Artificial Intelligent System for Integrated Wear Debris and Vibration Analysis in Machine Condition Monitoring

Thesis submitted by

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Then you will know the truth, and the truth will set you free.

Jesus in John 8:32 (NIV).

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Abstract

Machine condition monitoring has become a vital component of maintenance programs in machine intensive operations, such as the mining, mineral processing and manufacturing industries. Vibration and oil analysis have become the two most commonly used techniques for fault detection and tracking. These techniques are generally used independently as expert knowledge is required in each field, and due to a lack of understanding about how to integrate them. However, numerous case studies of machine failures have reported on the benefit of a correlated approach. This project focused on the development of an analytical strategy that, for the first time analyses vibration data in conjunction with oil and wear debris data for machine health assessment.

In order to achieve the goal of developing a strategy for correlated application of vibration, oil and wear particle analysis using artificial intelligence, a number of project objectives were identified. The project objectives were to investigate the fault detection abilities of condition monitoring techniques as a basis for developing a correlated strategy, and finally to implement this strategy using artificial intelligence. These objectives were collated into a project plan that consisted of a comprehensive survey of condition monitoring techniques and correlation investigation, correlation strategy development, expert system development and a testing phase.

The project was performed in a number of stages to allow the progress to be monitored. The first stage comprised a thorough literature review to ascertain the current research status in the condition monitoring field, as well as confirming the project objectives. The second and third stages were concerned with the preparation of spur and worm gearbox laboratory test rigs, and the operation of suitable experiments. The measured condition monitoring data allowed the fault detection of the vibration, oil

and wear particle analysis techniques to be assessed. The data was also used for verification of the correlation strategy developed in stage four. Stage five was concerned with the development of three expert systems for vibration analysis, oil and wear particle analysis, and correlated condition analysis respectively. The expert system for correlated condition analysis was constructed using the correlation strategy of stage four of the project. All expert systems were thoroughly tested using laboratory and industry derived data to verify correct operation.

The outcomes of this research project contribute to the current academic knowledge of the condition monitoring field, as well as provide industry with potential economic and environmental benefits. The novel strategy for correlation of vibration, oil and wear particle analysis techniques, as well as the demonstration of the effectiveness of the developed expert systems are contributed to the academic research community. The expert systems include additional innovative features such as a fault root-cause analysis algorithm, and a new strategy for machine remaining lifetime estimation using a wear approach that can be updated using condition monitoring data. The fully functional expert system software package complete with user interface is contributed to the industry partner Industrial and Technical Services for potential future commercialisation.

The developments of this project can provide significant benefits to the mining, mineral processing and manufacturing industries if the project outcomes are implemented. The correlated condition monitoring strategy allows improved early fault detection, more reliable fault diagnosis and the ability to perform root-cause analysis, compared to conventional vibration, oil and wear particle analysis. These advances combine to improve the efficiency of the maintenance program resulting in increasing machine uptime, reduced maintenance costs and lower environmental impact. The adoption of the project developments could therefore ultimately improve the profitability of the venture, and help Australian operations to remain financially viable on a global scale.

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Chapter 1

Introduction

1.1 Project Purpose

The prime purpose of this research project was to improve the knowledge of vibration, oil and wear particle analysis techniques for machine condition monitoring, to benefit both industry as well as the research community. This purpose was embedded in the three project objectives:

- To better understand the fault detection abilities of condition monitoring analysis techniques, and
- To provide a strategy for improved fault detection of industrial machinery, and
- To automate the developed strategy.

As the absolute fault detection abilities of each condition monitoring technique were not well established, it was not possible to perform an analysis of how the techniques complemented or correlated with one another. This presented the need for a comprehensive study of possible condition monitoring techniques to be conducted, which could then be used for a basis of a correlation investigation. The second dot point is concerned with the investigation of how the analysis techniques correlate in fault detection and diagnosis, and whether a correlated use would provide more accurate fault diagnosis. Although case study type scenarios had confirmed potential benefits of a correlated analysis [1], complications were also reported [2].

The project objectives stated above focus on improving the efficiency of a maintenance program, and reducing the workload of the expert analyst. The improved performance of a maintenance program would be facilitated through earlier fault detection and better accuracy of fault diagnosis, as provided by the potential benefits of a correlated condition monitoring approach. The automation of the correlated analysis would reduce the manual labour associated with the data analysis which is typically performed by an experienced analyst, thereby reducing the cost of the condition monitoring program.

An improvement of a maintenance program has significant benefits for machine intensive industries, such as the mining, mineral processing, manufacturing and aviation industries. Economic benefits are generally the most significant [3], however environmental benefits can also be considerable including less spare part replacement (component energy of manufacture of spare parts), and improved lubricant life (lower lubricant usage).

1.2 Scholarly Context of Research

Vibration, oil and wear particle analysis represent the most commonly used techniques for machine condition monitoring. Although these techniques have been used individually for considerable time for fault detection and diagnosis, their combined use has not been investigated in an academic manner. Vibration analysis has traditionally been used for health monitoring of fixed plant (and aviation, due to the absence of road noise), while oil analysis has often been selected for moving machines such as in the transportation industry.

This project was aimed at using a correlated analysis approach for fixed plant installations typical in the mining, mineral processing and manufacturing industries. It was therefore necessary in assessing the elements of vibration, oil and wear particle analysis techniques used in industry, to allow easy adoption of the project developments by industry currently operating in Australia. This was considered beneficial for the project industry partner Industrial and Technical Services (ITS), so the project developments could be commercialised at a later stage, and sold to industry with minimal training and changes to data sampling procedures required.

Condition monitoring is predominately performed on a manual basis, with experts interpreting the data and diagnosing machine faults. Due to the volume of data obtained for analysis of large installations, expert staff are occupied by performing repetitive analysis of data. Companies could therefore benefit from automated data interpretation, which would reduce the dependence on expert staff, and provide these with more time to collaborate with the maintenance departments.

1.3 Explanation of the Project Structure

1.3.1 Rationale for the Research

The research project was structured into a number of sub-projects to allow each module to be completed in an organised manner. The first sub project included a comprehensive literature review as published in Chapter 2, in order to establish a strong academic foundation of the project. An extensive literature review ensures that the project can commence at the current research status of the field, while allowing the project objectives to be confirmed. At this stage, local industry as well as the industry partner ITS were surveyed about the condition monitoring techniques used, the type of plant monitored, and the typical faults encountered. Spur and worm gearbox laboratory tests were then designed that reflect the most common occurring faults.

Once the research stage was completed, the laboratory test rigs were prepared which comprised sub-project 2. The spur gearbox test rig was already available, while a worm gearbox test rig was designed and constructed. These test rigs are discussed in detail in Sections 3.2.1.2 and 3.2.1.3, and the tests were performed as discussed in Sections 4.2 and 4.3. The objective of using the experimental test rigs was to obtain condition monitoring data from gearboxes operating under controlled operating conditions. The test rigs were sampled to allow the required data to be extracted, as determined in the research stage of the project.

The laboratory derived data and research of sub-project 1 were used in a study of sub-project 3 to assess the fault detection ability of each condition monitoring analysis technique. As a machine fault may be detected by various indicators, the objective of this sub-project was to identify all indicators for all possible faults of each technique relating to gearboxes. This information was required in order to assess the possibility of correlating vibration, oil and wear particle analysis techniques.

Sub-project 4 was concerned with the investigation into the ability of correlating the analysis techniques, and subsequent development of a strategy to use a correlated approach for improved fault detection of gearboxes. This component represents one of the core components of this research project. The successful completion of the correlation strategy allowed its implementation in an automated software package developed in sub-project 5. This was a substantial development, as it included the design and implementation of individual expert systems for vibration analysis, oil and wear particle analysis, and the implementation of the correlation strategy. This sub-project also included substantial testing of the algorithms to ensure correct and reliable operation. The developments of this sub-project are discussed in Chapters 5, 6 and 7.

The successful completion of all 5 sub-project 2 months ahead of schedule satisfied the original research project aim and objectives. However, it was decided to expand the research project into the machine remaining lifetime estimation field. This was the case as remaining lifetime estimation has not generally been adopted by industry in a structured manner, and the project developments presented an opportunity to advance this field. This sub-project 6 consisted of a literature review of publications and wear estimating methodologies, followed by the development of a strategy of integrating remaining lifetime estimation algorithm with the expert system developments of sub-project 5. The objective of this sub-project were to develop a strategy to use the accurate machine condition information of the correlated expert system and knowledge of operating conditions to estimate the remaining operating life of a gearbox. Although this sub-project caused the research project to extend to 42 months, the results complement the developments of sub-projects 1 to 5 well, as described in Section 8. The remaining lifetime algorithm provides additional potential benefits to end-users of the software, including further improved performance of the maintenance program by allowing more accurate planning of machine maintenance scheduling and spare parts inventory management. This is in line with the primary project objective of improving the available maintenance programs to benefit industry and the research community.

1.3.2 Scope of the Research

The scope of the research and development conducted as part of this project consisted of the development of an advanced automated algorithm for condition monitoring of spur and helical gearboxes, as well as associated components. Spur and helical gearboxes are common in industry, and represent a class of machines that can be monitored by vibration, oil and wear particle analysis. It is therefore an ideal type of machine for research into correlated strategies for condition monitoring. Apart from gears, the additional machine components included in the project scope are roller and journal bearings, V and cog type belts, couplings, centrifugal pumps and axial fans. However, some of these components may not allow condition monitoring via all techniques. The additional components were included solely to provide broader machine monitoring ability and hence a more versatile product for future commercialisation.

In order to meet the scope stated above, the project outcomes would need to present the development of a strategy on correlating the fault indicators from the vibration, oil and wear particle analysis techniques. This would require all information obtained from the condition monitoring techniques to be presented in a comprehensive machine health report. The data processing and fault diagnosis would need to be performed in an automated manner, and include a suitable user interface to allow operators to execute the analysis procedure. The analysis algorithms should be verified for correct operation and tested using real condition monitoring data. The completed software package made up of the user interface and analysis algorithm back bone should be operational, and thus suitable as a prototype for commercialisation by the industry partner ITS.

It is anticipated that the success of this research project be evaluated by considering the scope and outcomes stated above. The anticipated outcomes would provide the research as well as the condition monitoring communities with a novel condition monitoring technique in an automated software package. The intellectual property developed as part of the project outcomes would be of potential value to the industry partner ITS, with the possibility of additional revenue from commercialisation.

Chapter 2

Literature Review

2.1 Introduction

The competitive nature of todays business environment has significantly impacted the maintenance approaches of equipment used in industry. With a view to improve a business efficiency and market share, company assets tied up in plant and equipment was reduced to a minimum, resulting in a need to increase the availability of the equipment. This was achieved by changing the maintenance procedure from a Run-to-Failure approach to a Preventative Maintenance or even Condition-Based-Maintenance program [3]. The move to a Preventative Maintenance program significantly reduces the occurrence of unscheduled machinery downtime and thus increases the availability of the machinery.

Machine condition monitoring is concerned with determining the condition of a machine to allow the detection of faults at an early enough stage to allow the fault to be corrected at the next scheduled service. Apart from increased availability and reliability of machinery, machine condition monitoring also detects faults before secondary damage results, thus also reducing repair costs.

Machine condition monitoring is applied to a machine by utilising appropriate monitoring techniques to be able to determine machine faults. The common monitoring techniques include oil analysis and vibration analysis, which are discussed in Sections 2.2 and 2.3 respectively.

2.2 Oil Analysis

The practice of oil analysis involves the sampling and analysis of oil from the machine of interest. The sampling and analysis of oil can be performed either on the machine, analysing the oil while passing between the oil pump and lubricated components (in-line), on the machine but where oil is bypassed to the oil analyser (on-line), or an oil sample is withdrawn from the machine and analysed in a laboratory (off-line). This principle is demonstrated graphically in Figure 2.1, and in a flow chart in Figure 2.2.

The analysis of oil can be categorised into two main groups; oil condition monitoring and wear particle analysis. Oil condition monitoring was principally used to establish an optimum oil change interval of machines with large oil sumps such as truck engine sumps, to maximise the use of the oil until the additives were close to depleted [3]. Maintenance cost reductions of up to 30 percent can be achieved through monitored extension of oil drain intervals, while minimising unscheduled downtime of machinery [4].

The oil condition is generally determined by the analysis of certain performance indicators which relate to additive concentration or physical changes of the oil properties. The oil performance indicators chosen depend on the common failure modes of the lubricant in the specific application and environment. Commonly used performance indicators include Viscosity, Total Acid or Base Number (TAN or TBN), carbon deposits (suspended/insoluble) and sludge, and water and fuel contamination [3–7].

The use of the oil condition monitoring technique in maintenance program versus the more complicated oil particle analysis technique has the advantage of using simple less-costly tests to determine the condition of the lubricating oil. If the oil is changed before being contaminated or additives depleted, accelerated metal wear can be avoided. Conversely, as oil particle analysis involves the analysis of wear metal, faults are detected once initiated. Condition oil monitoring thus has the ability to notify faults due to degradation of lubricating oil, before damage in the form of specific wear particles results [3, 8]. Faults not due to degraded lubricating oil such as metal fatigue cannot however be determined earlier by condition oil monitoring than oil particle analysis.

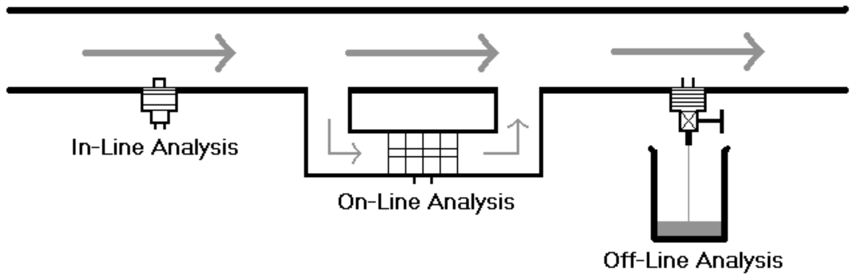


Figure 2.1: *Different types of oil analysis strategies.*

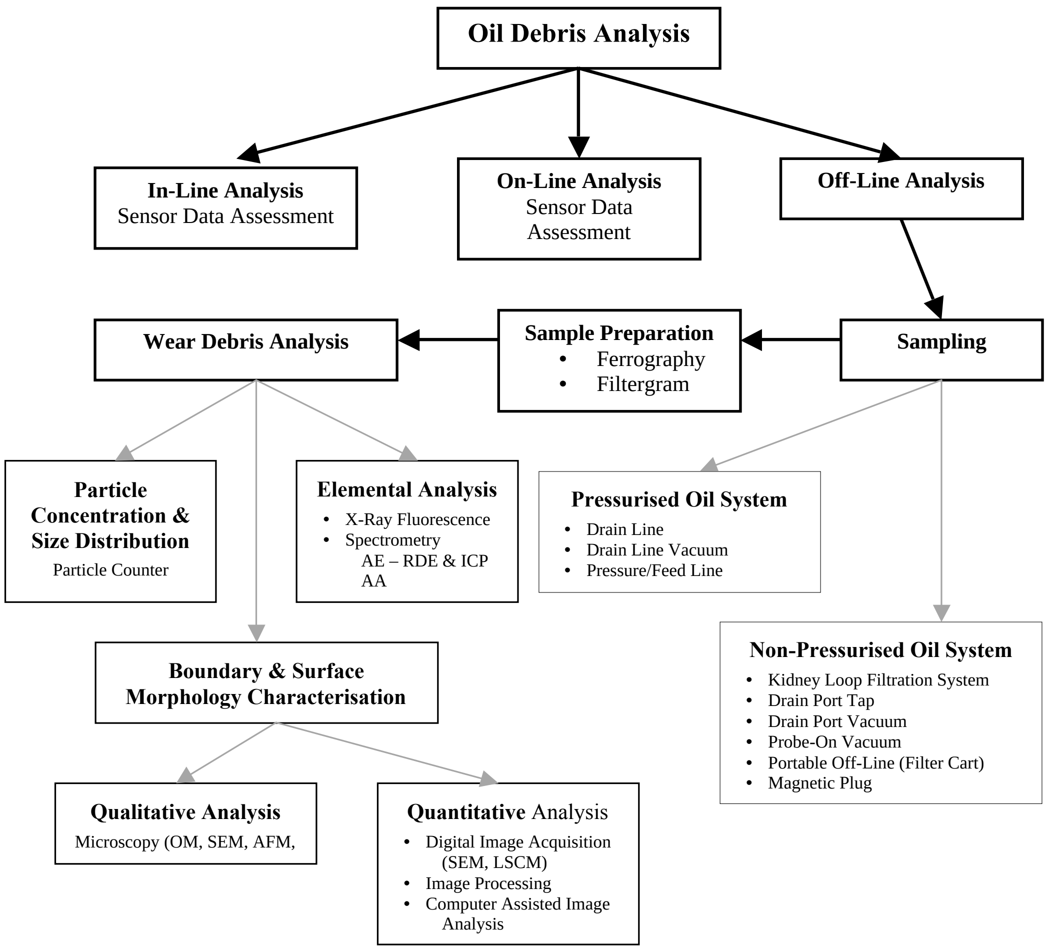


Figure 2.2: *Flowchart of oil debris analysis.*

The main difference between the two techniques is that in oil condition monitoring, physical and chemical properties of the oil and oil additives are determined and compared to the properties of new oil. Wear debris analysis however involves the collection and analysis of the wear debris contained in the oil sample to determine the condition of the machine. This section outlines the procedures required for undertaking the wear debris analysis, as this machine condition monitoring technique applies to this project. The general procedure detailed in Figure 2.2 includes sampling, sample preparation and sample analysis (wear debris analysis). Several steps of the wear debris analysis technique are also shared by the oil condition monitoring procedure, including sampling and sample preparation.

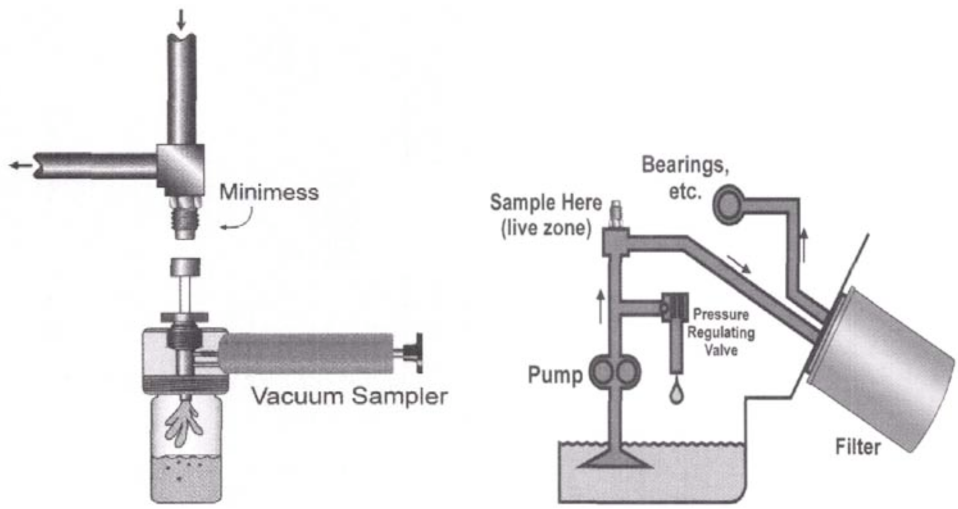
2.2.1 Sampling

Sampling is the process of collecting a small quantity of the lubricant from the machine to be examined. The sampling process is a critical step in the analysis process as the sample must be collected such that it represents the true condition of the lubricant while not introducing additional contaminants [9, 10]. A number of factors therefore need to be considered when obtaining an oil sample for further analysis, including not sampling directly after an oil change and using clean equipment. Industry practice sampling procedure is outlined in the Australian Standard 4002—2001 [11]. The specific factors for various sampling systems are discussed in the following sub-sections.

2.2.1.1 Sampling Positions

In order for the sample to a represent the oil condition including contaminants of the bulk oil, the sample must be obtained when the machine is operating under normal conditions, and before any oil filters or separators. If oil is sampled after filters, contaminants and wear particles may have been removed, and the sample is not a true representation of the bulk oil. However, if the efficiency of the filter is to be determined, sampling must be done after the filter.

When taking samples from pressurised oil lines, it is advantageous to install the sampling valve at points of high oil turbulence, such as at elbows or sharp bends in the



(a) **(b)**

Figure 2.3: *Sampling positions (a) Drain-Line Vacuum Sampling (b) Pressure or Feed Line Sampling [9].*

flow line. This helps to mix the oil flowing in the line, and reduces the occurrence of particle fly by where particles will flow past the sampling valve if installed at right angles on a straight oil line [9]. Common sampling arrangements are shown in Figure 2.3.

Sampling points can also be located on oil return or drain lines from components likely to wear, ingress particles or moisture. This is useful for machinery with large oil sumps, as wear debris can be analysed at the true concentrations as it is produced, rather than waiting for the general wear debris to accumulate in the oil sump [9]. If an abnormal condition is detected by the sample analysis, samples can then be taken from individual components to isolate the failing element.

