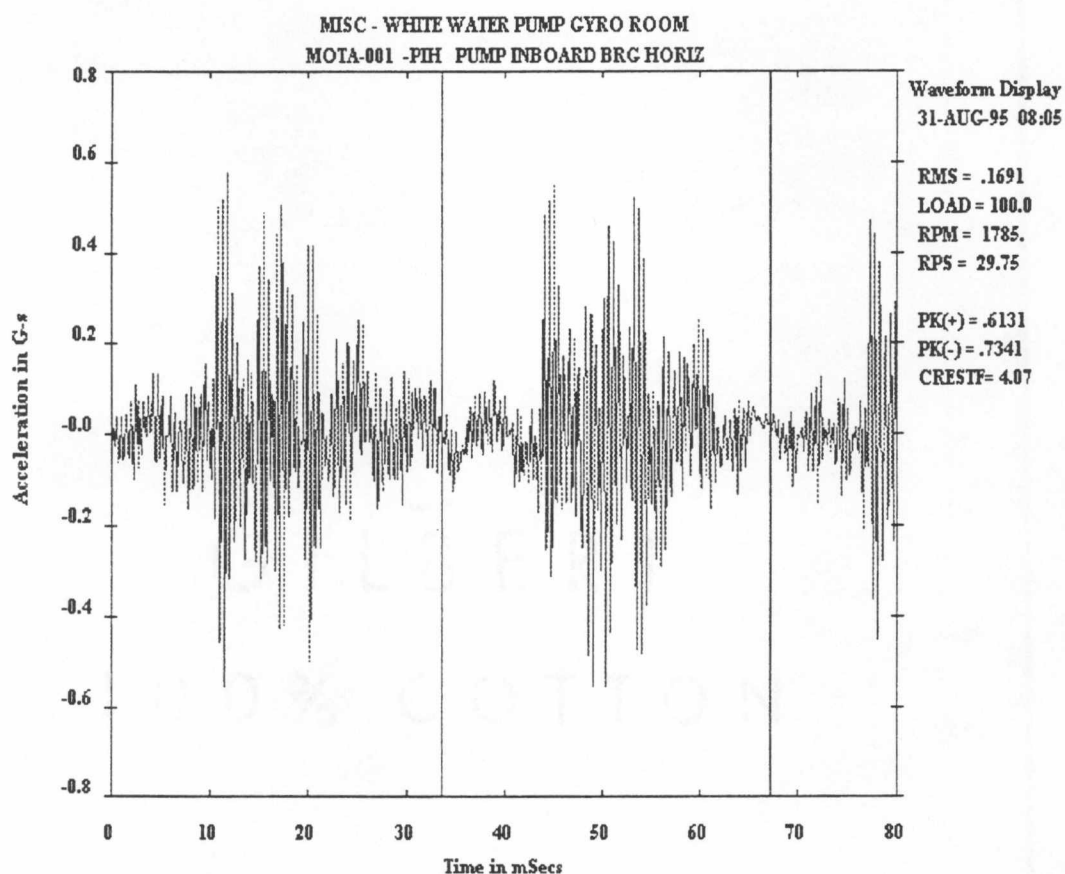


Figure 6.6. Early-Stage Bearing Defect

6.4 Sinusoidal Defect Detection Parameters

The next group of parameters that will be discussed can be used to detect the presence of significant sinusoidal vibration in time waveform data. Low-frequency sinusoidal vibration in rotating machinery most commonly indicates an imbalance or a misalignment condition. A directional resonance condition may also be present if significant sinusoidal vibration amplitudes are notably higher in a single orientation. The sinusoidal fault detection parameters are also effective when significant impacts are present in the waveform in addition to sinusoidal vibration patterns. These parameters can detect underlying sinusoidal vibrations even when impacts visually dominate the time waveform. This allows the sinusoidal parameters to be used in conjunction with the impact parameters to identify cases where multiple machinery faults may be present. As with the impact detection parameters, the calculation of the sinusoidal detection parameters relies on the technique which divides the time waveform into intervals that correspond to the individual shaft revolutions that are present. These sections of the time waveform data are then subdivided into five and also twenty equal subintervals.

6.4.1 SINARA and SINARC

The first sinusoidal detection parameter to be discussed will be referred to as SINARA.

Two different calculations of SINARA will be identified by the subscripts $_5$ and $_{20}$, where the subscript denotes the number of subintervals used in the parameter's calculation.

SINARA $_5$ and SINARA $_{20}$ are both calculated by first finding the average value of the data points located in a given subinterval. An area calculation is then performed by taking the magnitude of the average vibration level and multiplying it by the width of the subinterval.

These individually calculated areas are summed for the entire time waveform, and the total area is then normalized by dividing it by the number of shaft revolutions that are represented by the time waveform. The equation for this calculation is

$$\text{SINARA} = \left(\sum_{i=1}^r \sum_{j=1}^n |y_{\text{avg}_j}| * \text{width}_j \right) / r \quad (6.4)$$

where

r = number of revolutions

n = number of revolution subintervals

Figure 6.7 shows a single revolution of a time waveform signal that has been divided into twenty subintervals. The figure also shows the average value for each of these subintervals. Figure 6.8 shows a complete time waveform, and the calculated value of SINARA_{20} in this figure is 2.6. SINARA is derived from the fact that a time waveform that has significant sinusoidal vibration present will have certain regions whose average vibration level deviates from zero. If there is no low-frequency sinusoidal vibration caused by imbalance or misalignment, then the average level of vibration for each revolution subinterval will be approximately zero. Thus, high levels of SINARA_5 and SINARA_{20} indicate that certain regions of a time waveform have average vibration levels that are not close to zero.

Two additional waveform parameters will be referred to as SINARC_5 and SINARC_{20} . These parameters are similar to the two SINARA parameters, the difference that in the calculation of the SINARC parameters, the average vibration level of each subinterval is not used. Instead, the central value of the region is used for the calculation.