Numerous machines utilise wet sumps where oil feed or return lines are not accessible or do not exist, as the sump within the casing serves as the reservoir. These machines typically include circulating gearboxes, circulating compressors and diesel engines. Oil sampling can be performed by either collecting samples from the oil supply lines leading to the gears or bearings, before the oil filter if one exists. Alternatively, if the equipment has an external filtration system, a valve can be installed into the pressurised line leading to the filter, as shown in Figure 2.4. These external oil filtration systems are typically referred to as kidney loop filtration systems.

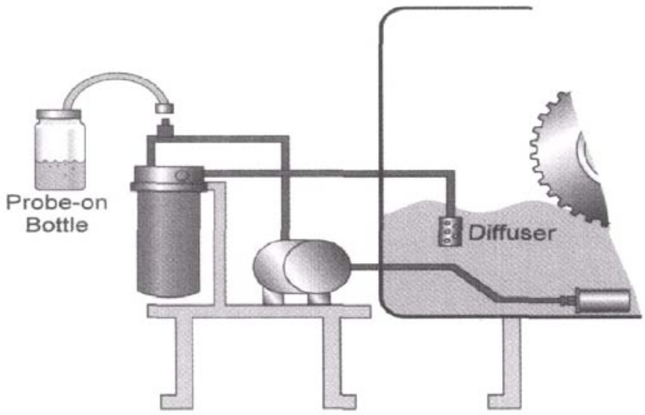
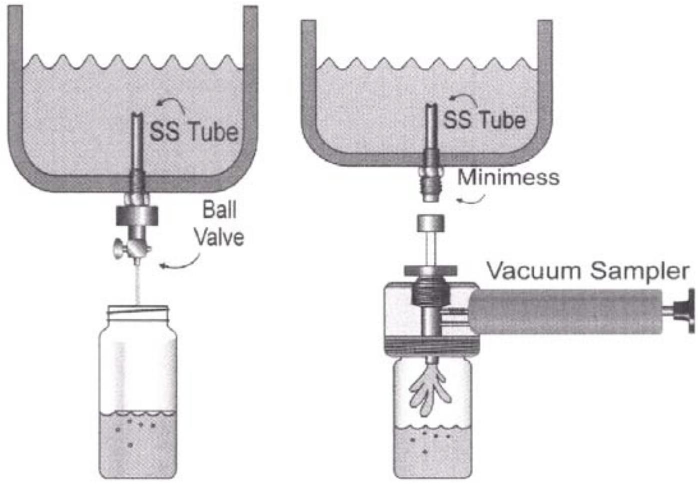


Figure 2.4: *Kidney loop oil filtration system [9].*

While the collection of lubricants from circulating systems is the preferred method, some machines may not allow samples to be collected from oil lines due to the absence of pressure fed lubrication system. Sampling for non-circulating systems generally involves the removal of oil from the sump at a position such that the sampled oil is a representation of the bulk oil in terms of wear particles and contaminants. The removal of the sump plug and collection of sufficient oil is considered to be an unacceptable sampling practice as sediment accumulated at the bottom of the sump is allowed to enter the sample bottle. Concentrations of both wear particles and contaminants are therefore not representative of the wear debris found in the oil near the lubricated components.

Commonly used and accepted sampling methods can be employed to collect oil from non-circulating systems, including drain-port tap sampling, drain-port vacuum sampling, and portable off-line sampling. Drain-port tap sampling involves a valve installed instead of the drain plug, which has a thin tube extending up into the active moving region of the sump, as shown in Figure 2.5(a).

Drain-port vacuum sampling is a modification of the first method, where the oil is withdrawn from the valve by aid of a vacuum pump. Figure 2.5(b) displays the general setup of the drain-port vacuum sampling technique, and the use of a Minimess valve. Vacuum sampling is beneficial in systems using high viscosity oil, which is difficult to



(a) (b)

Figure 2.5: *Drain Port (a) Tap Sampling, (b) Vacuum Sampling [9].*

sample through the small tube. Another vacuum sample technique is probe-on vacuum sampling, which involves the valve and tubing to be installed on the side of the sump. The tube extends into the moving region of the oil, as shown in Figure 2.6.

Portable off-line sampling involves the use of a portable oil pump and filter to set up an off-line sampling system similar to the one used for wet sumps. The portable pump is connected to valves installed into the oil sump, and allowed to circulate the oil until the fluid becomes homogenous, typically 5 to 15 minutes depending on size of the machine, sump and flow rate of the pump [9]. An oil sample can then be collected from the sampling valve installed on the portable pump. Portable oil pumping carts generally also include an oil filter, which can be connected into the pumping circuit after the oil sample has been collected. Figure 2.7 shows a typical portable off-line sampling setup.

2.2.1.2 Sampling Apparatus

Oil samples can be collected from valves installed into pressurised oil lines. Several types of valves are used for the collection process, generally ball, needle or Minimess valves. Minimess valves incorporate a sealing mechanism which is opened when the corresponding quick fit connector is inserted. Common sampling configurations are

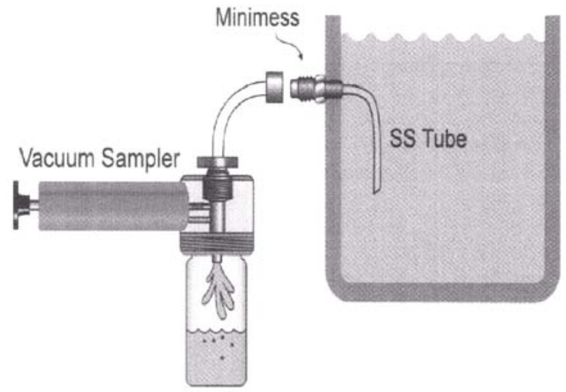


Figure 2.6: *Probe-on vacuum sampling [9].*

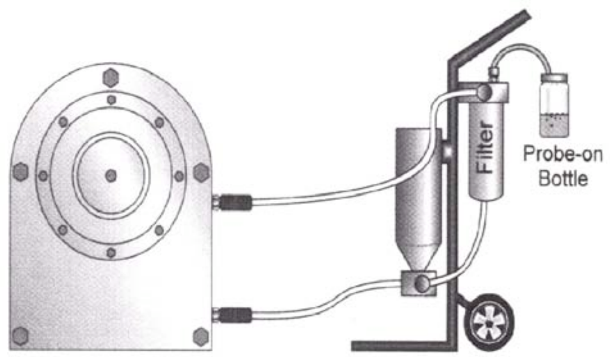


Figure 2.7: *Portable off-line sampling setup using portable filter cart [9].*

shown in Figure 2.8. If valves are not covered, additional flushing should be performed before the sample is taken to avoid contamination. When sampling low pressure lines, a vacuum pump may be required if the line pressure is not sufficient to force oil into the sample bottle.

Sampling bottles and associated hardware such as vacuum pumps and tubes must be of high cleanliness in order to avoid sample contamination. The equipment should therefore be flushed with 5 to 10 times the volume capacity of oil before collecting the sample. Bottles are produced in both clear plastic (PET) and glass, glass bottles usually exceed the cleanliness of plastic bottles. The cleanliness is generally rated according to ISO 3722-1976 [9,12,13], which grades bottles according to three categories:

- Clean fewer than 100 particles greater than 10 microns per mL of fluid
- Super Clean fewer than 10 particles greater than 10 microns per mL of fluid
- Ultra Clean fewer than 1 particle greater than 10 microns per mL of fluid

Common bottle sizes range from 50mL to 200mL, the larger bottles are preferred if a number of tests are to be conducted. For tests such as particle count and viscosity analysis, 100 or 120mL bottles are generally used.

Sampling of machinery where the use of valves at standard sampling positions is not possible such as bath or splash lubricated wet sumps, drop tube vacuum sampling can be employed. This method involves a small tube to be inserted into the machine through a fill or dipstick port, and approximately midway into the oil level. The application of the drop tube vacuum sampling method for sampling through a dip-stick hole is shown in Figure 2.9. While this method requires no machine modifications such as the installation of valves for oil sampling, it should be avoided if another sampling method can be used, due to the possibility of contamination and machine intrusion. As the tube is inserted into the machine, debris can be allowed to ingress into the machine from either dirt from the machine housing attaching to the tube, or a dirty tube from manufacture or storage. Drop tube vacuum sampling also requires the removal of a plug or dipstick in order to insert the tubing, which generally requires the machine to

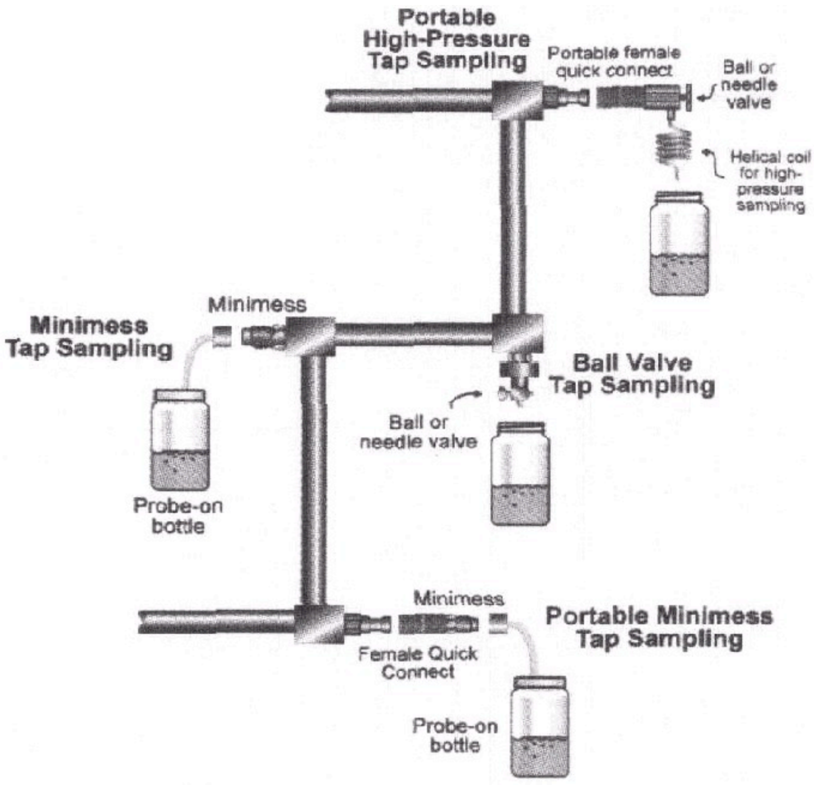


Figure 2.8: *Common sampling arrangements from pressurised lines [9].*

Figure 2.9: *Drop tube vacuum sampling — sampling oil through dip-stick [3].*

Figure 2.10: *Magnetic insert mounted on oil drain plug [14].*

be shut down [3]. This is a disadvantage as it adds to the machinery downtime, as well as the possibility of large particles settling to the bottom of the sump.

The collection of wear particles for wear debris analysis can also be done by collecting the metallic particles with a magnet, and periodically inspecting the deposited particles. This is a common system for gearboxes which are splash lubricated and thus do not have a pressurised lubrication system [14]. Magnets are commonly mounted on oil plugs and either inserted in special locations or to replace the standard filler plug. Figure 2.10 shows a typical magnetic plug used for particle collection in gearbox applications.

An advantage of the magnetic plug particle collection system is that metallic particles are collected on the magnet and removed from the lubricating oil. The particles are therefore not able to cause abrasive wear by circulation with the oil [3]. Due to the use of magnets for particle collection, non-ferrous and non-metallic particles cannot be analysed using this sampling technique. Therefore, if all wear and contaminant particles are to be analysed, an oil sampling technique as discussed previously should be adopted.

2.2.1.3 Sampling Frequency

The ideal sampling interval or frequency is dependent on the type and operating conditions of the machine to be monitored. The sampling frequency should be chosen so that it is at least two to four times the frequency of failure [3, 15]. High speed equipment such as helicopter engines, gearboxes, and air force fighter planes are sampled at short intervals, typically after every flight or 10 to 25 hours.

Medium speed equipment including reciprocating engines are usually sampled at intervals of 100 to 500 hours, depending on the duty of service, or if an abnormal condition is anticipated. Low speed equipment is often sampled at intervals between 300 to 1500 hours, the longer interval being possible as the lubricant is not usually exposed to high temperature or stresses as in the high and medium speed applications. Sampling intervals for common machines are summarised in Table 2.1.

In general, the sampling frequency should be adjusted for each machine depending on the load and speed of operation, as well as environmental factors including ambient temperature, humidity and amount of dust [3, 14].

Table 2.1: *Typical sampling intervals of common machinery [9, 16].*

Machine	Hours
Diesel engines — off highway	150-250
Transmission, differentials, final drives	300-1000
Hydraulics — mobile equipment	200-500
Gas turbines — industrial	500
Steam engines	500
Air/gas compressors	500
Chillers	500
Gear boxes — high speed/duty	300-500
Gear boxes — low speed/duty	1000

2.2.2 Sample Preparation

Oil samples to be analysed in the laboratory should be mixed thoroughly prior to analysis using either Ferrography or the filtergram method, to ensure that the portion withdrawn from the sample bottle is representative of the oil of the machine.

2.2.2.1 Ferrography (Analytical)

Ferrography involves the separation of ferrous particles from the oil sample by exposure to a magnetic field. A measured amount of the oil sample is diluted to the required viscosity by a fixer solvent, and passed over the ferrogram slide under the influence of a graduated magnetic field [6]. Tetrachloroethylene is commonly used for the fixer solvent.

The magnetic field causes large metallic particles to deposit near the entry position on the ferrogram slide, while small particles deposit near the exit point on the slide. The ferrographic oil analyser includes a bichromatic microscope with typical magnification of 1000 times, which is used to examine the dispersed debris particles. Ferrous particles can be distinguished by their alignment to the magnetic field lines, as well as their size, morphology, particulate count and colour, compared to examples from the Wear Particle Atlas [3]. Non-ferrous particles cannot be identified using the Ferrography method, as these are not influenced by the graduated magnetic field.

The metallurgy of the debris particles can be determined by heat and/or chemical treatment of the ferrogram slide, resulting in a change in particle colour or structure. Particle data and metallurgical information is then used to determine the wear mechanisms, wear source and degree of damage, using machine experience and maintenance history [3]. The particle morphology, size, size distribution and elemental composition cannot however be determined using Ferrography, which would require the use of other equipment discussed in Sections 2.2.3.1 and 2.2.3.4 [17].

The analytical Ferrography technique can be used to obtain extensive information about the wear debris found in an oil sample. It does however require high operator experience and substantial sample preparation, generally making this technique too expensive for routine oil analysis [18]. Even so, analytical Ferrography has been used extensively for the condition monitoring of critical manufacturing process equipment and in the aircraft maintenance industry.

2.2.2.2 Filtergram

The filtergram method of wear debris analysis utilises the sampled oil to be passed through a cellulose nitrate filter, generally of 3 micron pore size. Solvent is then flushed through the filter to remove all traces of remaining lubricant. The collected particles will then have a size of that corresponding to the filter pore size or larger. Analysis of the particles can be done under an optical microscope after chemical and heat treatment of the membrane filter in order to make it transparent.

This technique has the ability to collect both ferrous and non-ferrous particles, allowing the wear debris to be analysed for impurity particles [3]. However, the particles are not sorted according to size, as is the case with the ferrogram method.

The use of either Ferrography or filtergram techniques is dependent on the expected failure modes of the particular machinery. In cases where ferrous, non-ferrous and liquid debris is encountered, both techniques can be employed to analyse all of the wear debris contained in the oil sample. The filtergram is also a cheap and quick method to test for wear particle concentration qualitatively on-site, and has now become widely used as a laboratory technique [17].

2.2.3 Wear Debris Analysis

Wear debris analysis involves the sampling of lubricating oil and the analysis of the wear particles contained in the sample. Information obtained from the wear particle analysis can be used to identify the type of wear occurring. This condition monitoring technique can be used to determine if the components of a machine are wearing at a normal rate, or whether a component is experiencing severe wear.

The wear debris analysis techniques are generally off-line techniques, as laboratory microscopes are required for the particle analysis. This requires sampling intervals to be established, of sufficient frequency to allow early detection of developing machine faults. Limited particle information such as size and count distribution can be performed by in-line techniques [19].

The typical information that can be obtained from wear particle/debris analysis includes particle size and count distribution, angularity, shape, surface roughness and composition. Particle size and count distribution can be determined using a particle counter, while particle shape and morphology information can be obtained using microscopy techniques, such as an optical microscope.

The accuracy of the description of the particle shape and surface detail results in either a qualitative or quantitative description. Qualitative description of a particle involves the analyst describing the particle using categories such as outline is round or angular, and surface is rough, smooth or scratched. While qualitative analysis can be used for successful identification of wear related faults, expert knowledge is required to correctly associate the wear found particles with their corresponding wear mode [20]. Quantitative description of a particle involves the use of precise objective descriptors, generally numerical values, which can describe the particle shape and surface features with high repeatability, and not dependent on human judgement. The use of quantitative numerical descriptors allows computers to be utilised to aid particle analysis, by performing mathematical or Boolean operations on the numerical descriptors.

Elemental analysis of wear particles can also be an effective technique for determining the origin of particles, and components likely to wearing. As different components are manufactured from different metallic alloys (due to special material property requirements), the constituent elements found in wear particles can be used to identify the material of the particle, and hence, the likely origin. While every machine contains components of slightly differing materials or alloy constituents, specific metals are commonly used for certain components due to their beneficial material property.

2.2.3.1 Particle Concentration and Size Distribution

The number of particles and size distribution in an oil sample can be obtained by inexpensive methods such as particle counters, to warn of abnormal wear conditions. While particle counts cannot be used to determine where in the machine the wear is occurring, trending from the oil analysis history can be used to detect sudden increases or decreases in particle of a certain size. This data can be used to determine whether other machine condition monitoring techniques should be utilised in order to deter-

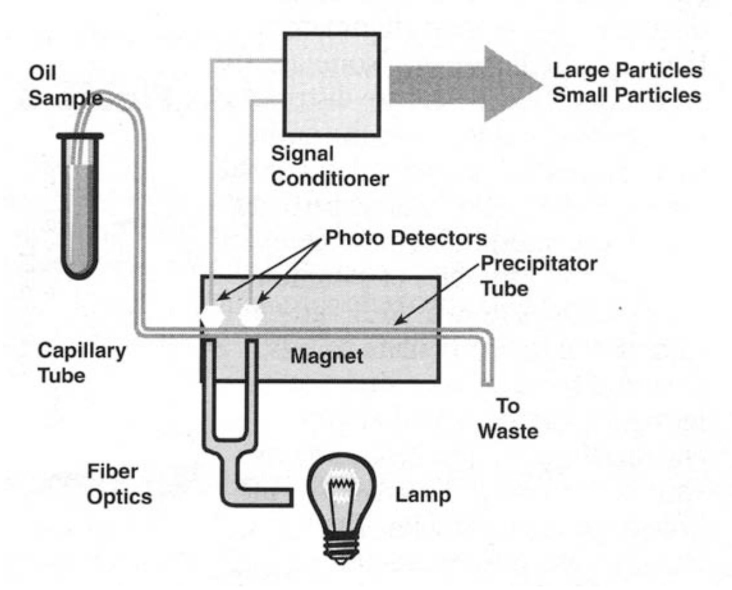


Figure 2.11: *Operation of direct reading ferrograph [3].*

mine whether excessive wear is indeed occurring, and which parts of the machine are responsible for the wear particles.

Wear particle counting is often done using either particle counters or using the Direct Reading Ferrograph (DRF). The DRF can be used to measure the relative concentration of ferrous particles above (large particle count, or DL) and below 5 microns (small particle count or DS) [3]. The qualitative parameters of wear rate index, wear intensity index and wear severity index can then be calculated by the following formulae:

- Wear Rate Index, WR = DL + DS
- Wear Intensity Index, WI = DL DS
- Wear Severity Index, SI = (DL + DS) (DL DS) [17].

The DRF uses optical methods to detect the presence of particles, as shown in Figure 2.11.

Particle Counters

Particle counters are commonly used to determine the number of particles of a certain size that exist in an oil sample. Sensors able to count particles and grade particles by size have been developed for on-line applications, and are therefore often part of on-line machine condition monitoring systems [10, 19]. The concentration of particles in the three size ranges are generally reported, which are: >4 microns, >6 microns and >14 microns [18]. If particles are counted manually using an optical microscope, two size ranges are used consisting of >5 microns and >15 microns according to ISO 4407-2002 [21]. The concentrations are then converted into ISO cleanliness codes, a two digit number for each size range and the numbers separated by a slash. Samples from particle counters therefore receive three numbers, while manually counted samples are reported in two numbers separated by a slash. In the manually counted case, the first number indicates the quantity of particles found to be larger than 5 microns, while the second number refers to the number of particles larger than 15 microns. The two numbers correspond to the exponential coefficients of the particle counts expressed in binary (to a base 2) [16].

Particle counters are an inexpensive wear debris analysis tool, which can be used to detect the occurrence of an abnormal wear condition. Further analysis with more sensitive and costly debris analysis techniques can be performed, based on particle count and size distribution data.