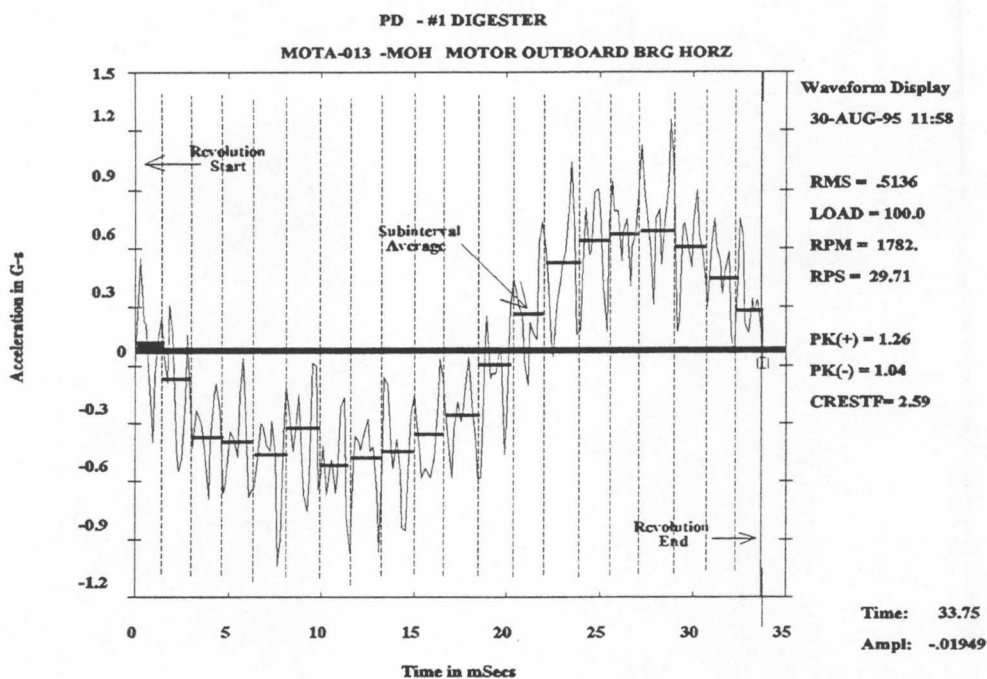


Figure 6.7. Time Waveform With Average Subinterval Values Identified

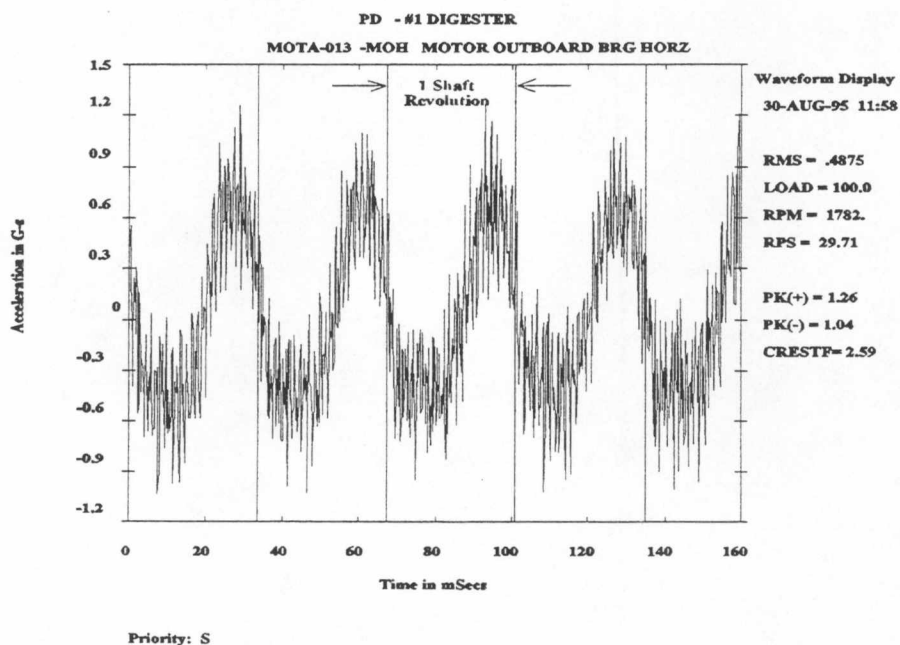


Figure 6.8. Time Waveform With Significant Sinusoidal Vibration

This central value is simply the average of the two highest and lowest data points that are present in a given subinterval. The SINARC parameters work in conjunction with the SINARA parameters to prevent false alarms when identifying potential sinusoidal fault patterns.

6.4.2 SINCORA and SINCORC

The SINCORA parameter measures the correlation between the values calculated for $SINARA_5$ and $SINARA_{20}$. The degree of correlation between the calculated values of the SINARA parameters gives an idea of the frequency of a sinusoidal vibration that may be present. SINCORA is calculated by dividing $SINARA_5$ by $SINARA_{20}$. The equation for SINCORA is

$$SINCORA = SINARA_5 / SINARA_{20} \quad (6.5)$$

If the vibration that is present has a frequency equal to the rotational speed of the shaft, then the values that are calculated for $SINARA_5$ and $SINARA_{20}$ will correlate closely. This will result in a calculated value of SINCORA that is close to unity. For a sinusoidal frequency equal to the rotational speed of the shaft, both calculations can accurately represent the behavior of the simple underlying sinusoidal vibration.

A value of SINCORA that is close to unity generally indicates a sinusoidal vibration whose frequency is equal to the machine's shaft speed. Figure 6.8 illustrates such a time waveform, where the forcing function is clearly tied to the fundamental rotational speed of the shaft. A value of 0.98 was calculated for SINCORA from the time waveform in Figure 6.8. In this case, an accurate and practically equal area approximation

was calculated for both $SINARA_5$ and $SINARA_{20}$. Fault conditions such as misalignment can generate significant levels of sinusoidal vibration whose frequency is a multiple of the shaft's turning speed. In a case such as this, $SINARA_5$ cannot accurately represent the behavior of the more complex sinusoidal vibration. This is a direct result of the fact that $SINARA_5$ divides the time waveform data corresponding to each shaft revolution into only five subintervals, and this does not allow an accurate area approximation to be calculated for $SINARA_5$. Consequently, the value that is calculated for $SINARA_5$ does not correlate closely to the value that is calculated for $SINARA_{20}$. This results in a value of $SINCORA$ that is less than unity. Figure 6.9 shows a time waveform with significant sinusoidal vibration present, and the frequency of the sinusoidal vibration is equal to three times the rotational speed of the shaft. $SINARA_5$ was calculated to be 1.34 in this figure, and $SINARA_{20}$ was calculated to be 2.2. These values result in a calculated value of 0.61 for $SINCORA$. The calculation and interpretation of $SINCORC$ is similar to that of $SINCORA$, but this parameter uses the two values of $SINARC$ for the ratio calculation. This parameter is used along with $SINCORA$ to prevent false alarms when identifying potential machinery faults.