The operating principals generally used for particle counting and determining the size distribution are either by light extinction, such as the DRF, flow decay or mesh obstruction. The counting techniques used by these three types of particle counters are unable to distinguish between ferrous and non-ferrous particles. Light extinction particle counters use a light beam and detector as shown in Figure 2.12, to sense the presence of particles in the fluid.

Due to the use of a light beam, fluid opacity, air bubbles and water contamination affect this type of particle counters, as these can either result in false readings or the inability to detect particles, as is the case of very high fluid opacity. These types of contamination can however be resolved, by agitation in case of air bubbles, or dilution if the fluid has a high opacity.

Flow decay can be measured by using the primary, secondary and tertiary blocking behaviour of a particle-size distribution exposed to a calibrated mono-size micro

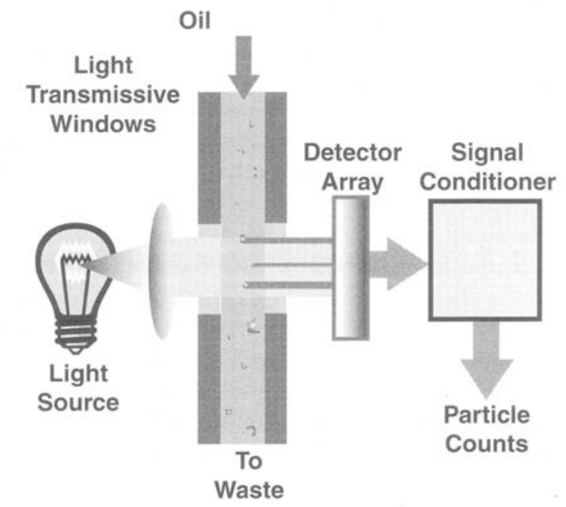


Figure 2.12: *Operation of light extinction particle counters [3].*

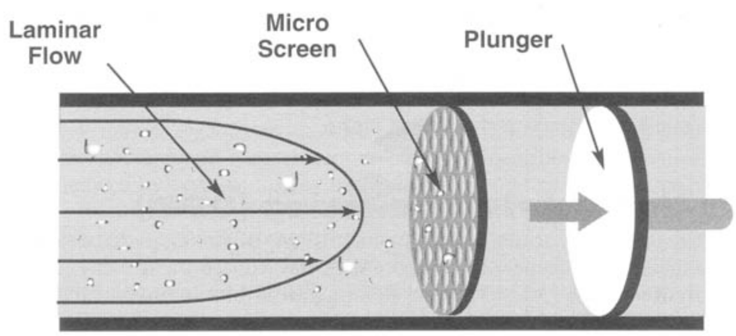


Figure 2.13: *Flow decay counter principle [3].*

sieve [3]. The device is calibrated by a standard fluid with known particle count and size distribution, and results are then referenced to the standard. Flow decay particle counters are generally calibrated for a number of viscosities, and the operator must enter the relevant viscosity of the fluid to be tested. Standard sieve sizes of 5, 10 and 15 microns are generally used, which allows the correlation of flow decay data with an ISO cleanliness code. The operation is demonstrated in Figure 2.13.

Mesh obstruction particle counters work on the pressure difference across three precision micro-screens. As the number of pores in each screen is known, a relative pressure drop across each screen can be correlated to a number of particles retained by

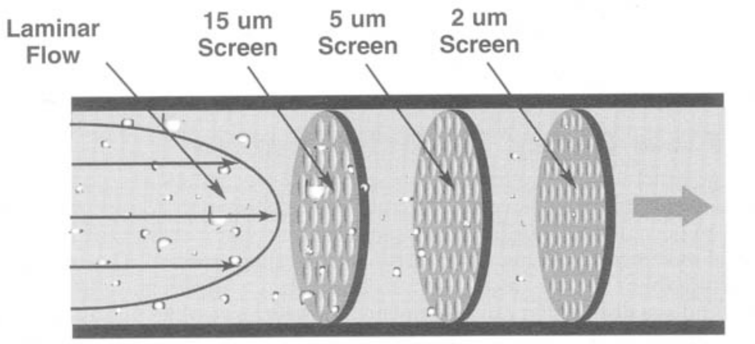


Figure 2.14: *Operating principle of pore blockage particle counter, and typical screen sizes [3].*

the screen, for the particular fluid viscosity. This principle is shown in Figure 2.14.

The results of unknown oil samples depend on the accuracy of calibration with a standard fluid with known particle count for each of the three mesh sizes [3]. The count data is then generally converted into an ISO 4406 cleanliness code for further evaluation.

Particle counters have two key disadvantages when used for wear debris analysis. Firstly, particle counters are unable to distinguish wear particles from contamination particles found in the wear debris. It is therefore difficult to assess whether a wear problem condition is occurring. The second disadvantage of particle counters is that due to lubricant contamination, random fluctuations of particle counts can occur for systems in good condition, leading to either false alarms or high alarm levels [18]. Increased contamination control of the lubricant system is therefore beneficial in reducing the noise in wear particle detection, resulting in a more reliable analysis technique.

Despite the disadvantages, particle counting has become a popular and effective technique for determining the onset of component wear [18]. Although debris particle definition and characterisation are not possible, particle counting can serve as an indicator to warn of failing seals or breathers, causing high concentrations of contamination particles to enter the lubricant and leading to excessive wear. High particle counts can therefore be used to highlight the possibility of an excessive wear problem or lubricant contamination, allowing further analysis to be performed.

2.2.3.2 Particle Analysis Techniques

Morphology and shapes of wear particles can enable the analyst to determine what type of wear mode is occurring, as well as the degree of wear that has occurred. Machine condition can therefore be determined more accurately with knowledge of wear particle morphology and shape, than with just particle count and size distribution. Due to the small size of most wear particles, determining the morphology accurately requires high powered microscopes, and this topic has received attention by researchers [22,23]. The research outcomes, concerned with methods to quantify the shapes and surface morphology of wear particles, are discussed in Sections 2.2.3.2.1 to 2.2.3.2.5.

Particle shape can be correlated to a specific wear mode by comparison with a wear particle atlas. These databases contain large amounts of information about particle morphology, shapes and sizes for each wear mode of common machines. Wear modes are generally classified into the following categories: rubbing wear, cutting wear, rolling fatigue, combined rolling and sliding, and severe sliding wear.

Rubbing wear particles usually occur when two surfaces rub against each other under pressure, such as two gear teeth of a gearbox. The particles are generally small platelets, ranging in size between 0.5 to 15 microns, and originating from the mixed shear layer. Rubbing wear particles are generated in systems in good condition, although contamination such as sand can cause the concentration of particles to increase by an order of magnitude [24].

Cutting wear particles commonly have long elongated shapes, 2 to 5 microns wide and 25 to 100 microns long. These particles are produced if one surface is penetrating another, similar to a lathe tool creating swarf, although on a microscopic level. Hard abrasive particles in the lubrication system can also cause cutting wear. Cutting wear particles are a sign of an abnormal wear condition, and their concentration should be monitored to avoid sudden component damage [24].

Rolling fatigue particles are the result of failing rolling contact bearings, due to surface fatigue of the rolling elements or surfaces. Three types of rolling fatigue particles have been observed: fatigue spall, spherical and laminar particles [24]. Fatigue spall particles are generated when a fatigue pit occurs on the surface, and generally reach a maximum size of 100 μm during the micro-spalling process. During bearing failure, macro-spalling produces particles in the form of platelets with larger sizes, and an increase in the number of particles of 10 μm size. Spherical particles associated with rolling bearing fatigue are generated in the bearing fatigue crack, and are usually below 3 μm in diameter. These can be detected before any spalling occurs, although spherical particles may not be produced in significant quantities under certain loading conditions during bearing failure. Spherical particles can also be the result of cavitation erosion or welding or grinding processes, which generally produces spheres with diameters commonly above 10 μm. Laminar particles are very thin free metal particles with a length of 20 to 50 μm, and an aspect ratio of about 30:1. They can be used to diagnose bearing failure together with the presence of spherical particles and detection of a severe wear condition of uncertain origin.

Severe sliding wear occurs when the wear surface stresses become excessive due to high load or low speed. High wear rates are usually encountered as the shear mixed layer breaks down, while catastrophic wear rates results once the surface is worn away. The ratio of large to small particles is dependent of how much the surface stress has exceeded the stress limit of the material. Generally, the higher the stress level, the higher the ratio [24]. Severe sliding particles typically range from 20 μm up, with a major dimension to thickness ratio of 10:1. Straight edges and surface scratches due to sliding wear can be used to identify these particles.

Combined rolling and sliding wear is often associated with gear systems experiencing pitch line fatigue, scuffing or scoring. Particles produced from gear pitch line fatigue are similar to those produced from rolling bearing fatigue. The particles generally have major dimension to thickness ratios of 4:1 to 10:1, depending on the gear design. A high ratio of large particles (about 20 μm) to small particles (about 2 μm) is also generally observed. Scuffing is caused by too high a load and/or speed, and is the consequence of excessive heat breaking down the lubricant film resulting in adhesion of the mating gear teeth. Scuffing wear results in a large volume of wear debris, the particles tend to have a rough surface and jagged circumference [24]. As scuffing occurs at high temperatures, oxides are usually present and particle oxidation may also be detected (brown or blue temper colours).

2.2.3.2.1 Microscopy Techniques

The morphology and three-dimensional (3D) shape can be hard to detect, due to the small size of most wear particles. Numerous techniques have been used for the analysis of wear particles including Optical Microscopy, Scanning Electron Microscopy (SEM), Atomic Force Microscopy (AFM), and Laser Scanning Confocal Microscopy (LSCM). While optical microscopy requires the least expensive equipment and training, the low magnification of about 100 times can be used to detect particle outlines, sufficient only for qualitative wear particle analysis [14].

LSCM has higher resolution than the optical microscope with a significant increase in setup cost and a resolution of 0.2 μm, which is sufficient to analyse the surface morphology of wear particles above 5 μm in size [25]. SEM has again higher resolution, with magnification up to 200,000 times. The highest resolution can be obtained with AFM, in the nm region. However, this resolution and resulting cost is generally considered excessive for wear particle analysis [25]. The specific operating features of each microscopy technique is discussed in the following Sub-sections 2.2.3.2.2 to 2.2.3.2.5.

2.2.3.2.2 Optical Microscopy

Optical microscopy (OM) is the simplest of the microscopy techniques and involves placing the wear particles to be analysed onto a glass slide, and using the magnification to observe the particle outline. A CCD camera is also often fitted to specially designed optical microscopes, which allows the images to be saved for later analysis or review. Particle outline and colour information can be used for qualitative wear particle analysis. Although the operation of the OM is simple, considerable operator expertise is required for reliable evaluation of the observed wear particles. Due to the simplicity and low cost, optical microscopy is still used [14].

2.2.3.2.3 Scanning Electron Microscopy

Scanning Electron Microscopy (SEM) is a surface imaging technique where an electron beam is used to probe the surface of a specimen. This analysis technique can therefore obtain a high resolution image of the specimen surface, at magnifications typically ranging to 200,000 times. Compositional information can also be obtained by monitoring secondary x-rays generated by the electron beam-specimen interactions [3].

Images obtained from a scanning electron microscope are transferred to a computer for visual and numerical analysis of the particle morphology. The accuracy of the particle analysis is dependent on the amount of uncertainty or noise present in the transferred image [26].

One form of noise often introduced by metallic particles is edge highlighting, and is due to electric charge build-up at the edge of the particle. Treating the particle with a special coating prior to scanning can reduce this problem [25]. However, this has the potential to both alter the surface chemistry as well as modify the surface morphology by covering holes and other depressions.

2.2.3.2.4 Atomic Force Microscopy

Atomic Force Microscopy (AFM) has good image resolution, typically around 0.1 nm in the vertical and about 0.2 nm in the horizontal direction, which enables the AFM machine to provide very accurate surface morphology data [23]. However, the application of AFM to wear particle analysis is limited by the vertical range, which is typically 4 microns. Wear particles generally have surface features with surface relief up to 10 microns [23]. The very high resolution of AFM is generally not required for wear particle analysis, a lateral resolution of 0.2 μm is adequate [25]. Another drawback of AFM is the difficulty of securing the wear particle such that it will not move during the scanning process. The high cost of AFM is therefore not justified, as the resolution is higher than required, and difficulties with mounting and vertical range limit its use.

2.2.3.2.5 Laser Scanning Confocal Microscope

The Laser Scanning Confocal Microscope (LSCM) technique can be used to study the outlines of particles, as well as the 3D surface topography. The outline of a particle can be obtained quickly, by positioning a light source behind the sample on the opposite side of the sensor, and using a transparent slide. Edge effects of the beam, such as bending are reduced by the use of a laser. The outline shape of a particle can be used for wear particle identification, and correlation to a wear mechanism in the case of cutting, spherical and rubbing particles [22].

The surface topography of a particle can be obtained by using the laser to illuminate a very small section of the particle, and obtaining an image in the focused region. An aperture is used to capture only light from the illuminated part of the particle. The region in focus corresponds to a thin slice of the particle surface. The light that passed through the aperture is detected using a photomultiplier, which converts the light into a digital image [25]. Once images of the entire particle have been obtained, computer software can be used to reconstruct the 3D surface. This technique is further discussed in the Digital Image Acquisition Section 2.2.3.3.1.

LSCM is well suited for wear particle analysis, as it is easy to use (being similar to an optical microscope), and the particles do not need to be pre-treated. Special mechanisms or precautions for securing the particle on the slide are not required for LSCM.

2.2.3.3 Quantitative Boundary & Surface Morphology Characterisation

Boundary and surface morphology can be used to characterise wear particles according to the wear mode generating them. As discussed in the previous section, qualitative analysis utilises simple visual inspection techniques for particle analysis, which requires substantial operator experience for correct diagnosis. Quantitative wear particle characterisation uses numerical descriptors of wear particles to be able to link a wear mode with a set of unique numerical descriptors [20, 27, 28]. Extensive expertise is therefore not required once the numerical descriptors have been determined for the particle. Unlike qualitative analysis, quantitative analysis is not a subjective diagnostic process, resulting in consistent and reliable wear particle characterisation [29].

Quantitative analysis of wear particles requires three steps to be performed: sample preparation, digital image acquisition and image analysis. Sample preparation is required by some image acquisition techniques, and generally relates to the cleaning or securing of the wear particles to be analysed. The digital image acquisition stage involves the scanning of the particle outline and/or surface in order to obtain a high resolution image, in a digital format, suitable for computational analysis using computers. Image analysis of the digital image can then be performed, and is concerned with describing the particle outline and surface using numerical descriptors.

In order to examine wear particles using numerical descriptors, a digital image of the wear particle must be obtained, detailing the particles shape and surface morphology. The surface morphology can be calculated once a 3D surface map of the particle has been compiled using a number of two-dimensional (2D) images. Image processing techniques are then used to improve the quality of the obtained images, mainly by removing noise which has been introduced in the digital image acquisition process [30]. Once a good quality 3D surface morphology map has been compiled, image analysis techniques are performed to describe the particle using numerical descriptors. The three steps of image acquisition, processing and analysis can be automated by using computer software, allowing analysts to diagnose wear debris with minimal experience or training [20].

2.2.3.3.1 Digital Image Acquisition

Image analysis is concerned with the acquisition of 3D surface morphology data of wear particles. Five techniques have been developed which allow the acquisition of 3D data suitable for quantitative study of wear particle surfaces: stylus profilometry, atomic force microscopy (AFM), interferometric microscopy (IM), scanning electron microscopy (SEM) and laser scanning confocal microscopy (LSCM) [25]. The two more common techniques for wear particle analysis are SEM and LSCM, which are discussed in this report.

Conventional SEM machines have a major limitation for analysis purposes, that the signals do not directly reveal the topography of the particle surface [23]. Podsiadlo and Stachowiak [23] developed a new SEM stereoscopy method which enables accurate acquisition of 3D surface topography maps of wear particles. The surface elevation map is obtained from a stereoscopic pair of SEM images, corresponding to two images of the same object at slightly differing angles. Surface feature points are located on both images, and the difference between the points, called the disparity, is determined and used to calculate the surface elevation. The surface elevation map can then be used to reconstruct the surface in three-dimensions, by using the elevation points and interpolating between them. However, the 2D image compilation requires a substantial amount of time, making stereo SEM impractical for large throughput wear particle analysis at this time [23].

The LSCM technique can also be used efficiently for wear particle analysis as both particle boundary and surface morphology information can be obtained. Two image acquisition channels are often used to allow for boundary and surface scanning. A typical layout of a LSCM is shown in Figure 2.15. The stage is often of variable height design, and can be controlled by a stepper motor to allow sequential acquisition of particle images at set height intervals. The potential benefits of using confocal microscope imaging to determine wear particle morphology and possible wear mechanism has been widely accepted [31–33].

The image resolution of LSCM is generally lower than that of SEM, however the resolution of a quality LSCM with lateral resolution of approximately 0.2 μm is usually adequate to provide images for wear particle analysis. The resolution of LSCM is significantly higher than that obtainable by optical microscopy (OM), by about one to two orders of magnitude. Peng [25] found that 3D images of wear particles can be obtained quicker and easier by using the LSCM technique compared to the SEM technique. This is due to the absence of particle preparation, and less computer image processing required to compile the 3D surface morphology map from 2D images [23,25].

2.2.3.3.2 Image Processing

Image processing involves the quality improvement of digital images by reducing

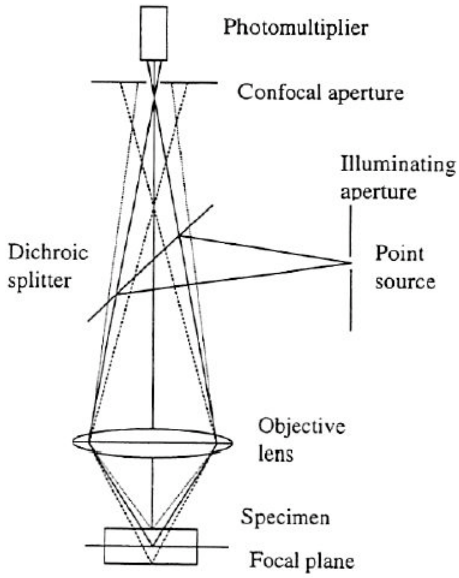


Figure 2.15: *Sketch of a laser scanning confocal microscope [34].*

the noise introduced during image acquisition, followed by the compilation of a number of 2D images to obtain a 3D surface topography map. Noise can result in an image due to instrument error and quantisation of an analogue signal. Instrument noise can result from both the limit of resolution of the scanning and detection mechanism, as well as noise introduced by the electrical circuitry of the machine, introducing random errors in pixel brightness. Electrical noise typically includes thermal noise arising from the random motion of electrons in a conductor, and shot noise which is introduced by the discrete nature of current flow in photodetector circuit components (diodes and transistors) [35].

Digital image filters perform a particular mathematical operation on the brightness of a pixel relative to the neighbouring pixels [36]. Many digital image filters have been developed, for a diverse range of applications including noise reduction, altering the brightness and contrast of an image, or sharpening edge details [35]. Podsiadlo and Stachowiak [30] tested a median-sigma filter for its ability to reduce Gaussian and shot noise, as well as preserve subtle details, edge and shape features. The test data demonstrated that the median-sigma filter performs better than the Mean, Standard

Median, Hybrid-Median, Recursive Separable Median and Sigma filters.

The use of digital filters for noise reduction has been applied by numerous researchers. An important property of the digital filter is that additional image features must not be introduced, such as reduced contrast across the particle boundary, or distortion of the particle shape [37].

Random noise can be reduced by comparing multiple images from the same particle section, and extracting information (surface features corresponding to pixel brightness values eg dark places) common to all images [30]. Quantisation noise is introduced in the conversion of an analogue signal with infinite shades of grey (between black and white), to a digital image that has a finite number of grey shades. Digital images of 256 bits (colour variants) is typically used, leaving 254 shades of grey, and one for each black and white. Noise introduced by quantisation can be reduced by increasing the number of grey levels, but is generally low as 256 bit images can adequately show the image details required for wear particle analysis [30, 35].

The surface morphology of a wear particle can be reconstructed from a set of 2D images to obtain a 3D surface topography map. The operation of this process is dependent on the types of images being used for surface compilation. Two image formats have been developed, the Maximum Brightness Image (MBI) and the Height Encoded Image (HEI). Both images grade the height in terms pixel brightness, using a grey scale of 256 bits; white corresponds to 0 and black to 255. The MBI classifies the height according to the brightness of the pixel, where low numbers correspond to high places. Alternatively, the HEI classifies the heights of the pixels at each strip in the case of LSCM, since the thickness of each slice is known. The HEI image format is used for the construction of a 3D surface map, while the MBI format is used to qualitatively observe whether the obtained image is of good quality (low noise) and the microscope settings were correct [38].

2.2.3.3.3 Computer Assisted Image Analysis

Computer assisted image analysis allows the wear particles to be analysed by quantitative numerical characteristics, and thus the development of expert systems for wear particle characterisation and interpretation becomes feasible. The use of computer analysis for wear particle characterisation and identification reduces the need for expert technical staff and increases the throughput and efficiency of samples to be analysed [25].

Wear particles can be characterised using numerical parameters to describe shape features [22, 39], such as particle length or area. Numerous parameters have been developed by researchers, in order to describe and successfully characterise the observed wear particles. Fractal parameters were also developed, which are a measure of the complexity of the particle outline. The rationale of fractal geometry is to use the boundary to describe the shape or surface. While Euclidean geometry describes particles by shapes including circles, triangles and rectangles, Fractal geometry uses shapes natural to the particle. The characteristic feature of natural irregular shapes is that successive magnification of a section of the particle, reveals a structure that is closely related to the original structure. Fractal parameters can therefore be a more effective descriptor of the particle boundary, than by using Euclidean shapes [26].

Surface features of wear particles aid in the identification of the responsible wear mode, thus effective parameters for surface description has become an area of interest to researchers. The same authors [26] also recommended four parameters which could be used to describe the surface of a particle. These parameters were RMS deviation (height descriptor), ten-point height, skewness (symmetry descriptor of height distribution) and kurtosis (a peakedness description of height distribution) [39]. Podsiadlo and Stachowiak [40] applied three new texture surface parameters (texture aspect ratio, texture minor axis and texture direction) together with the modified Hurst orientation transform for surface topography characterisation of wear particles.

As many numerical parameters do not satisfactorily describe all the required geometry and functionality of the surface [39], criteria for the use of parameters for wear particle characterisation were developed by Dong, Sullivan and Stout [39]. The criteria were (i) only some important topographic features are needed to be described; (ii) parameters should describe a unique feature; (iii) parameter rash should be avoided; and (iv) parameters should be based on mathematical and/or statistical principles and allow easy implementation on microprocessors.

The correlation between wear mode and wear particle characteristics, using complex numerical descriptors, has been studied by a number of researchers. Peng and Kirk [22] found that six types of wear particles, cutting, spherical, rubbing, laminar, fatigue chunk and severe sliding wear, can be characterised and distinguished by using nine descriptors. The nine descriptors are: area, length, roundness, fibre ratio, fractal dimension, height aspect ratio, average surface roughness (Ra), root mean square of Ra, and a spectral moment analysis descriptor.

Typically, numerical descriptors are ratios of different geometrical aspects of the particles, such as angularity of a particle, being the ratio of the length (longest dimension) to width (shortest dimension). Numerical descriptors have been used for both shape characterisation as well as surface description. The use of scale-independent numerical descriptors, by fractal methods, has been applied for wear particle characterisation [37]. Fractal methods are ratios of particle properties and thus describe the particle in dimensionless form, allowing particle shapes and surface features to be compared regardless of particle size [39]. Fractal parameters and computer image analysis have been applied to wear particle morphology recognition, to increase the ability of computer software to aid in wear particle identification and analysis [37]. The current trend in wear particle characterisation is to use both shape and surface information to distinguish particles from differing wear modes.

2.2.3.4 Elemental Analysis

Elemental analysis involves the analysis of the oil sample, and determining what elements are contained in the wear debris. This information can be used to locate the machine components producing the wear particles, if the metallurgy of each type of component is sufficiently different [3]. This technique is often used in wear debris analysis, even if a number of components are identified which could be responsible for the wear particles. While the metallurgy is machine specific, common alloys, and hence elements, have been used in certain machinery parts, as shown in Table 2.2.

Elemental analysis can be done on particles once collected from samples, such as by Ferrography. If particles are to be burnt and analysed by spectroscopic methods, the particle size must be sufficiently small to be within the size limit of the spectrometer [10]. Spectrometry utilises x-rays or high temperature (up to 10,000 K) in order to excite the atoms of the particles, which give off energy in the form of a photon of characteristic wavelength [10, 41].

2.2.3.4.1 X-Ray Fluorescence

The X-ray fluorescence (XRF) method of wear debris analysis is gaining popularity for on-line and on-site elemental analysis, and has been used in industry for automated process control. Due to the ability of the XRF process to determine concentrations and elements present in a sample, this technique can be used to give early warning of equipment failures, where wearing components can be identified by metallurgy [3,42,43].

The operation of XRF is similar to spectrometric analysis, but uses x-ray radiation and detection instead of atomic emission in the visual or UV range [18]. XRF can be used to monitor solids, fluids or suspensions. However, as some absorption and scattering occurs due to the oil, lighter elements such as aluminium, magnesium and silicon need to be separated from the fluid, usually on a micro pore patch [3].

2.2.3.4.2 Spectrometric Oil Analysis

Spectrometric analysis techniques of wear particles in lubricating oils are often used for elemental analysis. Elemental analysis can be performed by either atomic emission (AE), atomic absorption (AA), or XRF as discussed in Section 2.2.3.4.1. AE has become the most common wear metal analysis technique for general-purpose oil analysis. It operates by exciting atoms to a high-energy state using a high temperature source. Characteristic emission lines occur when the atoms loose energy by emitting photons at specific wavelengths according to the elements present in the particle [44]. The spectral lines are separated into a diffraction grating by an entrance slit, and are detected by a photomultiplier. The intensity is determined and correlated to a concentration, measured in parts per million (ppm), of the particular element by prior calibration with a standard of known concentration.

Table 2.2: *Elements used in common machinery parts [10].*

Element	Possible Source
Aluminium	Spacers, shims, washers, pistons on reciprocating engines, cases on accessories, bearing cages in planetary gears, some bearing surfaces.
Antimony	Bearing alloys, grease.
Barium	Oil additive, grease, water (leaks).
Boron	Seals, airborne dust, water, coolants.
Calcium	Oil additive, grease, some bearings.
Chromium	Plating metal, seals, bearing cages, piston rings and cylinder walls on reciprocating engines, chromate corrosion inhibitors (coolant leaks).
Copper	Main or rod bearing thrust bearings, wrist pin bushes, oil coolers, gears, valves, turbocharger bushes, washers, copper radiators (coolant leaks). Also copper alloy, if tin also: bronze, if zinc also: brass.
Iron	Reciprocating engine components, ball & roller bearings, spring gears, safety wire, lock washers, locking nuts and pins, bolts.
Lead	Bearing metal (usually in addition to high copper or aluminium), seals, solder, paints, greases.
Magnesium	Aircraft engine cases for accessories, component housings, marine equipment (affected by water), oil additive.
Manganese	Valves, blowers, exhaust and intake systems.
Molybdenum	Piston rings (some diesels), electric motors, oil additive.
Nickel	Bearing metal, valve train metal, turbine blades.
Phosphorus	Oil additive, coolant leaks.
Silicon	Airborne dust, seals, anti-foaming additive (some oils).
Silver	Bearing cages (silver plating), puddle pumps, gear teeth, shafts, bearings in some reciprocating engines.
Sodium	Coolant leaks, grease, marine equipment (affected by water).
Tin	Bearing metal and thrust metal bushes, wrist and piston pins, pistons, rings, oil seals, solder.
Titanium	Bearing hub wear, compressor blades and discs (aero-engines).
Zinc	Brass components, neoprene seals, grease, coolant leaks, oil additive.

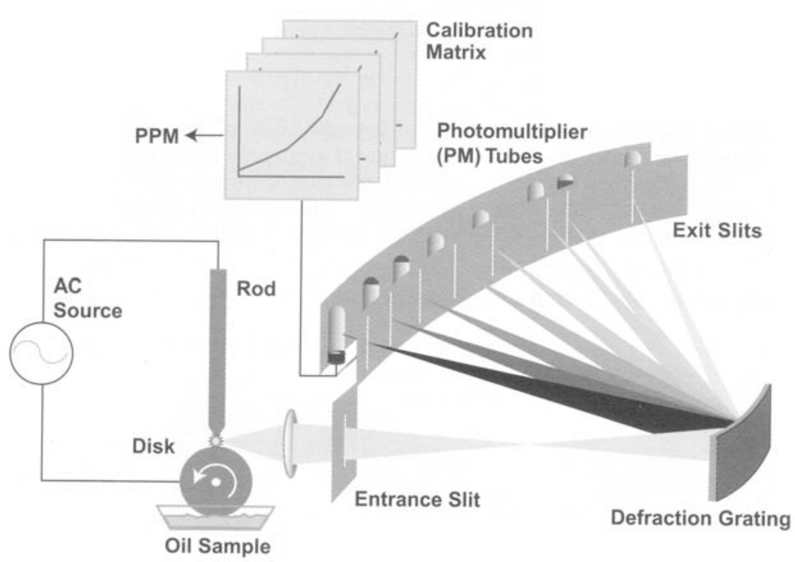


Figure 2.16: *Operation of a rotary disk spectrometer [3].*

AE machines differ in the type of scanning as well as excitation source used. Scanning can either be done in multiple runs, where the presence and concentration of each selected element is measured, or simultaneous, where all selected elements are scanned at a single run. Simultaneous machines can provide data on 20 to 60 elements in less than one minute, and are well suited for laboratories with high throughput [3].

The two most common excitation sources for AE are the rotary disk electrode (RDE) and inductively coupled plasma (ICP) method. RDE utilises a rotating carbon disc immersed in the sample fluid, to transport fluid into a high temperature arc. The arc can be established by several methods, generally either by an AC voltage source, as shown in Figure 2.16, or by a low voltage AC source ignited by high voltage pulses from an igniter circuit.

Direct current arcs are also sometimes used. RDE spectrometers are low cost instruments with good precision and repeatability, as well as allowing fast and simple operation with no sample preparation.

ICP spectrometers operate on an argon gas, which is passed through a radio frequency induction coil and heated to a temperature of 8,000 to 10,000 K, resulting in

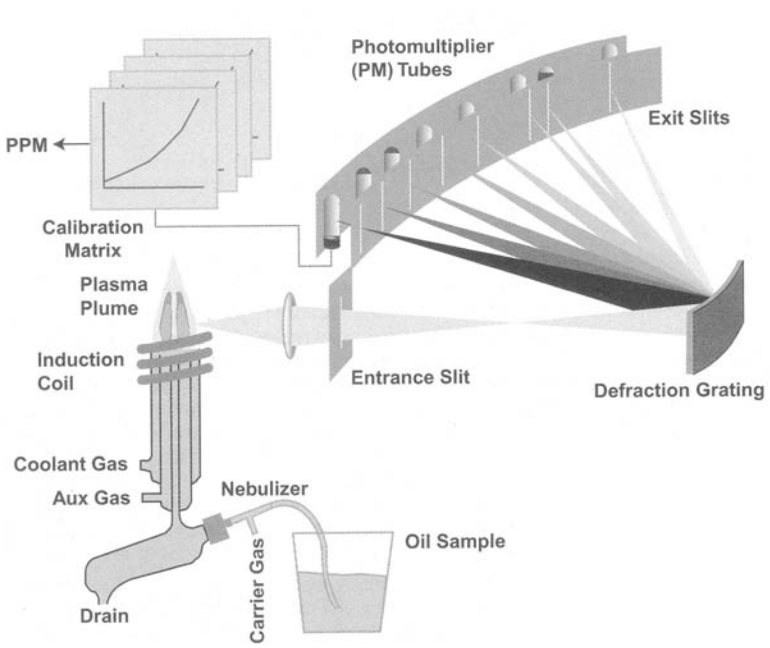


Figure 2.17: *Operation of inductively coupled plasma spectrometer [3].*

the production of plasma. The oil sample is diluted in xylene or kerosene, nebulised and transported to the centre of the plasma torch by argon gas. This process is shown in Figure 2.17.

The ICP spectrometers are available in both sequential and simultaneous scanning modes, similar to the RDE spectrometers. The ICP method has superior accuracy, precision and repeatability over the RDE technique, while providing sensitivity to parts per billion (ppb) for particles less than 3 microns in size. Disadvantages of the ICP technique include low resolution for particles larger than 8 microns in size, more complicated and expensive technique, higher operating cost, and higher waste costs due to the use of hazardous chemicals. ICP spectrometers are commonly used in the oil analysis industry, especially high volume used-oil analysis laboratories.

Atomic absorption (AA) spectrometers have become a popular use for determining the wear metal concentration in lubricating oil samples. In AA spectrometers, a small portion of the oil sample is burned in a high temperature flame, hot enough to dissociate the sample into a plasma state of constituent atoms. The plasma cloud is irradiated

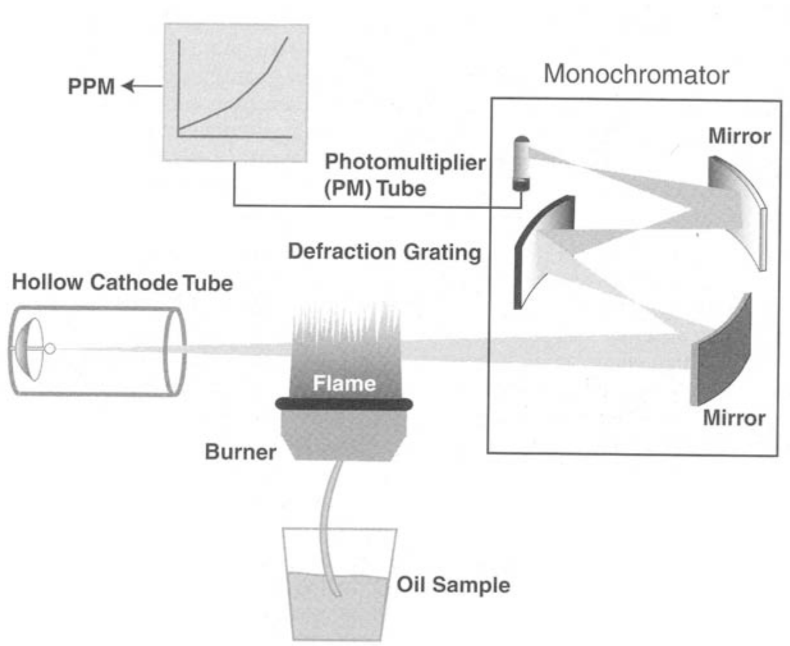


Figure 2.18: *Atomic absorption spectrometer [3].*

by a hollow cathode lamp at the characteristic wavelength of the selected metal. The absorption of light is dependent on the concentration of the metal, which is measured and converted to ppm. As a different wavelength is required in order to detect each element, the bulb needs to be changed and another portion of sample burned for each element to be detecte [3]. The operation is shown in Figure 2.18.

The operation of the AA spectrometers is thus of sequential type, which increases the required scanning time compared to simultaneous scanning spectrometers as discussed above. While modern machines feature automated scanning cycles, the longer scanning time and sample preparation make AA spectrometers popular with smaller oil analysis facilities [3]. The benefit of AA over RDS is increased accuracy, precision and repeatability at comparable cost.

Computer assisted image analysis is being combined with artificial intelligence techniques to allow more particle analysis to be done by computer software [27]. Research into the use of expert system type computer software for wear particle recognition and categorisation has been conducted [33, 45], however commercial applications of this technology have not been developed.

2.3 Vibration Analysis

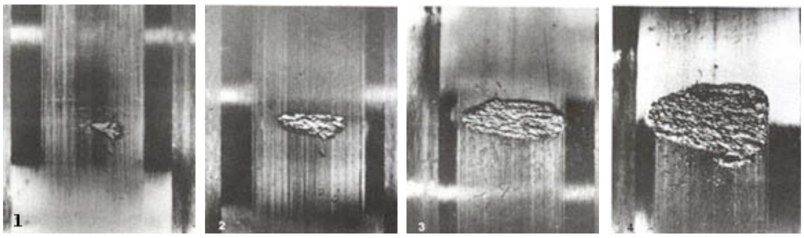
The vibration analysis technique for machine condition monitoring has been applied for fault diagnosis for decades, and has received substantial attention from researchers. Improvements in the field are today concerned with improving the ability for early fault detection, as well as more accurate fault diagnosis of complex machinery. The relevant Australian Standard for the vibration analysis by measurement of non-rotating machine surfaces is ISO 10816—3:1998 [46].

The generation of vibration frequencies in rotating machinery such as gears and bearings is due to deformation of the gear teeth or bearing rollers at the point of maximum force transmission. Typical frequencies emitted from machinery in good condition can include gear mesh frequencies, imbalance, and blade pass frequencies in the case of fans [47]. Modulation of these frequencies in the form of sidebands should not be present in the spectral analysis, as this could indicate a fault condition. Gear faults can generally be determined by frequency modulation of gear mesh frequencies resulting in side lobes. These faults are discussed further in Section 2.3.2. Bearings in good condition should not emit any frequencies [48].

The vibrations emitted by worn or damaged gears or bearings can be characteristic of the particular fault and may provide evidence as to the fault severity. The identification of particular failure mechanisms of gears and bearings from vibration data is the key research area of this field [47, 49].

2.3.1 Causes of Bearing Damage and Fault Identification Signals

Bearings generally fail in three ways: flaking (spalling), cracking and cage damage [50]. Flaking occurs when the bearing contact surfaces have fatigued and pits are forming on the surface, and is generally caused by the bearing reaching the end of its service life. Premature flaking may occur however as a result of higher than anticipated loading, excessive preloading due to incorrect installation, or thermal expansion. It may also be caused by indentations, deep seated rust, electric current damage or smearing. These forms of bearing damage are discussed in the following sub-sections. The development



(a) (b) (c) (d)

Figure 2.19: *The development of flaking — increased run time from (a) to (d) [50].*

of flaking with bearing age is shown in Figure 2.19.

Cracking of the bearing ring can occur due to both rough treatment during installation, or by crack propagating from a fracture notch as a result of flaking or fretting corrosion [50, 51]. The result of cracking of the bearing ring is accelerated wear due to the slot, and possible height difference between the two ends of the ring.

The third failure mode of bearings is cage damage, commonly caused by excessive speed or vibration, wear or faulty assembly. A broken cage results in the uneven spacing of the rolling elements around the bearing, and thus renders the bearing unserviceable. Excessive speed and/or vibration result in high inertia forces on the bearing cage, leading to fatigue of the cage material. The cage is usually made of softer material than the other bearing components, causing it to wear preferentially in cases of inadequate lubrication or the presence of abrasive particles. Hard particles can also become lodged between the cage and a rolling element, causing accelerated wear of the cage. The bearing cage can also fail if the bearing ring has been misaligned during assembly, causing the balls to adopt an oval path. This leads to cyclic loading of the cage, resulting in fatigue failure.

Fault conditions in bearings can be detected using spectral analysis of the vibrations emitted from the machine. Due to the differing rotating velocities of the bearing components (ie rollers, cage, inner ring), the location of faults inside the bearing can often be determined with analysis of the vibration spectrum. Frequencies typically indicating bearing fault conditions include ball pass frequency (BPF) of the outer (BPFO) and

Figure 2.20: *Deep seated rust development in the outer ring of a deep groove ball bearing [50].*

inner (BPFI) bearing races, ball spin frequency (BSF) and fundamental train frequency (FTF). The formulae for these frequencies are summarised in Appendix Section A.1.

The generation of sidebands of the BPF can sometimes be observed, and is due to the movement of the rotating unit, thus modulating the BPF with the speed of the rotating unit (ie ball or roller). The spectral peak is therefore at the BPF, with the sidebands at BPF+ unit rotation speed and BPF - unit rotation speed. As the defect grows, more sidebands are generated. Once the defect is longer than the length required to generate one to two BPF, the BPF may no longer be generated [47]. This phenomenon occurs for both radial and axial loads.

2.3.1.1 Corrosion / Acid Etching

Bearings operated in an environment of high humidity, acids or other corrosive conditions will often fail by corrosion or acid etching. This occurs if the corrosive liquids or vapours are allowed to enter the rolling elements of the bearings in quantities that the additives of the lubricant cannot sufficiently protect the steel surfaces [50]. Faulty or inadequate seals are often the cause for this fault condition [52].

Bearing corrosion will begin with acid etching patches and propagate rapidly and form either deep seated rust or fretting corrosion, depending on the operating conditions. Deep seated rust is generally formed, and can initiate secondary damage in the form of flaking and cracks. Figure 2.20 shows the surface of a bearing which developed deep seated rust.

Figure 2.21: *Fretting corrosion of the outside surface of a bearing [50].*

Fretting corrosion is often formed when a corroding bearing also has a loose fit between the bearing ring, shaft or housing. The relative motion of the loose components can result in the removal of small particles from the corroding surface, as shown in Figure 2.21. These small particles are quickly oxidised by the atmospheric oxygen, adding to the wear debris accumulating in the bearing. The removal of small particles from the rolling surface can result in the bearing rings not being evenly supported, resulting in uneven load distribution.

Corroding bearings can be identified by vibration spectral analysis using a number of indicators. The spectrum shape can have a low amplitude (0.15 IPS or below), with amplitudes above 0.15 IPS indicating that spalling has occurred. The fundamental BPFO, BPFI, or two times the BSF may or may not be present in the spectrum. However, harmonics, as well as sum and difference frequencies can be present, ranging to 2000 Hz and beyond. Ball bearings which have shallow flaking fatigue spall around the inner race can generate approximately 6 true harmonics of BPFI, while bearings with the same conditions around the outer race can generate 7 harmonics. In general, bearings that generate many harmonics at low amplitudes can be diagnosed with probable corrosion or acid etching [47].