6.5 Repeatability Parameter

The final waveform parameter is referred to as $REPEAT$. It is used to determine if the levels of a vibration pattern are repeatable for the different shaft revolutions that are present in a time waveform. $REPEAT$ is calculated by finding the ARMS vibration level for each of the twenty revolution subintervals. Beginning with data representing the

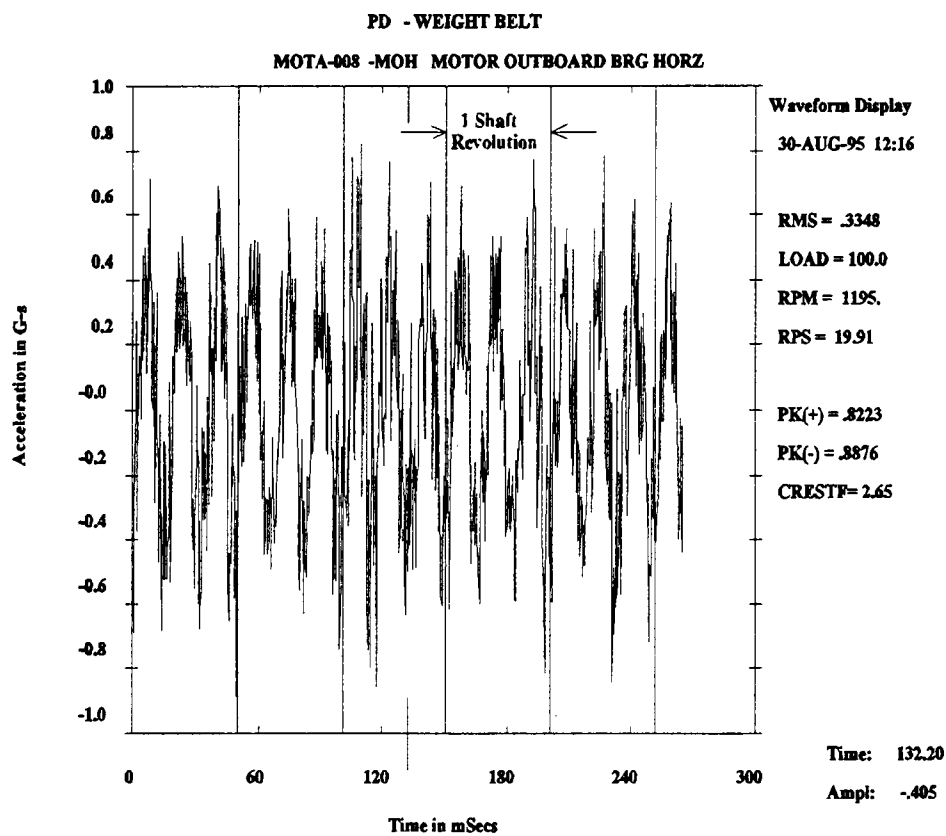


Figure 6.9. Sinusoidal Vibration With Frequency Equal To Three Times Shaft Speed

second shaft revolution in the time waveform data, the ARMS energy of the subinterval is subtracted from the value that was calculated for the subinterval corresponding to the same relative shaft position in the previous revolution. The square root of the absolute value of these individual differences is summed for each revolution subinterval, beginning with the second revolution and continuing until the end of the time record. The value representing the sum of the individual differences is then divided by the number of subintervals over which the summation is performed. This average value is then subtracted from unity. REPEAT can be calculated by

$$\text{REPEAT} = 1 - \frac{\sum_{i=1}^n |a_{ij} - a_{(i-1)j}|^{1/2}}{(i-1)*j} \quad (6.6)$$

where

a = subinterval ARMS

i = revolution index

j = relative subinterval index

n = number of revolutions

The calculated value of REPEAT gives an idea of the correlation between the nominal vibration levels present in the subintervals which correspond to the same relative shaft position. A value close to unity can be interpreted to mean that there was little difference in the vibration levels present from revolution to revolution.

It should be noted that a time waveform must contain data representing at least two shaft revolutions for this parameter to be calculated, but the setup of the proper data

collection parameters in the database can insure that data representing at least two shaft revolutions is captured during data collection. When significant vibration levels are present, REPEAT is useful in identifying faults such as imbalance, misalignment, and electrical defects, since these fault patterns are generally quite repeatable. If significant vibration levels are present, low values calculated for REPEAT often indicate the presence of random machinery faults, such as looseness and some bearing defects. Figure 6.8 shows an example of a time waveform illustrating a repeatable vibration pattern, since the levels remain relatively constant for a given subinterval from revolution to revolution. A value of 0.84 was calculated for REPEAT using the waveform in Figure 6.8.

6.6 Diagnostic Rule Development

To this point, the individual parameters that are designed to detect faults in rotating machinery by analyzing their time waveform signature have been defined. Effective detection of fault patterns in time waveform vibration data requires that the calculated values of these parameters be considered simultaneously. The presence of a fault pattern is generally reflected by significant levels in more than one of the defined waveform parameters. If individual parameters are used as alarm criteria, then a high false alarm rate will result. In order to design a technique that simultaneously considers each of the parameters calculated for a single time waveform data set, logical rules have been developed that use the waveform parameters in their premises. The diagnostic rules were developed heuristically using vibration data from a condition monitoring program including approximately 140 machines. The machines in this vibration program include a

wide variety of production and support equipment. A list of the machines included in the condition monitoring program can be found in the Appendix. Spectral and waveform vibration data that was collected during the August, 1995, routine measurement survey was used as the training data set in order to develop the rules that are used to detect machinery faults. The reported fault diagnoses of the analyst responsible for this condition monitoring program were also used to develop and optimize the set of diagnostic rules.

For the time waveform data associated with machines reported to be operating with a significant fault present, the calculated levels of the waveform parameters were examined. At this point, the definition of "significant," when referring in this thesis to machinery faults, should be established. An analyst's definition of a significant fault is tied to the priority code that he assigns as part of a final machine fault diagnosis. Table 6.1 shows a commonly accepted set of priority codes.

Table 6.1. Machine Fault Diagnosis Alarm Priority Codes

Priority	Explanation	Machine Status
1	Immediate Attention	Failure Imminent
2	High Alarm	Repair At Earliest Opportunity
3	Alarm	Repair Next Scheduled Outage
4	Low Alarm	No Immediate Action
5	Other	Additional Testing Recommended

In this thesis, only fault conditions rated as a Priority 1 or Priority 2 are considered to be "significant" when classifying machinery faults. This decision is based on the fact that the significance of faults receiving a rating below Priority 2 is often interpreted differently by various analysts. For the fault conditions which received Priority 1 and Priority 2 ratings,

the waveform parameters were identified that tended to be associated with the diagnosed fault. The next step was to define levels of the calculated parameters that tended to indicate the presence of the diagnosed Priority 1 and Priority 2 machinery faults. At this point, the values of the individual waveform parameters were calculated for each time waveform data set included in the August measurement survey. These values were used as the inputs for the diagnostic rules. If the premises of a given rule were satisfied, then it was triggered. This was interpreted to mean that a given piece of data required further examination by a vibration analyst. The diagnostic rules were optimized by comparing the output of the rules for each machine considered to the machines with reported faults in the analyst's diagnostic report. This optimization included an attempt to have at least one of the diagnostic rules fire for each of the machines that were diagnosed with a fault condition by the analyst. For the machines that were not reported by the analyst, an attempt was made to have no rule fire for the data sets that were associated with that machine. This is in effect a screening technique that is designed to identify only machines that require further examination by an analyst, thus filtering out the machines which are operating in an acceptable state. Table 6.2 shows the five rules that were developed for bearing fault and looseness detection. The table includes the waveform parameters and their calculated levels that must be present for the individual rules to fire. Table 6.3 shows the rules that were developed for detecting faults involving sinusoidal vibration patterns. Table 6.4 shows the rules that were developed to detect electrical defects in rotating machinery.