2.3.1.2 Fluting / Electric Current Damage

Electric current damage of bearings generally occurs on the inner and outer race, as well as balls or rollers, as a result of electric current passing between these bearing elements. The surfaces experience a condition similar to electric arc welding, with temperatures in the tempering to melting ranges. This leads to discoloured areas where the material has been tempered, re-hardened or melted. Fluting (corrugations) of the raceways and rollers is a common result of bearings conducting electric current [50].

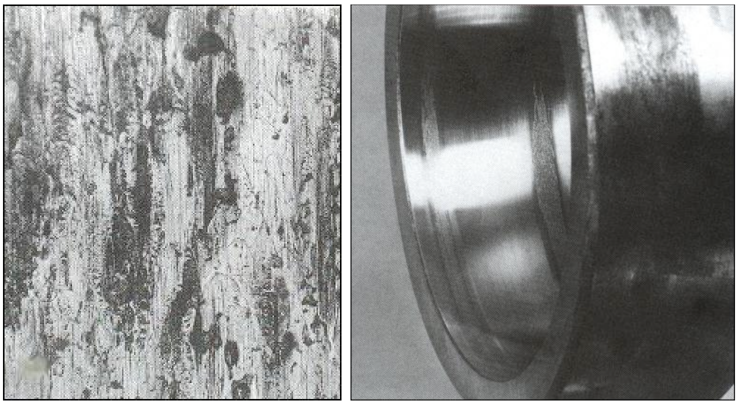
Bearings can be subjected to the conduction of electric current due to welder error, or eddy current build-up and discharge. Equipment that requires electric arc welding should be earthed such that electric current does not pass through bearings. Eddy currents responsible for fluting can occur at eddy couplings used for speed control. Some newer DC motor drives also cause fluting of the motor bearings [47].

Fluting damage results in the bearing generating the BPFI and/or BPFO harmonics, with the fundamental frequencies not developing until spalling begins. The typical spectra contains high frequencies (from 900 Hz to 5000 Hz) modulated by ball passing frequencies. Frequencies in this range can also be caused by inadequate lubrication. Therefore frequencies not corresponding to modulation by the ball pass frequency should be analysed for the inadequate lubrication fault condition [47].

2.3.1.3 Inadequate Lubrication / Smearing

Inadequate lubrication of bearings causes the wearing surfaces to slide together under load, resulting in material being transferred from one surface to the other. Figure 2.22 shows the scored surface of a roller bearing, damaged due to inadequate lubrication. The surfaces are generally heated to temperatures where rehardening occurs, producing localised stress concentrations that may lead to flaking or cracking.

In roller bearings, smearing generally occurs at the roller end-guide flange interfaces, due to insufficient lubrication between the flanges and rollers. Operating conditions which may cause smearing in roller bearings include high axial loads in one direction for prolonged time, as is the case with tapered roller bearings with excessive preload.



(a) (b)

Figure 2.22: *Smearing on the surface of (a) a roller from a spherical roller bearing magnification 100x (b) the outer ring from a spherical roller bearing [50].*

Smearing in these conditions can be reduced by either reducing the duration of the axial load to allow lubricant to flow between the flanges and rollers, or the selection of a suitable lubricant. Smearing may also occur if the bearing rings rotate relative to the shaft or housing, or in thrust bearings operating at too light a load in relation to the speed of rotation.

An ineffective lubricant film can also result in metal to metal contact of two surfaces, causing small cracks to form in the surface, called surface distress [50]. These surface cracks are distinct to fatigue cracks, and are microscopic, increasing very gradually until they interfere with the smooth running operation of the bearing. If lubricant breakdown due to a decrease in viscosity or inappropriate lubricant selection is avoided, surface distress can be prevented.

The detection of bearings with inadequate lubrication has received substantial research, as the addition of lubricant can increase equipment life and prevent catastrophic failure [47]. Spectral analysis of bearings with an inadequate lubrication condition generally exhibit the following properties:

- When lubrication becomes marginal, the lubricant film may break down once every shaft revolution. This pulse or impact of the balls excites the natural frequency of the inner race assembly, as the oil film of the inner race is thinner due to rotation. The resulting natural frequency detectible in the spectra is modulated by the BPFI to produce sidebands.

- The natural frequency is generally not evenly divisible by the BPFI, and is in the range of 500 to 2500 Hz or beyond.
- The addition of lubrication should cause the spectral lines to disappear or reduce in amplitude.

2.3.1.4 Looseness

Looseness in bearings is generally a problem of tapered spherical roller bearings, as these require the adjustment of preload force. Apart from bad workmanship at installation, internal looseness can be caused by the bushing becoming better seated on the shaft, the lock nut becoming loose, or abrasive particles causing excessive wear. The typical damage caused by excessive looseness is shown in Figure 2.23. Characteristic spectra of looseness usually features low amplitude, a broad spectrum of random noise, and an extreme change in balance sensitivity [47]. Frequency peaks commonly occur at one times rotation speed or harmonics of the rotation frequency.

Vibration peaks at multiples of rotation frequency can also be caused by a bearing turning on the shaft or in the housing. The two conditions can be distinguished by the presence of the fundamental train frequency, which is usually only present in the excessive internal clearance scenario. If the BPFO and harmonics of the BPFO are generated, small defects in the outer race probably exist, which is common for bearings that fail due to a worn cage.

Bearings turning on the shaft or housing can cause considerable damage to the bearing, as well as the shaft or housing. The condition of a bearing turning on the shaft will typically produce frequency peaks at rotation speed or harmonics, with a low amplitude line at lower frequency than the main peak. These peaks correspond to the shaft not turning at the centre of gravity (the main peak), and the rotational speed of the inner race turning on the shaft. The difference in frequency between the two peaks is the speed of rotation of the bearing on the shaft.

Figure 2.23: *Bearing cup inner surface damaged by excessive looseness [53]. The scratches caused by slipping of the roller are clearly visible.*

A loose fit between the bearing and housing can generate second, third and fourth harmonics of rotation speed, with the fourth harmonic generally being of highest amplitude. If the bearing supporting a gear shaft is loose in its housing, the gear mesh frequency (GMF) would be modulated by the rotational frequency of the shaft. The amplitude of the fourth harmonic will usually be higher on the low side of gear mesh frequency, as looseness is an out of phase condition. In other applications, harmonics of shaft speed, half-shaft speed and modulation of shaft speed, including sidebands can also indicate looseness.

2.3.1.5 Wear

Excessive wear of rolling element bearings caused by factors other than those discussed above, include the presence of abrasive particles, or vibration of the equipment by external forces. Abrasive particles or grit can enter the lubricant through faulty seals, unclean assembly or dirty lubricant. Bearing surfaces will begin with a dull surface, and eventuate to a scratched appearance as the concentration of abrasive and wear particles increases. Figure 2.24 shows the worn outer race of a spherical roller bearing.

Vibration of equipment containing bearings, by an external source can cause significant wear in stationary bearings. This is the case as a sufficient lubricant film does not exist when bearings are stationary [50]. The resultant wear can cause fluting of roller bearings and sperical cavities in ball bearings, as shown in Figure 2.25. This type of wear can occur in machinery that is close to other vibrating machinery such as auxiliary equipment on ships, or equipment transported by rail, road or sea.

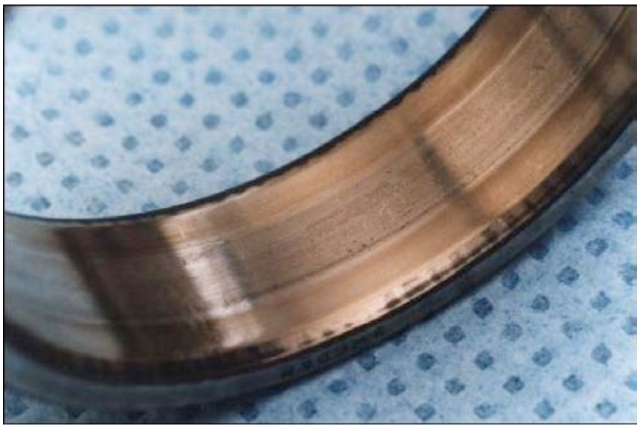
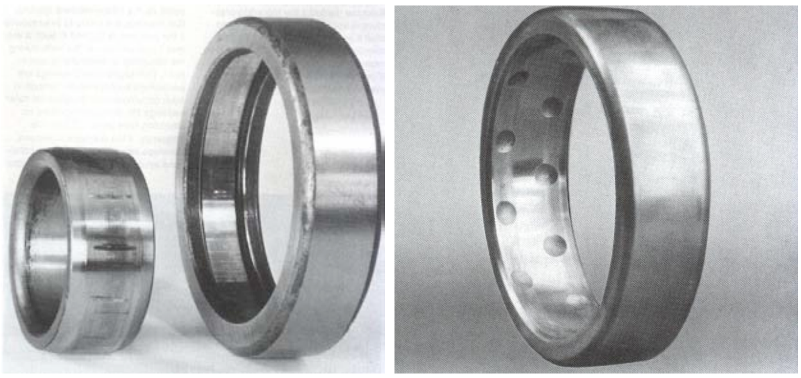


Figure 2.24: *Outer race of a spherical roller bearing worn by abrasive particles [50].*



(a) **(b)**

Figure 2.25: *Bearings damaged by external vibration (a) fluting of outer and inner ring of a spherical roller bearing (b) outer ring of a self aligning ball bearing showing spherical cavities [50].*

2.3.2 Causes of Gear Damage and Fault Identification Signals

The failure of gears can be attributed to a small number of factors, which significantly influence the life of the gear system. These factors include design, production technology and manufacture specifications, operating duty and environment [47,54]. Vibration generated from gear systems is generally caused by tooth faults, which cause a variation in gear stiffness and thus rotational speed. The nature of gear tooth interaction is typically non-linear due to the effects of friction, inter-tooth backlash and impact loads caused by periodic changes in tooth stiffness. The inter-tooth forces may therefore exceed the design load of the gears, and lead to rapid wear of the gear system components [54].

Gear vibrations can be used for fault detection and diagnosis, by analysing the vibration data and using various methods to compare to signature vibration data of known faults. Common faults are discussed in the following Sub-sections 2.3.2.1 to 2.3.2.5.

Vibration generated by a gear system commonly contains a number of frequencies which are characteristic of the system. The vibrational frequencies generated by two gears are dependent on the number of teeth, rotational speed of the gears and eccentricity. The gear mesh frequency is the multiplication of gear rotational speed by number of teeth [55]. While this frequency is often displayed even for gears in good condition, modulation by certain factors and side lobes are indications that a gear fault exists.

An example of frequency modulation is when a defective tooth on one gear produces an impact which excites axial natural frequencies in helical gears, and radial natural frequencies in spur gears. These natural frequencies are modulated by the impact frequency of the defective tooth. Similarly, the gear mesh frequency is modulated with the defect frequency resulting from misalignment, improper backlash or eccentricity of the shaft, teeth or gear [47].

Frequencies produced by meshing gears are summarised in Appendix Section A.2. Common gear faults and their corresponding vibrational information are discussed below.

2.3.2.1 Eccentric Gears

Eccentric gears problems can occur in many variations including meshing gears with or without a common factor, out of round gears, gears with high places, and gears mounted on a bent shaft. These scenarios can be differentiated by analysing the frequency spectra for difference frequencies equal to common factors, gear mesh frequencies and gear ratio.

The common factors of gears relates to the number of times one gear has to rotate in order for it to mesh to the other gear, at the starting position. If two gears have a common factor, and one gear is eccentric, the eccentric part of the gear will wear the round gear. This process can produce frequency peaks at the common factor multiplied by the gear speed.

When meshing gears do not have a common factor and one or both gears are eccentric, the analysis of the spectra is more complex. Typically, fractional gear mesh frequencies are the result of eccentric teeth meshing with a normal gear, or meshing with another eccentric gear. These two cases can be differentiated by analysing the time domain signal. The eccentric teeth can be determined by calculating the frequency corresponding to each time domain signal produced by two teeth meshing. The variations in meshing time, and hence frequency, can be used to determine eccentricity.

Gears that are out of round or have high places will show spectral lines at the frequency equal to the number of high places multiplied by gear speed. A second harmonic can also be present, as well as side bands around the gear mesh frequency, with difference frequencies equal to the gear speed.

Bent mounting shafts of gears may not produce meshing problems if the shaft is only slightly bent and is less than the tolerance of the gears. As a high amplitude peak at the gear mesh frequency is only detected if a gear problem exists, bent shafts may not always result in a fault condition [47]. Bent shafts can be detected by measuring the backlash of the meshing gears. If a condition is found where insufficient and excessive amounts of backlash are 180° apart, then a bent shaft of one of the gears can be suspected.

Figure 2.26: *Wear pattern of misaligned gears [56].*

2.3.2.2 Loose and Worn Gears

Loose or worn gears can be a source of wide-banded white noise, corresponding to a random motion of the gears. Specific frequencies can sometimes be detected, equal to the speed of the loose gear. If the gear is loose on the shaft, a side lobe will appear on the low frequency side of the 4 times running speed peak [47]. Alternatively, a bearing loose in its housing, supporting the shaft of a gear will display a side lobe on the high frequency side of the 4 times running speed (ie: GMF + 4 x Speed).

2.3.2.3 Misaligned Gears

The misalignment of gears can occur if gears are loose on the shaft, the supporting bearings are loose in the housing, or due to manufacturing error. Shiny areas are generally worn on the gear surface, as shown in Figure 2.26. The resulting vibrations usually produce the first three harmonics of the gear mesh frequency. The fundamental gear mesh frequency often has the highest amplitude, with the second and third harmonics having lower amplitudes [47].

2.3.2.4 Backlash Problems or Oscillating Gears

Backlash or oscillating problems in meshing gears have similar vibrational characteristics, by generating a high amplitude second harmonic of the gear mesh frequency compared to the fundamental and third harmonic. While the true cause of backlash and oscillating gear problems are of a complex nature, it has been observed that oscillation of gears is often caused by lightly loaded gears, inconsistent loading or excessive backlash [47].

Specific diagnosis of oscillating gear faults requires analysis of the time domain spectrum. Backlash faults can be identified by the second harmonic being 180° out of phase with the fundamental gear mesh signal. If both signals are in phase, this indicates that the gear fault may be a misalignment problem.

2.3.2.5 Broken, Cracked, or Chipped Teeth

Gears with broken, cracked or chipped teeth can generate a damped pulse, corresponding to the transfer of load from the damaged or missing tooth to the next good tooth. The generated pulse is damped due to the good tooth damping the impact, and stops the system from vibrating.

Defective gear teeth can be detected by measuring the pulse frequency, pulse width, repetition rate and amplitude [47]. The pulse frequency is generally an excited frequency or frequencies, caused by the impact of the defect tooth. The pulse width is also dependent on the system, as the damping and gearing systems impulse response govern the duration of the excited pulse. Similarly, the amplitude of the pulse is affected by the system transfer function, resonance, damping and loading conditions, as well as defect size and frequency addition and subtraction. The pulse repetition rate is equal to gear speed times the number of defective teeth. If the defective gear teeth are not spaced equally, ie: 45°, 90° or 180°, the difference frequencies between the spectral lines will be equal to gear speed.

The spectra generated by defective gears can be very complex to analyse due to the number of spectral lines produced. However, the use of sum and difference techniques of shaft speeds and gear mesh frequencies can reveal the gear faults of the system.

2.3.3 Measurement of Vibration

Vibration of machinery can be measured using three types of sensors: displacement, velocity and acceleration. All sensor types are used in vibration analysis for differing

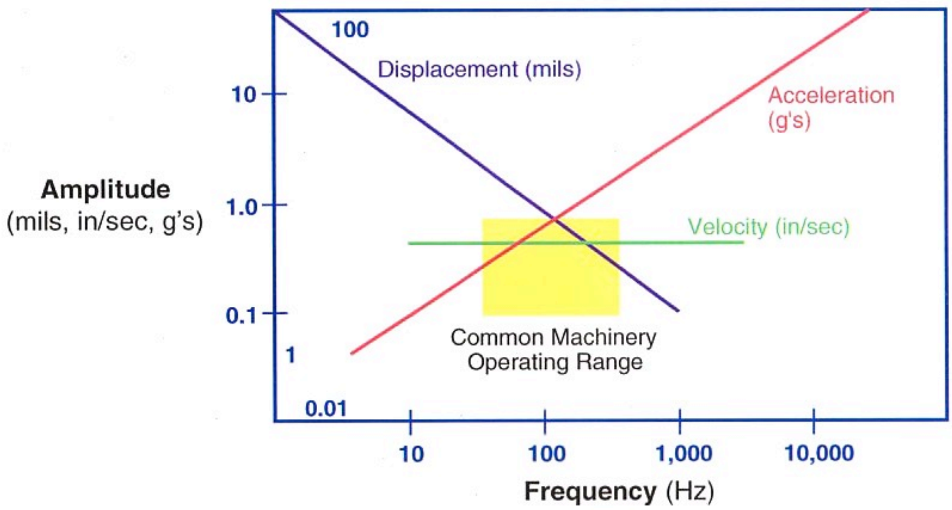


Figure 2.27: *Frequency response of various vibration sensors [57].*

applications, as each sensor type has certain advantages making it suitable for specific circumstances, as shown in Figure 2.27. Displacement between two surfaces can be used to analyse the frequency of vibration or fluid film thickness in fluid film bearings (hydrostatic and hydrodynamic). Another application of displacement sensors is the movement of light-weight gears and shafts relative to a heavy gear casing [47]. The vibration of the shaft and gears is insufficient to cause sufficient vibration in the gear casing for satisfactory detection using other types of sensors. Low frequency vibration can be detected with high accuracy. Tachometers also often utilise a displacement sensor, to sense a surface mark or hole and output the rotational speed of the shaft [57].

Displacement sensors are generally constructed from two flat wire coils mounted in a non-conducting protective sheath. An external power source is used to set up a high frequency energising current to establish an electromagnetic field. The change in proximity (displacement) of the conducting shaft being monitored alters the magnetic field inducted in the second coil (the induction of eddy currents), allowing the displacement to be determined to great accuracy [57]. Due to the small currents involved in the sensing circuitry, the wires connecting the energising coil to the power supply, and probe coil to the data collector must be impedance matched, to reduce the power loss during signal transmission.

Velocity vibration sensors are commonly used for applications with a frequency response between 10 hertz and 1500 hertz, which includes the majority of non-turbo machinery and general purpose vibration analysis [57]. The units of velocity (m/s) are directly related to severity of fatigue failure modes, making velocity sensing a popular choice for low to intermediate frequency range measurement. Vibration sensors are generally manufactured from solid-state electronic components, incorporated in a steel housing which is fitted to the machine to be monitored. Signal voltage is often used as sensor output, which correlates directly to a velocity reading. An advantage of the vibration sensor over the displacement sensor is the ease of fitment, as an external power source is not required [49].

High frequency vibration signals up to and above 40kHz can be detected using accelerometers. Accelerometers measure the acceleration of the base plate to which the sensor has been fitted. Construction generally consists of a piezoelectric crystal with a mass/spring arrangement which triggers the crystal. Internal circuitry is also often included in the housing, for signal pre-amplification. Accelerometers are the most common type of sensor for vibration analysis due to their small size, low cost, and relatively constant linear response over a wide frequency range. Many data collectors are capable of integrating the acceleration vibration data to obtain velocity data, for further analysis [35, 57].

2.3.4 Analysis of Vibration Signals

Analysis of vibration data of a machine can be used to assess its condition, and allows the detection of operating faults. Fault detection of machinery is generally done by analysis of time domain vibration data (amplitude variation with change in time), and observing the amplitude of the vibrations. If the amplitude of the time domain spectrum exceeds pre-determined threshold levels, further analysis for fault diagnosis can be performed.

Diagnosis of machine faults can be determined by analysing the vibration spectrum for characteristic vibration signals corresponding to common faults, as discussed in Section 2.3.1 and 2.3.2. The analysis of the vibration spectrum for characteristic vibration spectra can be performed once the frequency domain (amplitude of vibration at each generated frequency) has been calculated from the time domain signals.

Machine condition analysis using vibration data generally includes an investigation of the root-cause responsible for the development of the fault. Root-cause analysis is concerned with the primary damage of a machine, which led to the initiation of the secondary, and major operating fault.

2.3.4.1 Vibration Analysis for Fault Detection

Machine faults can be detected by observing the amplitude of the vibration data, and performing fault identification analysis if the amplitude exceeds pre-determined threshold levels. As the vibration data is generally contained in a computer file, listing the amplitude at increasing time intervals, simple computer programs can be used to graph amplitude and occurrence or frequency and amplitude.

Vibration analysis for fault detection can become very complicated for complex systems such as gearboxes with numerous stages or ratios, or engines. This is due to the large number of different vibrations generated by the rotating components. The measured vibration signals are therefore the result of interactions including frequency modulation, and often represented by non-linear coupling. The non-linear coupling effects are responsible for side bands of base frequencies, as detected in the vibration spectrum [58].

Machine condition monitoring of complex machinery often involves computational methods for fault detection, as spectral analysis is often ineffective in machine fault diagnosis of these complex signals. The techniques for condition monitoring are generally quick and easy to perform on a computer, but with insufficient resolution to diagnose a defect [59, 60]. Common techniques applied for this purpose include beta kurtosis and the Kolmogorov-Smirnov test.

Beta kurtosis has been found to be a reliable time domain vibration analysis technique for fault detection [60]. It also has applications in fault feature extraction, due to the ability to select significant terms from the transform equation. Various methods have been employed to discard terms of no significance and obtain a set of wavelet coefficients useful for fault classification [61, 62]. The beta kurtosis technique has been successfully applied to the identification of faults in ball bearing, power distribution systems and gears [61].

The Kolmogorov-Smirnov (KS) vibration analysis technique has been applied for spur-gear condition monitoring by Andrade, Esat and Badi [63]. The KS technique can be used to successfully identify and monitor the advancement of gear tooth failure, such as a fatigue crack. Known gear conditions can be detected by statistical comparison between the vibration data obtained from the machine under analysis, and a library of signatures from known gear faults.

The statistical analysis involves the use of the null hypothesis on the cumulative density function (CDF), of the machine vibration data. The null hypothesis states that the CDF of the vibration signal can be traced to one of the signatures of known faults. The sensitivity of the KS test is limited by the assumption that the fault condition is significant enough to cause a variation in the CDF, compared to the CDF of a known fault [63, 64].

The complexity of vibration signals from gear systems with a number of gear ratios can cause the signals to become too complicated for analysis. Specific sensor placement strategies and digital signal processing techniques may therefore be required prior to the statistical analysis. The KS technique for gear condition monitoring has been found to be able to detect early fatigue crack initiation and propagation in simple spur gear systems [63]. However, as it is a time domain analysis technique, it cannot be used for fault localisation as the phase information of the vibration data is not considered in the analysis.

When a fault condition has been detected, more computationally complex algorithms can be used in order to extract characteristic vibration signatures of known machine faults. This strategy is discussed in the next sub-section.

2.3.4.2 Extraction of Vibration Signatures for Fault Identification

Vibration data obtained from machines can be analysed by computational techniques to identify faults. The vibration spectra is analysed for unique frequency components produced by common machine defects. The spectrum analyser has been developed to extract information from vibration data in order to identify machine defects. Periodic waveforms of time domain signals (signals varying with time) or peaks of frequency domain signals (signals varying with frequency) can be extracted from the bulk information obtained from the vibration sensor. The amplitude and frequency locations of the signals can be used to identify specific problems of bearings and gear systems (as discussed in Section 2.3.1 and 2.3.2).

The frequency information can be calculated from the time domain data using the fast Fourier transform (FFT), which involves the use of a mathematical procedure performed on the individual digitised (sampled) vibration data. The result is a frequency spectrum, showing the amplitudes and frequencies of signals present. The FFT method has become one of the most widely used and well established fault diagnosis techniques. While the FFT can efficiently calculate frequency features from time domain data, it is not able to reveal the inherent information of non-stationary signals. The output of a running machine, such as reciprocating machines including engines and gearboxes, can contain non-stationary components relating to changes in operating conditions or machine faults. As the vibrations generated by these machines depend on the rotation speed, the appearance of smearing and frequency modulation often occur [58]. The analysis of non-stationary signals can aid in machine fault diagnosis, which has led to the development and application of other computational methods for machine condition monitoring. These techniques include the wavelet transform, and phase and amplitude demodulation [61].

The wavelet transform is a linear transform, and uses window functions to sample and translate the input signal. The window functions are a series of oscillating functions with different frequencies. Narrow time windows are used for high frequencies, while wide time windows are used at low frequencies, making the wavelet transform suitable for non-stationary signal analysis [60, 65]. The physical meaning of the modulus of the wavelet transform is that it shows how the energy of the signal changes with time and frequency. The wavelet scalogram [66] is also commonly used in engineering applications, which is the square of the continuous wavelet transform modulus. Although the wavelet transform has been used for many fault diagnostic applications, including gear, bearing and internal combustion engine faults, there is no standard or general method to select the wavelet function for different situations [61].

Modifications of the wavelet transform have been developed by numerous researchers. Zheng, Li and Chen [65] applied the continuous wavelet transform to gear fault diagnosis, which can provide a finer scale resolution than orthogonal wavelet transform. Peng, Chu and He [66] developed a reassigned wavelet scalogram, optimised for feature extraction of early fault detection, by decreasing the effects of interference terms. Another modification to the wavelet transform for increased feature extraction ability was developed by Wang and Gao [67]. The technique used for feature extraction was the application of the wavelet transform, followed by the Fourier transform. The combined techniques utilise the advantages from each technique, and the ability to detect developing structural defects in bearings has been demonstrated [67].

Non-stationary vibration signals produced from reciprocating machinery such as engines and gear systems can be analysed using the order bispectrum method, for machine condition monitoring. The order bispectrum method is similar to the estimation of power spectrum approach of machine vibrations. It has been used successfully for the condition monitoring of a car engine, using vibration data sampled uniformly in angle with respect to the shaft rotation [58].

Machinery defects can also be diagnosed using phase and amplitude demodulation. This technique involves the identification of frequencies responsible for the generation of modulated signals, as discussed in Section 2.3.1 and 2.3.2, of gear and bearing faults. Gear faults often cause the meshing frequency to be modulated with a fault frequency, resulting from one or more defect teeth. Phase and amplitude demodulation allows the type of fault to be determined, such as the number of defective teeth, as well as the relative positions of the defect teeth on the gear [47].

Machine faults can also be detected by analysing the time domain signal obtained from the vibration sensor. Techniques such as the time domain synchronous averaging method allow the extraction of vibration produced by a single gear, from the vibration data of the gearbox. Although the gear signature can be extracted using this approach, further signal processing is generally required in order to detect early gear faults [68]. Typical methods used for the signal processing include the FFT and other window functions such as the wavelet transform.

Autoregressive model based fault detection and diagnosis has been developed and applied to gear and bearing faults, with the ability to detect early defects in gear [69] and bearing [70] systems. The autoregressive (AR) modelling involves the modelling of a healthy section of the gear, and calculation of gear vibration data compared to the model. Gear faults will generate variations to the linear predicted model, the magnitude of the difference being equal to the severity of the gear fault.

2.3.4.3 Fault Root-Cause Analysis Using Vibration Analysis

Root-cause analysis is concerned with the identification of the primary machine fault which led to the secondary fault (resulting in machine failure), detected using the above mentioned techniques (Section 2.3.4.1 and 2.3.4.2). The detection of the root-cause (primary fault) which led to the major fault developing is very useful, as the primary fault would result in the same major fault developing again. The maximum life of a machine can only be achieved if both the major fault condition (secondary fault) as well as the primary fault are rectified. The flowchart in Figure 2.28 shows the typical primary and secondary faults encountered in gearbox condition monitoring, as well as the possible causes of the primary fault and common detection technique.

The correct diagnosis of the root-cause of a failure is of great importance economically, as it has the potential to result in short component lifetimes and high repair costs if uncorrected. Vibration analysis can be used to detect many root-causes, including bearing failure, lack of lubrication, and lubricant contamination [47].

Root-cause analysis can also be performed using a predictive approach rather than the detection and diagnosis routine discussed above. Machine faults can be predicted and diagnosed using mathematical modelling and computer simulations of the production and operating factors. Bartelmus [54] simulated a one stage gearbox including four factors: design, production technology, operation and condition change. The study revealed that common machine faults can be predicted successfully before the faults

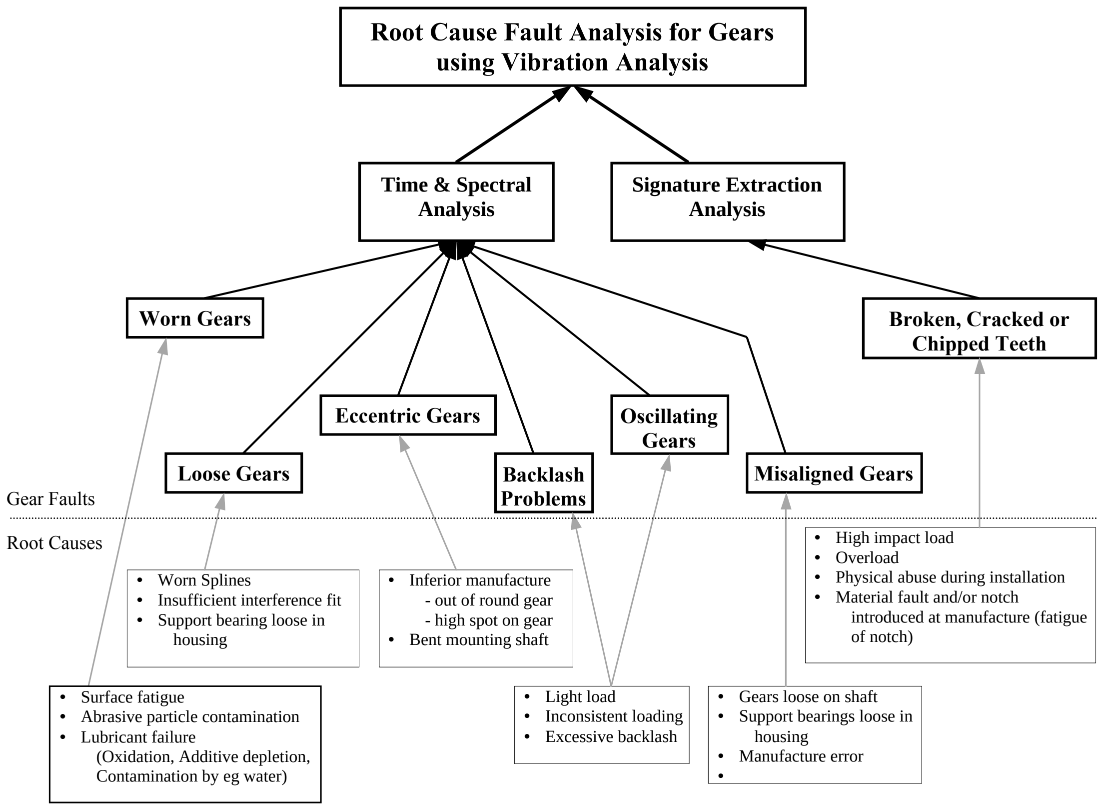


Figure 2.28: *Flowchart of primary faults (root-causes), secondary faults, and detection technique.*

develop, using mathematical models evaluated using computers. Identification of the relevant manufacturing and operating factors of a gearbox can therefore be used to assess the likely failure modes, and help with fault diagnosis.

Tooth errors are a primary source of vibration generation of gearboxes, and typically appear at the production stage and during a change in gear condition. Computer simulations have shown that operating conditions of resonating gears (discussed in Section 2.3.2.4) results in high inter-tooth forces, causing tooth errors including pitting, scuffing of teeth flanks, and bearing failure [54].

2.4 Integration of Oil and Vibration Analysis

Machine condition monitoring has conventionally been concerned with the detection and diagnosis of developing faults. Oil and vibration analysis are generally used as stand-alone techniques, depending on the machinery monitored and expected failure modes [2].

Oil analysis has traditionally been used for the analysis of lubricating oil physical properties (such as viscosity), the presence of vital oil additives (including anti-wear and anti-corrosion additives), and oil contamination (particles, water, and other machine fluids such as fuel or coolant) [3]. Wear debris analysis has become a common technique included in the oil analysis program, to provide information on machine health by examination of the wear modes and source of debris to assess the severity of wear occurring [2].

Vibration analysis has primarily been used in industries which operate large number of rotating equipment, and equipment from which it is difficult to obtain oil or grease samples [1]. It has become a popular condition monitoring technique due to machinery generally emitting vibration before failure, and the recent advances in computer technology allowing the signal processing and analysis to be automated [49, 71, 72].

The integration of oil and vibration analysis for machine condition monitoring has been proposed by a number of researchers, to take advantage of the unique detection and diagnostic abilities of each analysis technique [2]. The use of both oil and vibration analysis techniques have been applied to critical machinery in some industries, including nuclear power production. Maintenance departments have reported that a greater number of machine faults were detected than with either technique used independently [1].

2.4.1 Effect of Oil and Vibration Analysis Integration on Fault Detection

The oil and vibration analysis techniques currently used for condition monitoring have been shown to provide reliable fault detection and diagnosis for different machine faults. An effective machine condition monitoring program with high fault detection ability should therefore utilise both oil and vibration analysis techniques. The complementing nature of oil analysis and vibration analysis has been demonstrated by numerous researchers [1, 71, 73].

The machine condition monitoring program of Palo Verde nuclear generation facility was investigated by Maxwell and Johnson [1]. Common failure modes included vibration due to faulty couplings, belts, looseness and alignment, as well as internal machinery faults due to gear and bearing wear. Bearing faults were found to account for 16 % of machinery vibrations. The bearing faults were identified to consisted of 15 different types of defects, which needed to be diagnosed from the condition monitoring program. Implementation of both oil and vibration analysis revealed that only 27 % of bearing problems were detected by both techniques. Oil analysis techniques were used to detect another 40 % of failures, while vibration analysis detected the remaining 33 % of failures [1]. This study demonstrates that the oil and vibration analysis techniques compliment each other, by broadening the ability to detect and diagnose machine faults.

Laboratory testing of a worm gearbox under various operating conditions has been used to demonstrate the benefits of an integrated condition monitoring system [71]. The complementing nature of the analysis techniques was confirmed by vibration analysis providing a reliable and fast means of ascertaining bearing condition, while oil analysis provided insight into the true condition of the gear test rig.

The integration of oil and vibration analysis into a condition monitoring program will increase the confidence and detection rate of the program. The program will therefore provide improved reliability and equipment availability.

2.4.2 Benefits of an Integrated Condition Monitoring Program

The integration of oil and vibration analysis techniques incorporated in a machine condition monitoring program increases the effectiveness of the program. This can be achieved through better fault detection and diagnostic abilities as well as increased decision confidence and resolution for determining remaining machine service life.

The ability of oil and vibration analysis to each detect certain machine faults has been demonstrated by both practical and laboratory experiments, as discussed in Section 2.4.1. Condition monitoring programs utilising both oil and vibration analysis techniques can therefore detect more faults than either technique used by itself, as well as covering a broader range of faults [1]. The early detection of faults is essential to allow for maintenance scheduling of the machinery, and prevent an isolated primary fault to develop into extensive and expensive secondary component damage [3].

The diagnostic ability of a condition monitoring program is useful for determining the components experiencing a fault, and to assess the extent of the damage inside the machine. This information is vital for maintenance departments to aid with planning the maintenance or overhaul period, regarding length of outage period and spare part requirements. Once a fault has been detected and diagnosed, it is important that the technique used has a high confidence that the machine does indeed have that fault. The integration of oil and vibration analysis allows many faults to be detected by both techniques, which increases the confidence of the maintenance decision. This has important economic implications, as equipment that is overhauled prematurely wastes machine parts which had not reached the end of their service lives. Alternatively, if a machine is allowed to operate with a severe fault which has been categorised as developing, other components in good condition could be allowed to wear excessively due to secondary damage developing [3].

The economic advantages of an effective machine condition monitoring program are significant savings in spare parts and machine down-time costs, as shown by the industry trend to adopt proactive maintenance practices. If machinery breakdowns are reduced through the use of an effective condition monitoring program, spare part inventories and standby maintenance crews and equipment can also be reduced. Early fault detection and diagnosis not only allow for increased equipment availability, but also for maximising the efficiency of maintenance personnel and equipment. Extended time for ordering of machine replacement parts is another benefit of an effective monitoring program [3]. While these benefits can be achieved when comparing a program using either oil or vibration analysis techniques with a preventative maintenance program, the integration of both oil and vibration analysis into one program will yield further benefits as discussed above. The increased effectiveness of the condition monitoring program will result in further efficiency increases of the maintenance department, personnel, and standby equipment, and better machine availability.

Significant benefits can be realised when using a machine condition monitoring program that features an integrated approach of oil and vibration analysis. As machine maintenance costs are often a substantial component of the operating costs of operations, an improvement in the condition monitoring program should ultimately increase the efficiency and profitability of the operation.

2.4.3 Current Status and Research Trends

Research into the possibility of combining oil and vibration analysis has shown that the detection and diagnostic abilities of each technique are complimented by the other technique. This has been indicated by the numerous studies [1, 71, 74]. Troyer and Williamson [2] reported of cases when the data obtained from oil and vibration analysis did not correlate well. These authors have all indicated that the integration of oil and vibration analysis would be beneficial for the resulting machine condition monitoring program. The specific benefits mentioned by all authors were:

- Improved fault detection ability
- Improved fault diagnosis ability
- Increased confidence of the decision outcome, with less false alarms.

While the benefits of an integrated condition monitoring program have been well documented, the application of an integrated program has not been adopted by mainstream industry. This can be attributed to two main factors required in order to implement an integrated machine condition monitoring program: personnel with expertise in both oil and vibration analysis, and data correlation between oil and vibration analysis techniques.

The expertise of personnel in both oil and vibration analysis is required to implement an integrated oil and vibration analysis program, to enable the company to carry out and interpret the machine condition data of its equipment. As it is difficult for companies to recruit skilled personnel in one field of expertise, the requirement of staff skilled in two areas of expertise can be a limiting factor in the establishment of a machine condition program. Ideally, an integrated program would not result in more test being conducted, but rather a more efficient use of available analysis techniques. This could be achieved by using the quickest and cheapest tests from both oil and vibration analysis to monitor the common machine faults. An integrated program would therefore not require a larger workforce, but one that has expertise in both analysis techniques.

The efficient implementation of an integrated oil and vibration analysis program requires knowledge of the correlation between the two techniques. This would result in an objective data evaluation system, of both oil and vibration analysis data, to successfully detect and diagnose machine faults. Without data correlation, early fault detection, (thereby relying on one analysis technique to detect the fault) could result in a high occurrence of false alarms and consequent increase in unwarranted maintenance costs. While the majority of simple laboratory machine faults indicated good correlation between oil and vibration analysis, detailed correlation for machine faults, including those of complex machinery, are not well understood.

The method of integration detailing the specific tests to be conducted from both oil and vibration analysis in order to detect certain machine faults, and correlation of data have not been a significant area of research. It would be beneficial to identify the minimum number and quickest tests of each oil and vibration analysis, needed to be able to detect the typical faults in a certain machine. Expensive and time consuming tests designed to detect a certain fault using one technique may not be required, if another technique could detect the same fault within a relatively short time. Comprehensive tests in both techniques (oil and vibration analysis) would then only be required in the diagnosis phase of the condition monitoring program, to confirm that the detected fault actually exists.

Research into the integration of oil and vibration analysis has shown that one technique frequently acts as the primary indicator of a fault, while the other technique confirms the presence of the fault. Due to the different detection abilities of each technique, the other technique may only be able to detect the fault after it has developed further [2, 73]. The two factors limiting the implementation of integrated condition monitoring programs need to be overcome before this research can be utilised to benefit industry. The use of computers applied with artificial intelligence software could help reduce the dependence on human expertise for data evaluation and interpretation, as well as aid researchers in data correlation.

2.5 Remaining Lifetime Estimation

Remaining lifetime estimation is concerned with the approximation of the remaining operating time of a machine, either from the detection of a fault or from new condition. The remaining lifetime is typically expressed in the number of hours from the current condition to when the machine is anticipated to stop operating due to component failure. This information is of great economic benefit, as spare parts, machine overhauls and/or machine replacements can be scheduled for in advance, thereby minimising the overall cost of machine operation.

Since the implementation of condition monitoring practices into pro-active maintenance programs, remaining lifetime estimation algorithms have attracted research to improve knowledge on wear processes and thus lifetime prediction. However, while research into wear has received significant attention, the application of these principles into machine life estimation techniques have not been well developed [75]. Two streams of algorithms have emerged, one focusing on the statistical nature of failures of machines, and the other incorporating the research on wear of materials. Apart from these two different approaches discussed in Sections 2.5.1 and 2.5.2, a third technique has been commonly used to determine when to shut-down a machine using trending of condition monitoring data.

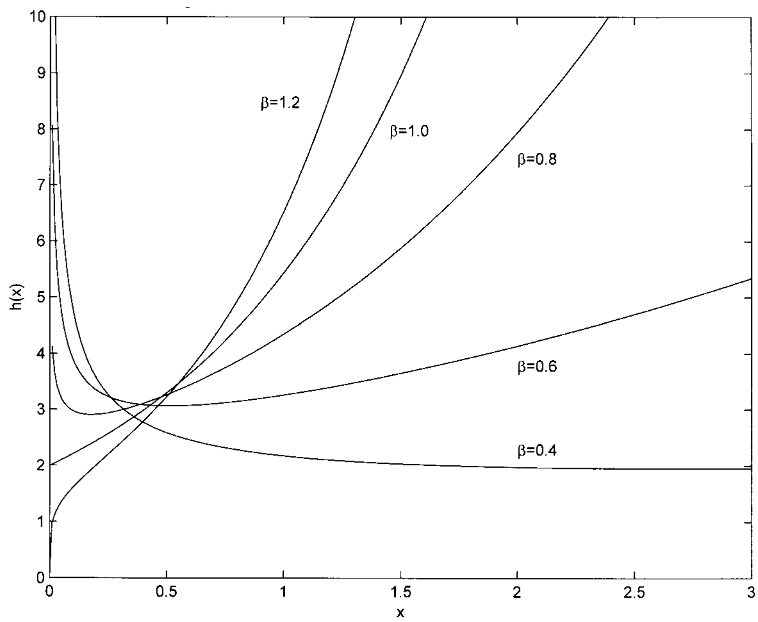
Remaining lifetime estimation has often been used as a component of machine condition monitoring by trending of vibration spectra or wear particle concentrations. This technique is commonly used in industry to track the rate of deterioration of components, and deciding on when the machine should be shut down to avoid catastrophic component failure. While this technique is one of the most widely used lifetime estimation algorithms, it has three distinct disadvantages. Firstly, significant experience is required to determine when the machine should be shut-down, which ideally is close to the catastrophic failure occurrence in order to obtain the maximum lifetime from the component. Secondly, this technique relies on historical trending of condition monitoring data, thereby allowing remaining lifetimes to be estimated once the machine fault has progressed to a substantial defect, and resulting short time to failure. The third disadvantage of this technique is the inability to predict the remaining lifetime of a machine from new condition, based on the operating conditions. Despite these limitations, this technique is still commonly used in industry.