Table 6.2. Impact Detection Rules

	Diagnosed Fault	REVPAR(20)	IMPRAT	IMPRMS	APERTOT
1)	Bearing/Looseness 1	≥ 40	≥ 8.0		
2)	Bearing/Looseness 2	≥ 25	≥ 10.0		
3)	Late Bearing 3	≥ 85	≥ 7.0		
4)	Late Bearing 4	≥ 75	≥ 7.0		≥ 0.70
5)	Early Bearing 5		≥ 12.0	≥ 100	≥ 0.75

Table 6.3. Sinusoidal Fault Detection Rules

	Diagnosed Fault	SINARA(20)	SINARC(20)	SINPARA	SINPARC	APERTOT
1)	Sinusoidal 1	≥ 1.25	≥ 1.25	≥ 0.75	≥ 0.75	≥ 0.80
2)	Sinusoidal 2	≥ 1.25	≥ 1.25	≥ 0.95	≥ 0.95	
3)	Sinusoidal 3	≥ 1.50	≥ 1.50	≥ 0.75	≥ 0.75	
4)	Sinusoidal 4	≥ 1.50	≥ 1.50	< 0.75	< 0.75	≥ 0.75
5)	Sinusoidal 5	≥ 2.00	≥ 2.00	max ≥ 0.75 / min < 0.75		≥ 0.75
6)	Sinusoidal 6	≥ 3.00	≥ 3.00			

Table 6.4. Electrical Defect Detection Rules

	Diagnosed Fault	REVPAR(20)	SINARA(20)	SINARC(20)	APERTOT
1)	Electrial 1	≥ 50	$(\max \geq 1.5 / \min \geq 1.25)$		≥ 0.90
2)	Electrical 2	≥ 75	≥ 1.5	≥ 1.5	≥ 0.85
3)	Electrical 3	≥ 75	$(\max \geq 2.0)$		≥ 0.90
4)	Electrical 4	≥ 50	$(\max \geq 2.0)$		≥ 0.95

CHAPTER 7

TESTING PROCEDURE AND RESULTS

7.1 Testing Procedure

To this point, each of the waveform parameters has been presented, and the development of the diagnostic rules that utilize these parameters has also been discussed. We now discuss evaluation of the effectiveness of these rules, which has been performed in two stages. The first stage involved using the diagnostic rules to screen the vibration data that was collected during five periodic measurement surveys. These measurement surveys were performed monthly, beginning in October, 1995, and ending in February, 1996. The diagnostic report that was generated by the analyst responsible for the condition monitoring program was available for each of the measurement surveys. For each machine on which time waveform vibration data was taken, a computer program cycled through the measurement points and calculated the waveform parameters for the correct data set. The calculated waveform parameters were then used as inputs for the diagnostic rules that were presented in Tables 6.2, 6.3, and 6.4. The program's calculation of the individual waveform parameters, their subsequent input into the diagnostic rules, and the generated diagnosis will be referred to as the waveform diagnostic system. Figure 7.1 shows a flowchart of the waveform diagnostic system.

7.2 Diagnostic System Output

The output of the waveform diagnostic system is designed so that only measurement points where the data is in a state of alarm are displayed. Table 7.1 shows an example of the output the waveform diagnostic system. The time waveform that was used to calculate the parameter values shown in Table 7.1 is shown in Figure 7.2. The value of IMPRAT (11.4) shown in Table 7.1 indicates the presence of distinct impacts in a time waveform. The displayed value of IMPAREA (46.0) indicates that some component degradation has occurred, but the value is not high enough to indicate a late-stage bearing defect (see Table 6.2). The low value of IMPRMS (11.5) clearly indicates that this is not an early-stage bearing defect. By examining the levels of the waveform parameters, it can be seen that the first and second rules in Table 6.2 were triggered. These two rules indicate the presence of a middle-stage rotating element bearing defect. A bearing defect was also the analyst's diagnosis for this particular bearing location in his diagnostic report. It should also be noted that the levels of the sinusoidal fault detection parameters and REPEAT were not high enough to fire any of the rules pertaining to sinusoidal faults and electrical defects.

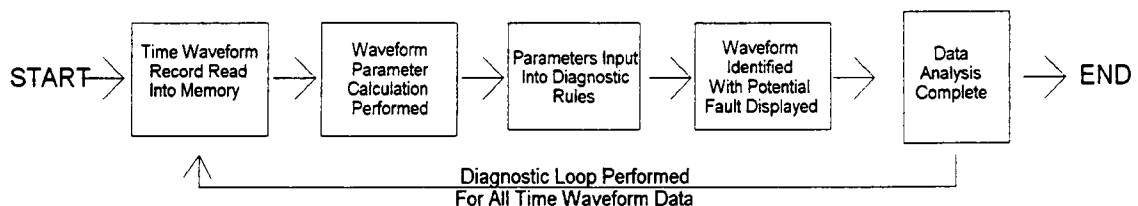


Figure 7.1. Waveform Diagnostic System Flowchart

Table 7.1. Waveform Diagnostic System Output & Rules Triggered

Diagnostic Waveform Parameter Report *****						
Database: Sthncell.dat						
Station: PD BUILDING						
Report Date: 07-APR-97 22:02						
Machine: (PD) SCALPING FAN (WEST)						
Point	IMPRAT	IMPAREA	IMPRMS	SINARA	SINCORA	REPEAT
FOH	11.4	46.0	11.5	.8	.40	.54
[Brng/Looseness 1	>=8.0	>=40.0	N/A	N/A	N/A	N/A]
[Brng/Looseness 2	>=10.0	>=25.0	N/A	N/A	N/A	N/A]