Machinery monitored using condition monitoring, and which would benefit from remaining lifetime estimation information often contains numerous components such as various bearings, gears and other power transmitting devices such as couplings. Research into remaining lifetime estimation has generally concentrated on algorithms for single component life estimation, such as rolling-element bearings [75–77].

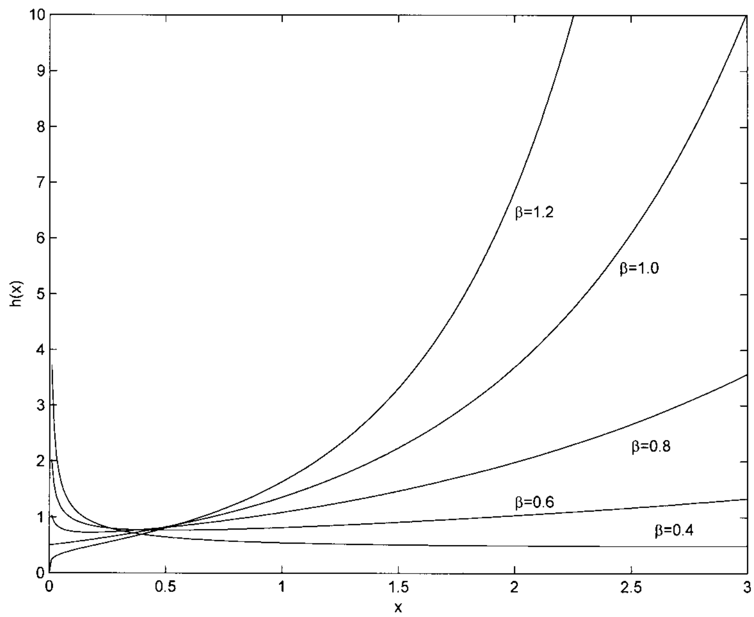
2.5.1 Method 1 — Statistical Lifetime Prediction

The statistical prediction approach to lifetime prediction often uses the idea of the bath tub curve of machine failure with time as an approximate probability function, in order to compute a probability for failure at a certain time interval. The model discussed by Adamidis and Loukas [78] uses a two parameter distribution with decreasing failure rate. The decreasing failure rate distribution effectively operates in the first half of the bath tub zone, commonly referred to as infant mortality or manufacture defects. A similar approach is discussed by Chen [79], who proposed a new two parameter lifetime distribution, which can be adjusted to a particular bath tub shape depending on the value of the two parameters. This is shown graphically in Figure 2.29, where the λ parameter is presented as 2.0 in Figure 2.29(a), and 0.5 in Figure 2.29(b).

The statistical prediction methodologies require the estimation of the parameters which are used to control the shape of the distribution. These are generally calculated by analysing the failure data of the particular machine, using various mathematical operations, such as the method of maximum likelihood (used by Adamidis and Loukas), or type-II censoring as used in Chen [79].



(a)



(b)

Figure 2.29: *Effect of varying λ parameter for two parameter lifetime distribution (a) $\lambda = 2.0$; (b) $\lambda = 0.5$ [79].*

This type of prediction modelling operates only by a static probability distribution, but does not take into account any condition monitoring data that may be available. An alternate approach is discussed by Myötyri, Pulkkinen and Simola [80], where the degradation of a component is considered when condition information is available. This method uses a three step stochastic filtering approach, by firstly defining the relationship between the lifetime and system degradation process. The second step is the connection between the condition monitoring measurement and the degradation that has occurred, and step three is the residual lifetime prediction using the Bayes rule recursively. The authors demonstrated the operation of this method using a simplified fatigue crack growth as degradation process. The data used to test this model was not derived from actual test data, but rather the degradation process was assumed to be a Markov process, and thus the data was obtained from a model.

The general principle used for statistical life prediction is to model the failure of the machine under investigation, and use this model to predict the remaining life of the operating machine. Previous failure data of the machine is typically required, as well as various condition monitoring information depending on the type of model prepared.

2.5.2 Method 2 — Wear Prediction by Modelling of Individual Failure Modes

The remaining lifetime of a machine can be predicted using models of wear modes, by estimating the average material removal rate or crack growth rate, and calculating when the condition becomes critical. This method contrasts the statistical method in that a model needs to be used for each particular wear mode that is causing a failure, and that detailed machine specifications are required. The required specifications are those that facilitate the calculation when the fault condition becomes critical, and could include type and hardness of materials wearing, lubrication regime, run-out limits for clearances or critical crack sizes. This method assumes that the wear mode and resulting failure mode can be diagnosed, as well as the damage that has occurred.

Many equations have been developed to calculate various wear phenomena, including abrasive wear [81–85], sliding wear [86], fatigue wear [87], as well as operating time for surface pitting or scuffing to occur under elastohydrodynamic (EHL) lubrication [86]. Lubrication regime is an important parameter in these equations, as wear rates are dependent on the amount of asperity contact and thus asperity stress imposed on the wear surfaces. Karmakar et al [87] discusses the modelling of fatigue wear in a rolling and sliding application, using data obtained from a pin on disc machine. The model takes into account the stress at the asperity, and thus requires numerous calculations to approximate quantities such as surface roughness, asperity size, contact area based on elastoplastic models, and contact pressure. Detailed machine specifications are also required including lubricating oil viscosity, load, and the dimensions of the wearing components [88].

The complexity of wear models developed such as by Karmakar et al [87] can limit their application in industry, as specifications of machinery are generally not available with the required details. Simpler models based on a limited number of calculations may prove easier to apply to real machines, however lack the accuracy in lifetime prediction to make significant maintenance decisions. These types of equations may miscalculate the remaining lifetime of a component by the order of 100 % [89].

The simple wear models adopted by handbooks do not allow the possibility of using data from machine condition monitoring to improve their accuracy. However, if machine condition data was used in conjunction with these equations, this would ensure that the correct equation was used only within its limitations, and the remaining machine lifetime could be corrected as more up to date condition data becomes available. Thus, a model could be constructed to operate on the commonly accepted wear equations for the common wear modes, that allows machine condition data to be incorporated in order to improve lifetime prediction accuracy.

2.5.3 Summary

The estimation of remaining machine lifetime has great potential in improving maintenance program efficiency by complementing the actual machine condition as provided by routine condition monitoring. Although numerous techniques have been developed for various machine components, these techniques have not been adopted by machine intensive industries such as the mining, mineral processing and manufacturing industries.

2.6 Artificially Intelligent Systems

Artificial intelligence encompasses a large number of intelligent data analysis techniques, for complex problem solving. This section discusses a number of common artificial intelligence techniques for numerical data analysis, that could be used for the analysis of data obtained from machine condition monitoring. As artificial intelligence (AI) is an extremely broad topic, with significant ongoing research being conducted, only a selection of possible techniques are discussed here.

Artificial intelligent techniques are useful for determining the relationship data has with its input variables, of applications where conventional methods such as statistics are too complicated or not valid. Non-linear systems are an example of applications which can be evaluated by artificial intelligent techniques, and which are difficult or impossible to analyse with conventional techniques [90].

2.6.1 Neural Networks

Artificial neural networks are based on the principle of biological neural networks, which allows organisms to gradually learn new tasks over time, and the ability to perform complex computations [90]. Numerical data with unknown relation to the system inputs can thus be evaluated by a neural network that is trained with experimental data.

Additional attractive features of biological neural networks being modelled in artificial neural networks include rapid computation of complex problems and robust processing. The robust processing of neural networks allows them to still operate if parts of the network are damaged, or if data is corrupted, such as from background noise or missing data. This is due to the inherent redundancy of the computational architecture, which represents a group of models each optimised for specific conditions. The neural network is therefore able to operate when parts of the network are damaged or inoperative due to missing or corrupt data [90].

The structure of biological neurons is transformed into a mathematical context by correlating the biological nucleus with a mathematical summing operation, and the neurons connecting to the nucleus are represented as scaling operations which are fed into the summing node. The nodes in the network hence sum the values of the incoming neurons, which were each scaled by a certain factor. This basic type of operation is common for all neural network systems, which differ in the flow of information around the network, and the training algorithms used to grow the network [90]. These variations of neural networks are referred to as architectures.

The different architectures used in neural networks result in variations of their mathematical operations performed, and thus their data handling. The most commonly used neural network architectures includes the Multilayer Perceptron [90], which is discussed in detail in Section 2.6.1.1. More advanced architectures designed to improve on some of the limitations of the Multilayer Perceptron are discussed in Section 2.6.1.4.

2.6.1.1 Multilayer Perceptrons

The perceptron is the simplest neural network architecture, which consists of a single layer of nodes connected by uni-directional feed forward neurons, connecting the inputs, nodes and outputs. Perceptrons can be trained by an input data set, in order to learn several complex tasks, but are unable to compute problems which are not linearly separable. This has been demonstrated by the logical operator XOR (exclusive OR) in the late 1960s [90]. Due to the common occurrence of non linearly separable problems, methods have been developed to transform the input vector into linearly separable form. This can be achieved by using the multilayer perceptrons (MLP) approach.

The MLP operates on the perceptron architecture, using multiple processing stages to pre-process the input space, while the second layer is concerned with the problem solving process [90]. The architectural principle of a MLP network is shown in Figure 2.30.

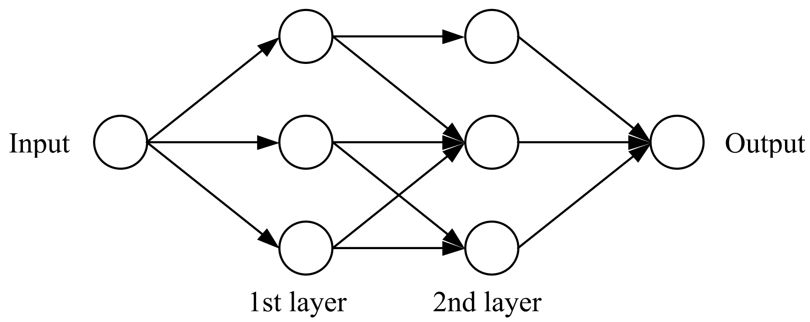


Figure 2.30: *Layout of a multilayer perceptron (2 layers shown).*

2.6.1.2 Training of Neural Networks

Training of the neural network is generally done by processing of training data, where the weighting of the network nodes are determined. The weighting of the nodes corresponds to the linking of neuron paths, necessary to optimise the network for the particular application. Depending on the availability of training data, a neural network can be set up by processing test data, called supervised learning, or by processing experimental data, referred to as unsupervised learning [90, 91]. These training techniques are discussed in the following sub-sections.

2.6.1.2.1 Supervised Network Training

Supervised neural network training can be performed by the back-propagation algorithm [90], which is a commonly used training technique. The back-propagation training algorithm determines the node weighting configuration by testing the output of the network to the training data input, and calculating the difference between the obtained network output and the expected output. This difference is called the error vector, and can be used to correct the node weighting by back-propagating the network from output to input (reversing the flow of the network). This training procedure has been used successfully for a wide range of problem solving networks, including classification, prediction as well as function approximation.

The principle of the back-propagation training algorithm is that the node weighting values will converge to an optimal value, which represents a minimum error value. The initial weighting configuration is generally chosen as small random values, in order to avoid early local converging of nodes. As the initial weighting configuration significantly influences the final node weighting, the network is generally trained a number of times with differing initial weighting configurations, and the one with the smallest error is then used. Numerous methods for determining the optimal initial weighting configuration have been developed, including Newtons and quasi-Newton methods, Line search routing, the Polak-Ribiere rule, Levenberg-Marquardt algorithm, and conjugate gradients method [90].

Important considerations when training neural networks are their property of generalisation and effects of over-fitting. The generalisation property of a network means that the relationship between input and output generated from the training data apply to a new set of data, without the training data. The main feature of the training data set is to establish the neuron connections (node weighting configuration) so that the network can learn the required rules. The training data set must therefore accurately and completely describe the rules. If too large a data set is used however, the network can memorise the noise and errors typically contained in the training data and thus result in poor generalisation for new data, due to being over optimised for the training data set. This phenomenon is called over-fitting of data [90]. Over-fitting thus occurs if a network is too large (has too many parameters) compared to the number of constraints (independent training data scenarios).

Techniques for training neural networks and avoid the over-fitting problem have been developed. The validation set technique is a common method, which requires the use of a small set of independent data. As the network is trained, the ability of the network to solve the validation data set is monitored by determining the resultant error. The training of the network will result in a decrease in error vectors for both training and validation data sets, followed by an increase in the error vector obtained from the validation data set once the network is beginning to demonstrate over-fitting behaviour. The principle is to stop the training algorithm once the error vector of the validation set has reached a minimum [90].

The validation set technique can be difficult to apply when sufficient data is not available to construct two independent data sets. An alternative technique called training with noise has been developed to overcome this problem. The principle of the training with noise technique is to add random noise to the input vector of training data, and thus make each vector of training data sufficiently different so that the network cannot fit all the data exactly. Over-fitting of training data can therefore be avoided [90].

2.6.1.2.2 Unsupervised Network Training

Training data used for supervised network training is not available in all problem solving applications, particularly if the relationship between input and output is unknown. In this case, the neural network can only be trained by unsupervised techniques, by which the network has to discover patterns, regularities and other relationships contained in the data by itself. The unsupervised training technique is therefore also useful even if a training data set is available, to test for unknown features and relationships contained in the data [90].

Unsupervised network training requires that the neural networks possess a self-organisation property, which allows the network to remember patterns and problem solutions. Another requirement for unsupervised learning is redundancy in the data used for training, as the network can only learn trends by reoccurring features in the data [90].

The unsupervised training techniques can be categorised into two approaches: the competitive learning, and the Hebbian learning methods. The competitive learning approach is based on the principle that the network nodes compete for an answer, and the node with the winning answer (based on the lowest error vector for example) will get its weighting increased. The nodes are therefore trained for certain input vectors corresponding to their weighting value, which results in the training of the network. The Hebbian unsupervised learning technique utilises the observation that patterns presented to a node most often will give the strongest answers [90].

2.6.1.3 Network Size

The network size is dependent on the complexity of the problem to be solved, with more complex problems such as an XOR operation, requiring an increased network size compared to simple problems such as AND, OR and NOT operations. As the network grows during the training process, the size is also dependent on the effectiveness of the training algorithm. The smallest network size that is capable of fitting the training data is generally considered the ideal network size, as this avoids over-fitting of data while providing good generalisation and relatively quick training [90].

The smallest network size cannot be calculated before training the network, although it has been proven that any function can be approximated to arbitrary accuracy using a network of two hidden (middle) layers, and a sufficient number of nodes [90]. Iterative techniques have been developed to allow optimising of the network size. These techniques include growing and pruning algorithms. Growing algorithms are concerned with the training of initially small networks, and allow the addition of new nodes and neuron connections during the training process. Pruning algorithms operate with an inverse principle to the growing algorithm, by starting with a relatively large network, and either decreasing the node weightings or removing redundant nodes.

2.6.1.4 Improvements in Neural Network Architectures

Modifications of the multilayer perceptron neural network architecture have been developed to improve certain aspects of the MLP network, including increased decision transparency. The MLP architecture results in a network where the decisions do not translate into symbolic knowledge, as there is no systematic processing by regions of the network. One approach has been to divide the network up into regions of specialisation, where the network is trained by only allowing that region to grow whose specialisation best corresponds to the problem description of the input vector. This architecture is called the Radial Basis Function (RBF) network, which apart from easier interpretation of the systems results, provides a quicker learning algorithm than achieved with the back-propagation method [90].

The learning algorithms of modified perceptron neural networks have also been modified to increase the speed of the learning process, and optimise network efficiency [90]. Training techniques developed for RBF networks include the modified back-propagation, hybrid learning, orthogonal least squares algorithms.

2.6.1.5 Problem Solving Using a Neural Network

The use of neural networks for problem solving involves a number of steps, beginning with the selection of an architecture, training and testing of the network, and finally, applying the network for the particular problem or situation. Selection criteria for a neural network architecture include the network transparency, preferred training methods (including whether supervised or unsupervised), and network efficiency. Requirements for network training is an important consideration, as the training method differ for supervised and unsupervised training. Unsupervised training algorithms can also be used to detect relationships of input data, which can aid in the classification of data [91].

Once a network architecture and training algorithm have been selected, and the network is trained, testing of the network is done to verify the operation of the AI system for the particular application. If the network performance meets the required benchmarks, it can then be applied to the particular data set or problem [90].

2.6.2 Fuzzy Logic

Fuzzy logic is an artificial intelligence data analysis technique designed to deal with information that cannot be classified into precise categories or groups. This kind of data is often found in practical applications, where the category boundaries are not well defined either due to imprecise measurement or subjective judgement [91]. Typical examples of data with vague boundaries is the classification of a continuous scale or population into discrete regions, such as labelling a temperature scale into regions of cold—warm—hot, or the age groups of a population into young—middle aged—old [90].

The operation of fuzzy logic is a data analysis technique that allows data to be displayed in both numerical and graphical representations, and uses Boolean logic to aid analysts to understand and draw conclusions from the data. Once established, the resulting fuzzy model can be used to analyse the underlying system, and help predict data [90].

2.6.2.1 Fuzzy Sets

Discrete cut-off limits of each region of a function with continuous domain may not be well defined, as the difference between one region to the next, such as warm to hot in the temperature example, may only correspond to 1 degree. It could therefore be argued that the temperature is already hot even though it is 1 degree below the hot category cut-off. The category boundaries may overlap, to correspond to the intuitive idea that the temperature is shifting from warm to hot, for example. The resulting category is an imprecise region, or referred to as a fuzzy set [90].

The principle of categorising a continuous variable into a number of fuzzy sets is generally called granulation, as the data is grouped into imprecise regions or fuzzy granules. Specific information of interest can thus be extracted (granulated) from a data set using fuzzy logic [90].

2.6.2.2 Operation of Fuzzy Logic Systems

The use of fuzzy logic results in the input data being grouped into fuzzy sets. This is generally done using mathematical functions which define the fuzzy sets, the graphical representation of common functions is shown in Figure 2.31. The centre value of the graphs is the typical value, and the decreasing slope on either side of trapezoidal, triangular and Gaussian functions represents the fuzzy boundary of the set. The grouping process (granulation) is typically performed using either five or seven overlapping fuzzy set functions, as shown in Figure 2.32.

Data analysis is performed on the granulated data, using common Boolean rules. As the fuzzy sets consists of a data interval, the Boolean logic operations are performed on two data intervals rather than discrete values. The output of the logic operation is therefore also a range of values. In fuzzy logic, Boolean rules are therefore referred to fuzzy rules.