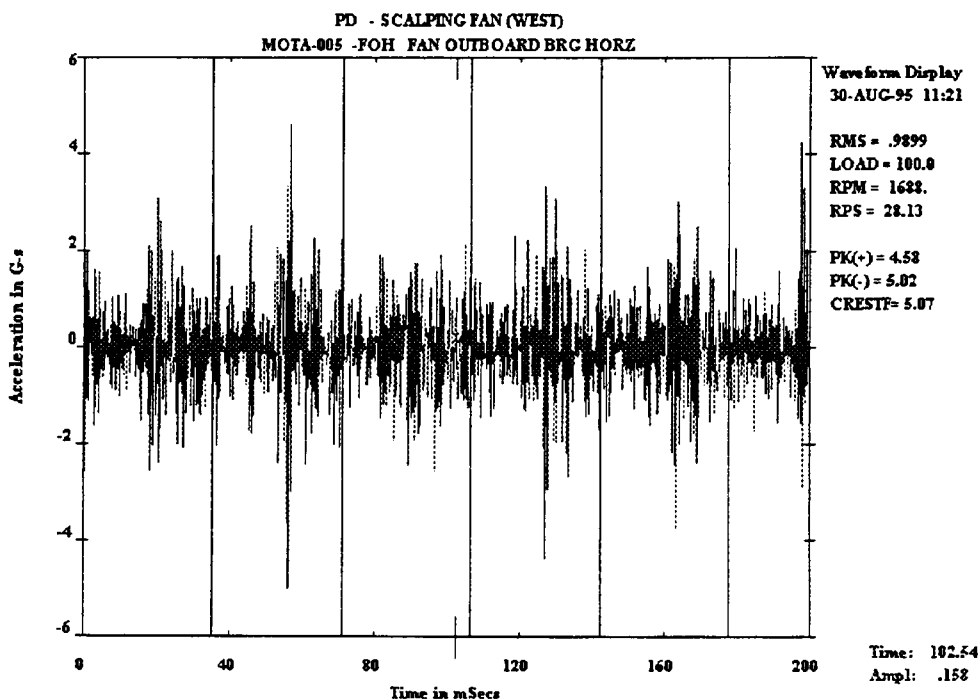


Figure 7.2. Time Waveform Used To Generate Diagnostic Output in Table 7.1

7.3 Using the Waveform Diagnostic System as a Data Screening Technique

The goal of the waveform diagnostic system is simply to screen the time waveform data and not necessarily generate a precise fault diagnosis. It should be recalled that the screening phase of the machinery diagnostic process involves identifying machines which require further examination. For machines that do not require further diagnosis, the output of the screening process should not report any potential faults. As a result, the diagnosis corresponding to a rule that is triggered by the waveform diagnostic system need not match exactly the diagnosis made by an analyst. If the calculated waveform parameters trigger a diagnostic rule, and an analyst also indicates that the machine has a fault present, then this is considered to be a correct diagnosis for the waveform diagnostic system. In a case where an analyst identifies a fault for a given machine and a diagnostic rule is not fired by the waveform diagnostic system, then this is considered an incorrect diagnosis by the system. If a potential fault is not identified by the waveform diagnostic system, then the system effectively screens the machine. In this case the waveform diagnostic system gives the analyst an indication that the data requires no further analysis. For a machine that is screened by the waveform diagnostic system, the screen is considered to be correct if a fault is not diagnosed by the analyst. For the case where the waveform diagnostic system indicates a potential fault, yet a fault is not reported by the analyst, a false alarm is considered to be the result. In the case of such a false alarm, the analyst is incorrectly given an indication by the system that the data associated with a machine requires further examination. Table 7.2 summarizes the four previously discussed diagnostic conditions that can be present depending upon the agreement or disagreement

of the waveform diagnostic system and the reported diagnosis of an analyst.

Table 7.2. Diagnostic Condition Summary

Diagnostic Condition	Waveform Diagnostic System Output	Reported Diagnosis of Analyst
Correct Diagnosis	Potential Fault	Fault Present
Incorrect Diagnosis	No Indication of Fault	Fault Present
Correct Screen	No Indication of Fault	No Fault Present
False Alarm	Potential Fault	No Fault Present

7.4 Waveform Diagnostic System Screening Accuracy

Table 7.3 summarizes the results that were found when comparing the output of the waveform diagnostic system to the diagnoses reported by the analyst responsible for the monitoring of the machines included in the analysis. This table contains the results of the analysis of data collected during six measurement surveys. The first set of entries in the table corresponds to the results of the waveform diagnostic system's analysis of the data that was collected during the August, 1995, measurement survey. It should be recalled that this is the training data set that was used in the iterative development of the diagnostic rules. The results found from analyzing data collected during the October, 1995, measurement survey and the four subsequent surveys are also included in Table 7.3. The overall accuracy of the waveform diagnostic system when identifying faults that were also identified by the analyst was found to be 82%. This value may seem acceptable, but in a condition monitoring program, an analyst needs to be 100% certain that he identifies

Table 7.3. Waveform Diagnostic System Fault Detection Results

Month	Correct Diagnosis	Missed Diagnosis	Diagnosis Percentage	Correct Screen	Incorrect Screen	Screen Percentage
August	8	1	89%	71	29	71%
October	6	1	86%	55	26	66%
November	2	0	100%	81	26	76%
December	3	1	75%	41	35	54%
January	4	2	67%	44	56	44%
February	0	0	N/A	52	46	53%
Total	23	5	82%	344	218	61%

the machines that have a potential to fail before the next measurement survey. The missed diagnoses would likely be quite disturbing to an analyst who was considering allowing the waveform diagnostic system to screen the data collected during a measurement survey.

For the machines that were not identified by the analyst as having a fault condition present, the waveform diagnostic system's effectiveness at screening the data was found to be 61%. Preventing the analyst from having to examine the data associated with the 344 machines that were screened by the waveform diagnostic system translates into a significant savings in time. Consider that approximately twelve measurement points are associated with each of these machines, and for each measurement point, a spectral data set was taken as well as the time waveform data set for each measurement survey. This would allow the analyst to omit the manual examination of over 8000 data sets for the six month period over which the comparison was performed. This does not include the consideration of trend data or the time required to apply other diagnostic tools to these 8000 data sets. For the examination of the effectiveness of the waveform diagnostic system, total analytical and reporting time would be reduced by a factor of about one half. However, if one of the five machines that were identified by the analyst, yet screened by the waveform diagnostic system, failed before the next measurement survey, the end result would most likely be a loss of production profits that exceed the savings incurred by the reduced analytical time.

7.5 Comparison to Commercially Available Diagnostic System

The second part of the examination of the effectiveness of the waveform diagnostic

system was to compare its diagnostic results to those of an automated fault diagnostic system that has been commercially available for approximately seven years. The commercially available expert system used to analyze the same data that was screened by the waveform diagnostic system includes only spectral data in its analysis. This is the case with most commercial expert systems that have been developed to diagnose faults in rotating machinery. The operation of the program follows the general algorithm that was presented for automated fault diagnostic systems in Chapter 5. It should be noted that the output of the commercially available system is not a simple flag that says if the machine should be identified further. The expert system's output includes its diagnosis for each problem that was found on the entire machine. Table 7.4 shows an example of a diagnostic report that can be generated by the commercially available automated fault diagnostic system. This table shows that the expert system indicated outer race bearing faults at points MOA and MIV. MOV is also diagnosed with a bearing fault, and it was given a severity level, or deviation magnitude, of sixty-one out of a possible one hundred. As was the case with the output of the waveform diagnostic system, if a fault diagnosis is made for any point on the machine, then the machine is not considered to be screened, thus indicating that further examination is required by the analyst.

Table 7.5 shows the results of the commercial diagnostic system that were generated from its analysis of the data taken from the same six measurement surveys that were analyzed by the waveform diagnostic system. The diagnostic accuracy for the cases where the analyst indicated that a fault was present was 75%. This percentage shows that it was slightly less accurate than the waveform diagnostic system. The correct screening

Table 7.4. Sample Automated Fault Diagnostic System Output

Diagnostic Summary For (MOTA-025) BROWN STOCK DISCHARGE PUMP		

Diagnostic Deviation Score (DEV): 66		
Data from <28-FEB-96 10:33> to <28-FEB-96 10:35>		
KEY POINT(s)	PROBLEM	DEV--CERT
MOV	BPFO and BPFI (race) defects in bearing	61-- 67
MOA	BPFO (outer race) defect in bearing	46-- 67
MIV	BPFO (outer race) defect in bearing	12-- 67

Table 7.5. Commercial Expert System Diagnostic Results

Month	Correct Diagnosis	Missed Diagnosis	Diagnosis Percentage	Correct Screen	Incorrect Screen	Screen Percentage
August	4	5	44%	64	36	64%
October	6	1	86%	30	51	37%
November	2	0	100%	43	64	40%
December	3	1	75%	28	48	37%
January	6	0	100%	23	77	23%
February	0	0	N/A	22	76	22%
Total	21	7	75%	210	352	37%

percentage was also significantly lower than that of the waveform diagnostic system. For the commercially available system, there were 75% more false alarms reported compared to the system that uses the waveform parameters. The low diagnostic accuracy and the high false alarm rate generated by the commercial expert system are typical for this type of diagnostic software. These are also two of the reasons why the acceptance of this type of diagnostic system is limited among vibration analysts. For the false alarms that are generated, the diagnostic possibilities that are presented in the expert system's output generate a number of potential faults to be further investigated by the analyst. The additional time that an analyst spends evaluating these potential faults is often greater than the time that can be saved in the cases where machines are screened correctly.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

8.1 Conclusions

The waveform diagnostic system presented in this thesis has been shown to screen rotating machinery with an accuracy of 61%. For each measurement survey this would reduce by a factor of approximately $2/3$ the amount of data that is required to be examined manually by an analyst. This savings in diagnostic and reporting time would allow a single analyst to monitor roughly twice the number of machines that he was previously able to monitor before utilizing the waveform diagnostic system. When considering the accuracy of the system's diagnosis compared to that of an analyst, the fact that 18% of the machines that were identified by the analyst were not reported by the waveform diagnostic system will generate concern. However, it should be noted that vibration analysis is by no means an exact science. No analyst is 100% accurate when reporting the machines that he believes to be operating with a significant potential for failure. An analyst's true diagnostic accuracy cannot be determined precisely. Consider a case where maintenance personnel do not heed the advice of a vibration analyst to remove a machine from service that was diagnosed with a fault condition. If the machine does not fail before the next measurement survey, can that be interpreted as an incorrect diagnosis by the analyst? If the machine is removed from service, would it have remained in service without failure until the next measurement survey? The point is that the accuracy percentage calculated

for the waveform diagnostic system is computed relative to an uncertain number. For simplicity, the calculation of this accuracy percentage conservatively assumes that the analyst was always 100% correct in his diagnoses. This fact should be considered when evaluating the accuracy results of the waveform diagnostic system presented in this thesis.

8.2 Limitations of the Research

The range of machinery and machinery faults for which the waveform diagnostic system is effective at screening vibration data should be discussed. Regardless of the machine type, the waveform parameters will characterize the fault patterns that they were designed to identify. However, there are a number of relatively uncommon faults that occur in production equipment. Several examples of these uncommon faults include rotor rubs, oil whirl, oil whip, and stall conditions in fans. Data which illustrates these faults can be difficult to find. Though the parameters themselves identify faults for a variety of rotating machinery, the range of machines for which the levels that are used to fire the diagnostic rules are applicable is a subset of this group. There are many specialized pieces of production equipment for which the parameter levels at which the diagnostic rules are triggered would be invalid. Individual machines can be used in a variety of applications, and a machine's application is often as important in determining its vibration signature as is the physical design of its components. A machine's mounting configuration can also greatly affect a machine's vibration signature. A mounting design which allows excessive flexibility in a certain orientation can result in excessive vibration levels in this plane due to the presence of a normally insignificant forcing function, such as a mild imbalance

condition. The effectiveness of these parameters will also be dependent upon the speed of the machine on which the waveform diagnostic system is applied. This is especially true of the impact detection parameters, since impact levels are highly dependent on the rotational speed of the machine. This means that the levels at which the individual waveform parameters trigger the diagnostic rules would potentially have to be modified for different machinery applications, mounting techniques, and other operational parameters.

A most striking example where the current trigger levels for the diagnostic rules might be inappropriate would be a comparison between a coal crusher and a high speed machine tool spindle. The vibration signatures for these two machines are obviously quite different, and the set of levels used to trigger the diagnostic rules for the group of machines considered in this thesis would most likely not be applicable for either type machine. One solution to this problem might be to use statistics to calculate appropriate limits using data associated with a group of machines that exhibit similar vibration characteristics. Another solution would be to calculate the parameter values for all of the data collected during a measurement survey. The calculated values of the individual parameters could then be scaled from zero to one. The trigger levels defined in the diagnostic rules could then be based on a certain percentage of the scaled waveform parameter values that are present for the group of machines being analyzed. This would result in the system identifying a certain percentage of the machines for which the highest values of the waveform parameters are calculated. The goal of this approach would be to identify the machines that have the most severe fault conditions.

8.3 Recommendations For Future Work

Further work in the area of waveform diagnostics includes optimization of the waveform parameters defined in this thesis. Additional parameters could also be developed to increase the system's diagnostic accuracy as well as its screening effectiveness. Alarm levels for the parameters could also be tailored to specific machine types, but this would add significantly to the complexity of the system. As mentioned previously, statistical analysis could be incorporated into the development of the appropriate alarm levels. This might involve the use of statistical correlations of the waveform parameters and the diagnosed faults, but the correlation algorithms might be "confused" by the fact that parameters calculated from data sets indicating no fault and data sets indicating an insignificant fault are considered the same. In the case of screening, there are no shades of gray in the diagnosis, there are only black and white. Perhaps the most significant implementation of this type of expert system would be as a component of an existing automated fault diagnostic system. The waveform diagnostic portion of this comprehensive system would screen the time waveform data collected during a routine measurement survey. The portion of the diagnostic system that examines the spectral data would then perform its detailed diagnosis only on the machines that require further examination. The waveform parameters could also be used to provide insight into the final diagnostics. It appears that the use of time waveform data in automated machinery diagnostics has significant potential for improving the way that production facilities perform their maintenance.

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APPENDIX

APPENDIX

The following machines were included in the condition monitoring program which was used as a basis for the development of the diagnostic rules and the evaluation of the accuracy of the waveform diagnostic system presented in this thesis.

Station: PD BUILDING

Machine	Machine ID	# PTS	TYPE	SPEED
-----	-----	-----	-----	-----
SCALPING FAN (WEST)	MOTA-005	10	Constant SPEED	1775.0 RPM
SCALPING FAN (EAST)	MOTA-006	10	Constant SPEED	1775.0 RPM
LIVE BOTTOM BIN	MOTA-007	8	Variable SPEED	1865.0 RPM
WEIGHT BELT	MOTA-008	8	Variable SPEED	1285.0 RPM
PRESS CONVEYOR (EAST)	MOTA-009	11	Variable SPEED	1800.0 RPM
PRESS CONVEYOR (WEST)	MOTA-010	11	Variable SPEED	1800.0 RPM
HYMAC PRESS (EAST)	MOTA-011	17	Variable SPEED	1800.0 RPM
HYMAC PRESS (WEST)	MOTA-012	17	Variable SPEED	1800.0 RPM
#1 DIGESTER	MOTA-013	23	Variable SPEED	1780.0 RPM
#2 DIGESTER	MOTA-014	23	Variable SPEED	1790.0 RPM
#3 DIGESTER	MOTA-015	23	Variable SPEED	1790.0 RPM
DISCHARGE VALVE PUMP	MOTA-015A	7	Constant SPEED	1780.0 RPM
CROSS CONVEYOR	MOTA-016	12	Constant SPEED	1800.0 RPM
FEEDER VALVE HYD PUMP	MOTA-018	7	Constant SPEED	1765.0 RPM
VERTICAL FEEDER	MOTA-017	8	Constant SPEED	1200.0 RPM
BLOW TANK STOCK PUMP	MOTA-019	10	Constant SPEED	1785.0 RPM
BLOW TANK AGITATOR	MOTA-020	10	Constant SPEED	1190.0 RPM
BROWN STOCK WASHER	MOTA-021	9	Constant SPEED	1800.0 RPM
BROWN STOCK WASHER	MOTA-021A	9	Constant SPEED	1800.0 RPM
BROWN STOCK SHOWER (N)	MOTA-022	10	Constant SPEED	1750.0 RPM
BROWN STOCK SHOWER (S)	MOTA-023	10	Constant SPEED	1780.0 RPM
BROWN STOCK WASHER VAC	MOTA-024	10	Constant SPEED	1785.0 RPM
BROWN STOCK DISCHARGE	MOTA-025	10	Constant SPEED	1780.0 RPM
BROWN STOCK DISCHARGE	MOTA-026	10	Constant SPEED	1190.0 RPM
T-1 STOCK PUMP	MOTA-027	10	Constant SPEED	1180.0 RPM
T-1 AGITATOR	MOTA-028	10	Variable SPEED	1185.0 RPM
T-2 AGITATOR	MOTA-029	10	Variable SPEED	1190.0 RPM
T-2 STOCK PUMP	MOTA-030	10	Constant SPEED	1780.0 RPM
WASHER 1 DRIVE	MOTA-031	9	Constant SPEED	1800.0 RPM
WASHER 1 DOCTOR	MOTA-032	9	Constant SPEED	1800.0 RPM
#1 WASHER SHOWER (N)	MOTA-033	10	Constant SPEED	1180.0 RPM
#1 WASHER SHOWER (S)	MOTA-034	10	Constant SPEED	1180.0 RPM

#1 WASHER VACUUM PUMP	MOTA-035	10	Constant	SPEED	1785.0 RPM
T-3 CONVEYOR	MOTA-036	7	Constant	SPEED	1800.0 RPM
DOUBLE SHAFT MIXER	MOTA-037	14	Constant	SPEED	1778.0 RPM
T-3 AGITATOR (N)	MOTA-039	10	Variable	SPEED	1185.0 RPM
T-3 AGITATOR (S)	MOTA-040	10	Variable	SPEED	1184.0 RPM
#1 SEAL TANK PUMP	MOTA-041	10	Constant	SPEED	1190.0 RPM
T-3 STOCK PUMP	MOTA-042	10	Constant	SPEED	1185.0 RPM
WASHER 2 DRIVE	MOTA-043	9	Constant	SPEED	1800.0 RPM
WASHER 2 DOCTOR	MOTA-044	9	Constant	SPEED	1800.0 RPM
#2 WASHER SHOWER (N)	MOTA-045	10	Constant	SPEED	1180.0 RPM
#2 WASHER SHOWER (S)	MOTA-046	10	Constant	SPEED	1750.0 RPM
#2 SEAL TANK PUMP	MOTA-047	10	Constant	SPEED	1180.0 RPM
#2 WASHER DISCHARGE PMP	MOTA-048	10	Constant	SPEED	1750.0 RPM
#2 WASHER VACUUM PUMP	MOTA-049	10	Constant	SPEED	1790.0 RPM
T-4 AGITATOR	MOTA-050	10	Variable	SPEED	1184.0 RPM
T-4 STOCK PUMP	MOTA-051	10	Constant	SPEED	1785.0 RPM
WASHER 3 DRIVE	MOTA-052	9	Constant	SPEED	1800.0 RPM
WASHER 3 DOCTOR	MOTA-053	9	Constant	SPEED	1800.0 RPM
#3 WASHER SHOWER (N)	MOTA-054	10	Constant	SPEED	1780.0 RPM
#3 WASHER SHOWER (S)	MOTA-055	10	Constant	SPEED	1180.0 RPM
#3 SEAL TANK PUMP	MOTA-056	10	Constant	SPEED	1780.0 RPM
#3 WASHER DISCHARGE PMP	MOTA-057	10	Constant	SPEED	1750.0 RPM
#3 WASHER VACUUM PUMP	MOTA-058	10	Constant	SPEED	1785.0 RPM
BOOSTER PUMP	MOTA-059	10	Constant	SPEED	1775.0 RPM
BLACK LIQUER EFFLUENT	MOTA-060	10	Constant	SPEED	1775.0 RPM
BLOW TANK DILUTION PUMP	MOTA-061	10	Constant	SPEED	1775.0 RPM
T-9 AGITATOR	MOTA-072	10	Variable	SPEED	1185.0 RPM
T-10 AGITATOR	MOTA-073	10	Variable	SPEED	1185.0 RPM
T-11 AGITATOR	MOTA-074	10	Variable	SPEED	1185.0 RPM
T-11 STOCK PUMP	MOTA-075	10	Constant	SPEED	1785.0 RPM
T-10 STOCK PUMP	MOTA-076	10	Constant	SPEED	1780.0 RPM

Station: SHEETING

Machine	Machine ID	# PTS	TYPE	SPEED
-----	-----	-----	-----	-----
THICKER CHEST AGITATOR	MOTA-216	10	Constant	SPEED 1195.0 RPM
WHITE WATER PUMP JORDAN	MOTA-001A	10	Constant	SPEED 1190.0 RPM
#2 BLOW TANK AGITATOR	MOTA-201	10	Constant	SPEED 900.0 RPM
#7 BLOW TANK AGITATOR	MOTA-202	10	Constant	SPEED 900.0 RPM
THICKER	MOTA-215	8	Constant	SPEED 1780.0 RPM
THICKENER CHEST STOCK	MOTA-217	10	Constant	SPEED 1780.0 RPM
JORDAN #1	MOTA-218	10	Constant	SPEED 1800.0 RPM

JORDAN #2	MOTA-219	10	Constant	SPEED	450.0 RPM
JORDAN #3	MOTA-220	10	Constant	SPEED	1800.0 RPM
JORDAN #4	MOTA-221	10	Constant	SPEED	1800.0 RPM
JORDAN #5	MOTA-222	10	Constant	SPEED	1800.0 RPM
JORDAN #6	MOTA-223	10	Constant	SPEED	450.0 RPM
JORDAN CHEST AGITATOR	MOTA-224	10	Constant	SPEED	1770.0 RPM
JORDAN CHEST STOCK PUMP	MOTA-225	10	Constant	SPEED	1200.0 RPM
JORDAN FAN PUMP	MOTA-227	10	Constant	SPEED	1800.0 RPM
POMONA PUMP	MOTA-229	7	Constant	SPEED	1800.0 RPM
COUCH PIT AGITATOR	MOTA-230	10	Constant	SPEED	1800.0 RPM
COUCH PIT STOCK PUMP	MOTA-231	5	Constant	SPEED	1800.0 RPM
FLATBOX VACUUM PUMP	MOTA-232	10	Constant	SPEED	1800.0 RPM
FLATBOX WATER REMOVAL	MOTA-233	10	Constant	SPEED	1800.0 RPM
COUCH ROLL VACUUM PUMP	MOTA-235	10	Constant	SPEED	1800.0 RPM
2ND PRESS VACUUM PUMP	MOTA-237	10	Constant	SPEED	1100.0 RPM
REFINER FEED PUMP	MOTA-449	14	Constant	SPEED	1785.0 RPM
BIG BERTHA STOCK PUMP	MOTA-451	10	Constant	SPEED	1800.0 RPM

Station: GEARBOXES

Machine	Machine ID	#	PTS	TYPE	SPEED
-----	-----	-----	-----	-----	-----
PAPER MACHINE CLUTCH	PD-DRV1531	4	Constant	SPEED	200.0 RPM
1ST PRESS CLUTCH	PD-DRV1532	4	Constant	SPEED	200.0 RPM
1ST DRY CLUTCH	PD-DRV1537	4	Constant	SPEED	200.0 RPM
2ND DRY CLUTCH	PD-DRV1533	4	Constant	SPEED	200.0 RPM
POPE REEL CLUTCH	PD-DRV1539	4	Constant	SPEED	200.0 RPM
FELT CLUTCH	PD-DRV1534	4	Constant	SPEED	200.0 RPM

Station: DRIVE TRAIN

Machine	Machine ID	#	PTS	TYPE	SPEED
-----	-----	-----	-----	-----	-----
DRIVE TRAIN BEARINGS	00001	11	Constant	SPEED	650.0 RPM

Station: MISC EQUIPMENT

Machine	Machine ID	#	PTS	TYPE	SPEED
-----	-----	-----	-----	-----	-----
#2 PICKER	MOTA-365	10	Constant	SPEED	1780.0 RPM

#2 BREAKER	MOTA-366	14	Constant	SPEED	1780.0 RPM
#1 PICKER	MOTA-362	10	Constant	SPEED	1780.0 RPM
#1 BREAKER	MOTA-363	14	Constant	SPEED	1780.0 RPM
BREAKER FAN	MOTA-369	10	Constant	SPEED	1780.0 RPM
PV FAN	MOTA-368	10	Constant	SPEED	1780.0 RPM
BOILERHOUSE COMPRESSOR	MOTA-356	10	Constant	SPEED	1800.0 RPM
#1 THICKENER FEED PUMP	MOTA-213	10	Constant	SPEED	1780.0 RPM
#2 THICKENER FEED PUMP	MOTA-214	10	Constant	SPEED	1780.0 RPM
GYRO FEED PUMP #2	MOTA-210	10	Constant	SPEED	1780.0 RPM
GYRO FEED PUMP #1	MOTA-209	10	Constant	SPEED	1780.0 RPM
NORTH UNDERGROUND TNK	MOTA-425	7	Constant	SPEED	1780.0 RPM
SOUTH UNDERGROUND TNK	MOTA-426	7	Constant	SPEED	1780.0 RPM
SOFT WATER PUMP	MOTA-100	10	Constant	SPEED	1185.0 RPM
NORTH COMPRESSOR	MOTA-353	10	Constant	SPEED	1800.0 RPM
SOUTH COMPRESSOR	MOTA-354	10	Constant	SPEED	1800.0 RPM
SEWER PLANT PUMP	MOTA-071	8	Constant	SPEED	1790.0 RPM
TERTIARY CLEANER PUMP	MOTA-207	10	Constant	SPEED	1780.0 RPM
QUADRIARY CLEANER PUMP	MOTA-208	10	Constant	SPEED	1780.0 RPM
SECONDARY CLEANER PUMP	MOTA-206	10	Constant	SPEED	1780.0 RPM
WHITE WATER PUMP GYRO	MOTA-001	10	Constant	SPEED	1800.0 RPM
GYRO #2	MOTA-003	5	Constant	SPEED	1790.0 RPM
GYRO #1	MOTA-002	5	Constant	SPEED	1790.0 RPM
SEAL WATER PUMP	MOTA-004	10	Constant	SPEED	1790.0 RPM
#5 BLEND TANK AGITATOR	MOTA-200	10	Constant	SPEED	910.0 RPM
#5 STOCK PUMP	MOTA-203	10	Constant	SPEED	1780.0 RPM
#5 AUX STOCK PUMP	MOTA-203A	10	Constant	SPEED	1800.0 RPM
SECONDARY REFINER	MOTA-383	10	Constant	SPEED	595.0 RPM
PRIMARY REFINER	MOTA-382	10	Constant	SPEED	595.0 RPM
#2 PRIMARY STOCK PUMP	MOTA-205	10	Constant	SPEED	1185.0 RPM
#1 PRIMARY STOCK PUMP	MOTA-204	10	Constant	SPEED	1185.0 RPM
REFINER SEAL WATER PUMP	MOTA-448	10	Constant	SPEED	1800.0 RPM
THICK FEED TANK AGITATOR	MOTA-462	10	Constant	SPEED	1800.0 RPM
MAIN COMPRESSOR	MOTA-0000	10	Variable	SPEED	1780.0 RPM

VITA

Mark William Slemp was born in Johnson City, Tennessee, in 1973. He graduated with an Honors Diploma from Farragut High School in the Spring of 1991. He then enrolled in the Engineering program at the University of Tennessee, Knoxville, later that same year and soon became a student in the Mechanical Engineering Department. He graduated Summa Cum Laude with a Bachelor of Science in Mechanical Engineering in the Spring of 1995. During his undergraduate studies, he was involved in the cooperative education program that is sponsored by the University. During this program, he was employed by Computational Systems, Inc., which is also located in Knoxville. This company specializes in improving the methods by which industrial facilities perform their maintenance. Mr. Slemp enrolled in the Graduate School at the University of Tennessee, Knoxville, in the Fall of 1995. He has pursued a Master of Science degree with an emphasis in Mechanical Engineering. His curriculum included machine design and dynamics with additional courses in artificial intelligence. He is currently employed as an Application Engineer by CSI.