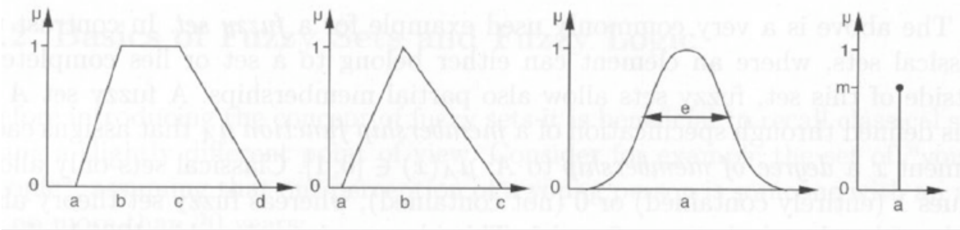


Figure 2.31: *Graphs of common fuzzy set functions [90]. The functions are (left to right): Trapezoidal, Triangular, Gaussian and Singleton.*

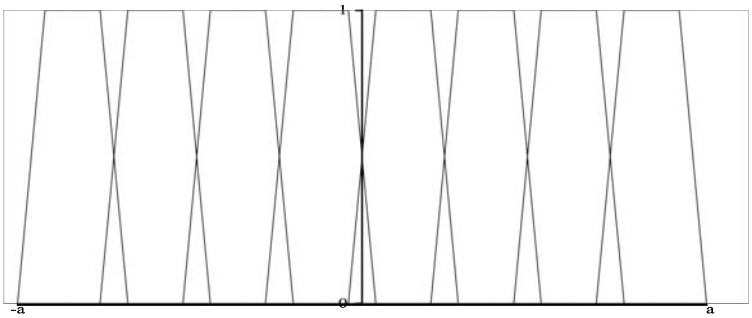


Figure 2.32: *Standard granulation procedure using seven functions.*

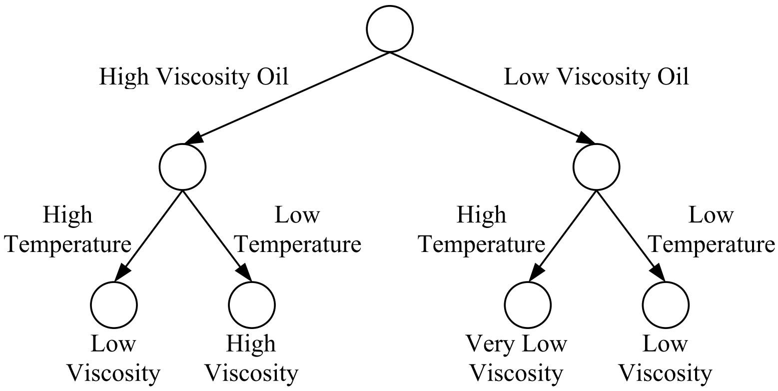


Figure 2.33: *Decision tree concept for operating oil viscosity, with decisions for viscosity grade of oil, and operating temperatures.*

The fuzzy logic data analysis technique allows features of the data to be extracted, and a model of the system to be identified. It also allows the construction of a decision tree, which is a graphical representation of the possible outcomes of a system. Similarly to the use of Boolean logic in fuzzy logic, decision trees display the outcomes of the fuzzy rules, using fuzzy logic constraints rather than discrete conditions [90]. The concept of a decision tree is demonstrated in Figure 2.33, for the viscosity of oil, at various temperature ranges.

2.6.3 Expert Systems

Expert systems are a class of artificial intelligence developed to allow the use of computers in decision making applications, which would normally be done by human experts. Their operation is dependent on the efficiency and knowledge of the three components that make up the expert system: knowledge base, reasoning mechanism, and output interface to communicate decision to users [92].

The use of expert systems has shown that a wide variety of problems can be solved by this artificial intelligence technique. Problem classification is an important technique which allows the use of generic problem-solving algorithms to be applied, with only minimal modification for the specific application [92].

2.6.3.1 Advantages of Expert Systems over Human Experts

The use of an effective and efficient expert system has many advantages over a human expert, including reduced cost, increased availability and reliability. Expert systems can be established with knowledge equivalent to that of a team of experts, which is therefore significantly cheaper than if a number of experts were employed for problem solving purposes. As an expert system can operate continuously if required without decreased performance, shift work applications can clearly benefit from the use of expert systems [93].

The knowledge base of an expert system, being in a form that can be read by experts as opposed to the knowledge of a human expert, allows it to be updated and refined. This improves the quality of the knowledge base, and results in improved expert system performance. A faster response time can also be achieved with expert systems, especially in real time operation where fast responses are required, such as emergency situations [93, 94].

Expert systems can be designed to incorporate the features necessary for a particular application, and can operate at peak efficiency without the human problems of stress and fatigue. Well designed systems with mechanism to counteract the limitations, as discussed in Section 2.6.3.3, expert systems can provide problem solving services with significant advantages over human experts.

2.6.3.2 Elements of Expert Systems

Expert systems are composed of three major parts, including the knowledge base, reasoning mechanism, and output interface. The knowledge base is the element which contains the knowledge normally possessed by the human expert, which allows the expert system to reason, and make expert decisions. While the knowledge base contains the information required to make expert decisions, an efficient reasoning mechanism is required to make a decision, given the type of problem and a set of conditions.

In order for expert systems to make decisions which are of value to the system users, the knowledge base must be as complete and accurate as possible. The establishment of the knowledge base using the information known by human experts is therefore a vital step in the construction of an efficient expert system. The collection of knowledge from an expert can be incorporated into a knowledge base by either interaction with a human, or by the program learning the conditions and rules from raw data, which contains the decisions from a human expert.

The purpose of the output interface is to communicate the decision of the expert system to the user. This is generally combined with the input interface, and is typically custom designed computer software for the particular application. An important property of the user interface, consisting of the user input and system output interfaces, is to allow easy operation of the expert system by the users. The user interface therefore often includes directions and hints for data entry, and extra explanations for decisions and recommendations output by the system.

2.6.3.3 Characteristics of an Expert System

Expert systems must have certain abilities to allow them to be used effectively in applications which would otherwise require a human expert. These abilities include high performance, sufficiently fast response time, high reliability, and be easily understood by users [93].

High performance of the expert system is required, so that resulting decisions are at least of a standard equivalent to a human expert. This requires that the information entered into the knowledge base is of high quality, and the information is gathered from one or more true experts in the specific field. An advantage of using expert systems is that information from a team of experts can be incorporated into the system, which can lead to more accurate decision outcomes [93].

Expert systems are commonly used for a wide range of uses including real time applications. Sufficiently fast response time is therefore required, which is the time the expert system needs to make a decision from a set of input parameters. The response time for small general purpose expert systems is not usually a design problem, due to the speed of todays computers. However, the response time for large expert systems operating in real time or high priority applications such as those for medical purposes, must be sufficiently small to guarantee a decision within the required timeframe [93].

The use of expert systems in industry has demonstrated that significant amounts of money can be saved, by improved decisions [92]. High expert system reliability is therefore required, as wrong decisions or system crashes can result in substantial financial losses, or even loss of human life in the case of medical expert systems [93].

The final characteristic of an expert system is the successful communication between the user and the expert system program, through the user interface. The user interface and decision output recommendations must therefore be designed and written in a way that the user can easily and quickly understand the inputs and outputs. Reports of expert system decisions should also contain information on how the decision was obtained. This allows the user to verify the reasoning performed by the system, as well as helping the system developers with debugging [94]. Output reports also help update the expert system knowledge base if an error has been detected.

2.6.3.4 Design Challenges of Expert Systems

The design of effective expert systems should include measures to minimise the effects of their limitations. Expert system designers are faced with a number of challenges, including brittleness, lack of own process understanding, efficient knowledge acquisition, and knowledge verification [92].

System brittleness is often referred to the condition when general rather than expert knowledge is required to make a decision. As expert systems possess expert knowledge, situations that require general knowledge, like the reversal of two fields of input data, can generally not be detected by the system. This is accompanied by the fact that expert systems lack knowledge about their own operating processes, which prevents them reasoning about their limitations [92]. System checks on the input data including notifications if values are out of the common range, could be used to minimise this problem.

The acquisition process of knowledge and processing to establish the knowledge base is generally a difficult and time consuming process. This is due to the difficulty of obtaining information from human experts and translating this into a number of rules. In order to help automate the process, a number of software tools have been developed, which interact with an expert to compile an initial knowledge base. The initial knowledge base is then refined, typically by supervised problem solving techniques. The human expert hence either supervises the expert system while it solves problems, or verifies the output of the system [92, 94]. Extensive testing of the expert system allows incorrect reasoning and decisions to be corrected.

Knowledge verification, including refining and debugging of the knowledge base, is a process which is required to ensure high performance and reliability of the expert system. The difficulty with knowledge verification is that non-quantitative data cannot easily be tested as formal proofs cannot be provided easily. In these circumstances, the knowledge base can be tested by real problems, and the decisions evaluated by a human expert [92]. This method of testing expert systems will also allow the expert to assess the systems key required characteristics, as discussed in Section 2.3.4.2, and design challenges.

2.6.4 Artificial Intelligence for Machine Condition Monitoring

Artificially intelligent systems have been applied for machine condition monitoring by numerous researchers [22, 95–99], to help with machine fault detection and diagnosis. However, these systems were designed to use either the wear debris or the vibration analysis machine condition monitoring technique. These systems developed for condition monitoring have focused on applications where maintenance, repair and downtime costs make up the principle business outlay. Typical applications include diesel engine faults, encountered in both on-highway, off highway and marine industries, as well as fault diagnosis in gearboxes, as used in industry and aviation, and electric motor malfunctions.

Diesel engine fault detection systems have focused on the use of vibration analysis for combustion malfunctions and water entry detection, which are detrimental problems in marine engines [95,96]. The diagnostic system for diesel engine condition monitoring developed by Grimmelius et al [95] was based on a neural network technique, to detect and classify complex faults without extensive knowledge about the fault patterns and signals. Results indicated that the neural network featured fast operation, and was found to be very tolerant to noisy signals. Limitations to the neural network approach were discovered to be the time consuming training requirement, lack of decision transparency, and inflexibility of the network for problem solving under new conditions outside of the trained region.

The diesel engine condition monitoring system developed by Li et al [96] was also based on vibration analysis and the neural network technique, utilising an unsupervised training technique. The system was reported to be able to distinguish from vibration signals of normal and faulty engines, using vibration feature extraction techniques to pre-process the signals. A similar approach by Parikh, Pont and Jones [100] allowed a system based on the fusion of classifiers by fuzzy logic, to detect static thermostat valve faults in diesel engines.

Artificial intelligence techniques have also been used successfully in the condition monitoring of gearboxes. Peng and Goodwin [101] developed an expert system to help interpret comprehensive data collected from particle analysis of oil samples. The expert system was able to assess the wear modes and wear rates present in the gearbox, and thus diagnose the most common wear related faults. The user interface was designed in order for ease of use, to allow the system to be used for training purposes. While the system was designed for routine analysis, limitations of the system include difficulty with complicated gearbox faults, which requires human expert assistance. As the expert system was found to correctly diagnose the common encountered faults, the researchers commented that the system could be expanded to laboratories. An expert system that could be used for this purpose is still in the development stages.

Artificially intelligent systems using both oil, wear debris and vibration analysis have to date not been developed for the condition monitoring of machinery. This is due to the limitations discussed in Section 2.4.3 — the difficulty of obtaining experts in both oil and vibration analysis fields, and a lacking knowledge of correlation between the two techniques. Systems utilising AI may help researchers with correlating the two techniques, which would allow the establishment of an expert system with better detection and diagnostic abilities for condition monitoring than currently available.

2.7 Summary

Machine condition monitoring has become an essential element of maintenance strategies, aimed at increasing the availability of machinery, and decreasing repair costs by reducing secondary component damage. Commonly used techniques for machine condition monitoring are oil analysis and vibration analysis.

Oil analysis consists of the investigation of an oil sample, in order to collect information to assess the condition of the machine under observation. Traditionally, oil analysis has been concerned primarily with the physical and chemical properties of the lubricating oil, also referred to as oil health monitoring. The rationale behind this is that while the lubricant has the correct viscosity and additive concentrations, and contaminants are not present, lubricant related faults will not occur. Lubricant utilisation is also maximised, as it is only replaced when the physical or chemical properties have exceeded a predetermined threshold.

An extension to the common oil analysis has become the analysis of particles contained in the oil sample. Particle analysis can reveal the presence of contaminant particles as well as the size and concentration of wear particles. Wear particle analysis involves the study of particles produced due to component wear, and allows the identification of wear modes and likely components experiencing the determined wear modes.

Vibration analysis is a popular machine condition monitoring technique, which utilises vibration signals with frequency components produced by wearing components to detect and diagnose machine faults. Once the vibrations produced by a machine have been recorded, signal processing and analysis techniques can be used to detect and diagnose faults.

The detection ability of oil (including wear debris analysis) and vibration analysis has been estimated to be in the vicinity of 67 % and 60 % respectively [1]. The overlap in fault detection ability for this study was 27 %, indicating that a machine condition monitoring program could greatly benefit from an integrated oil and vibration analysis approach. Despite the indications of researchers of the advantages in detection and diagnosis ability, integration of the two techniques has not been done successfully. Correlation of oil analysis and vibration analysis data has not yet been performed, such that efficient fault detection using both techniques is not possible. Another difficulty of integrating the two techniques is that expert knowledge of both techniques is required to implement an integrated condition monitoring program.

The difficulties currently limiting the integration of oil and vibration analysis techniques may be overcome with the use of artificial intelligence. Experimental data obtained from both techniques could be analysed using fuzzy logic and neural networks in order to correlate the two techniques. Once the correlation has been established, an expert system could be utilised to reduce the dependence on human experts for both oil and vibration data interpretation.

Successful correlation and integration of the oil and vibration analysis techniques would greatly improve the fault detection and diagnosis ability of machine condition monitoring programs. This therefore presents a potential for substantial cost reductions of maintenance and equipment overhaul, one of the key expenses of todays industrial operations.

Chapter 3

Methodology

3.1 Introduction

This chapter is concerned with the application of the knowledge contained in the literature review to the research project. The research project has been devised to help the mining, mineral processing and manufacturing industries to improve their maintenance programs by utilising a methodical and systematic approach to data processing of the common machine condition monitoring techniques: vibration, oil and wear particle analysis. The specific aims of the research project are to develop an artificially intelligent (AI) system that is capable of analysing machine condition monitoring data using commonly used techniques, and to correlate the results to obtain an accurate and comprehensive report. Furthermore, the AI system should include a suitable user interface and structure to allow it to be operated in a commercial environment by technically skilled operators who are not experts in the condition monitoring field.

In order to meet these project objectives, a survey of possible machine condition monitoring (MCM) techniques was conducted to decide on the techniques best suited to the mining, mineral processing and manufacturing industries. Once the suitable techniques with the best overall fault detection ability for the anticipated machines were selected, an investigation of their correlation ability was performed and compared to conflicting results in literature. This was the first step in verifying the existence of the complementing ability of MCM techniques.

The large amount of MCM data associated with using multiple techniques to diagnose the health of a machine has resulted in an additional difficulty to implementing this type of analysis in industry. The development of an AI system would negate this limitation, by automating the data fusion and interpretation process. The selection, development strategy and methods of appropriate AI type has been discussed in Section 3.3, which includes planning of the AI system structure and implementation. As the case-study type analyses presented in literature and verified in the correlation investigation could only be used for a small range of faults in specialised machines using manual data interpretation, the integration of the MCM techniques relied on the development of a knowledge base. In order to meet the project objectives, this innovative knowledge base would need to be able to diagnose a broad range of faults that can occur in the diverse range of machinery used in industry.

The development of a knowledge base and associated AI system for automated integrated fault detection allows additional features to be implemented that rely on the correlated analysis. These features include root-cause analysis and machine remaining lifetime to failure estimation. Root-cause analysis is very useful for maintenance departments in determining the chronological order of failures, and thus the impact of developing faults on other wearing parts of the machine. This information can be used to reduce the costs of secondary faults occurring, thereby improving both profitability and machinery availability. Remaining lifetime estimation is related to the root-cause analysis, by predicting the possible time until component failure will result. This is therefore a useful tool to assess fault severity, and aids in the timely replacement of the affected parts prior to unexpected failure. In order for these novel diagnostic and reasoning knowledge bases to be developed, the AI system utilising integrated fault detection techniques must be operational to allow accurate machine condition information to be available.

The root-cause knowledge base was developed using laboratory and industry machine failure data, as well as comprehensive machine failure analysis to construct the interaction between possible primary and resulting secondary faults. The comprehensive machine health report compiled by the integrated AI system allows the use of the developed automated root-cause analysis knowledge base to be applied for the first time. The remaining lifetime estimation knowledge base was constructed using the results of the machinery failure analysis as well as wear and lifetime prediction methods from literature. While remaining lifetime prediction techniques have been developed as discussed in Chapter 2, the inability to accurately determine the machine condition hindered the practical implementation of these techniques. The AI system allowed the knowledge base developed by integrating multiple remaining lifetime concepts to be applied to real-life machines, in an automated multiple-fault lifetime estimation system.

3.2 Experimentation and Correlation Analysis

The sub-project focused on a comprehensive analysis of fault detection abilities of each technique, and possible strategy to successfully correlate the analysis results. In order to verify the possibility of integrating these techniques, a series of experiments were conducted using laboratory test rigs. A spur and worm gearbox test rig were used to obtain MCM data for typically encountered faults utilising vibration, oil and wear particle analysis. The data was then analysed for fault detection of each technique, and potential overlap in diagnostic abilities. Once real MCM data had been obtained using the discussed test rigs, the feasibility of correlating vibration, oil and wear particle analysis was determined. The data was used to perform the initial correlation investigation, as well as for knowledge base development during the comprehensive analysis. Due to the large amount of information that needs to be processed for these comprehensive machine health analyses, an artificially intelligent system was developed to reduce the dependence on both operator time and expertise.

3.2.1 Experimental Verification of Correlation

The primary investigation of the project involved a study of the machine condition monitoring techniques to determine whether the results really complement each other for machine health assessment. This study included a number of experiments using two laboratory gearbox test rigs to collect real condition monitoring data of vibration, oil and wear particle analysis. The tests were organised to include common gearbox failure modes, which were analysed as case-study scenarios and thus determine both the fault detection ability of each individual technique as well as the extent of detection overlap. The use of laboratory testing equipment was chosen as the machines could be operated under controlled conditions to provide quality data on the individual gearbox failure modes. This contrasts to industrial machinery which may be subjected to several abnormal operating conditions, including overload, corrosive environmental factors or inherent installation faults.

3.2.1.1 Laboratory Testing Equipment

In order to verify whether vibration, oil and wear particle analysis complement each other in machine condition monitoring, a series of experiments were carried out to obtain MCM data under controlled conditions. The application of accelerated wear tests of specifically designed test rigs allowed multiple common machine failures to be investigated within the project timeframe, not possible with real industry data where machine lifetimes of several years are considered short. The laboratory test equipment contained similar machine components as typically used in the mining, mineral processing and manufacturing industries to allow the data collection and hence study of the failures associated with machinery used in these industries. Other equipment also commonly found in industry includes conveyor belts, pumps, fans, compressors, augers and turbines. Of these machines, gearboxes lend themselves for data collection as these can be monitored using vibration, oil and wear particle analysis. The test equipment was designed to enable the fault conditions to be imposed in a controlled manner, and conducted in a procedure that allows the results to be obtained independently.

3.2.1.2 Spur Gearbox Test Rig

The spur gearbox test rig was specifically designed for the study of gear wear under controlled conditions. The gearbox is equipped with a dedicated oil sampling port near the gear meshing point, and tri-axial (x, y and z axes) accelerometer mounting points (horizontal, vertical and axial directions) at each drive shaft to facilitate the acquisition of oil and vibration data. The gear ratio has a multiple other than 1, which allows the effects of preferential wear to be studied, when operating the gearbox for long periods, light load and no seeded faults.

The test rig was designed to include a mechanism for varying a uniform load transmitted through the gearbox. This enabled the equipment to be operated under normal and overloaded conditions, while a uniform load negates the problems of unknown component damage caused by sudden bursts of high amplitude impact loads. A loading device with these characteristics corresponds to a centrifugal pump, which is suitable for small spur gear type transmissions.

The experimental spur gear test rig set-up consisted of a single stage gear system with a 4:3 ratio, and an approximate power transmission capacity of 900 W. The gearbox parameters are summarised in Table 3.1. The gearbox was driven by a 2.2 kW three phase electric motor and variable speed drive, while the input load of the gearbox was determined by a strain gauge fitted to the motor.

Table 3.1: *Spur gearbox specifications.*

	Input Shaft	Output Shaft
Gear material	1045	1045
Number of teeth on gear	40	30
Gear pitch circle diameter (mm)	40	30
Gear width (mm)	8	8
Pressure Angle (degrees)	20	20
Bearings[a]	6001	6001

[a]Most tests were conducted using 63001 bearings which have identical internal and external diameters, but are wider. The equipment specifications of each test is summarised in Appendix Section B.

The output of the gearbox was used to drive an Onga 183 centrifugal pump to circulate water in a 200 litre reservoir. The recommended motor input power of the pump is 2.4 kW, with an approximate fluid power load of 1.2 kW. The schematic representation of the test rig set up is shown in Figure 3.1.

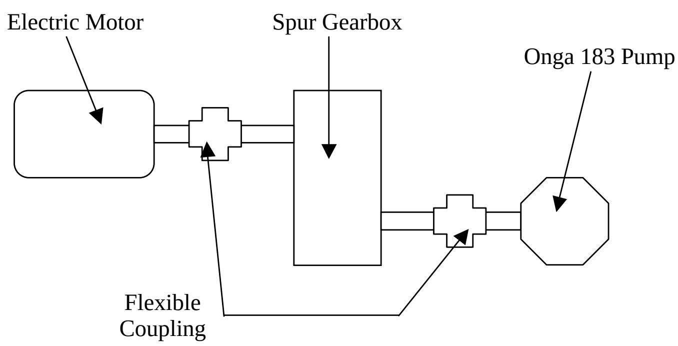


Figure 3.1: *Schematic diagram of the experimental spur gearbox test rig.*

The gears and bearings were splash lubricated, with no provisions for cooling or filtering. A synthetic oil of 320 ISO viscosity grade (321cSt @ 40°C) was used. The sampling point of the gearbox was located in the top gearbox cover, and allows oil to be drawn from adjacent to and below the gear meshing point. This facilitates oil samples to be obtained while the gearbox was in operation. The gearbox has been designed to improve oil circulation, and features a small oil capacity of 125 mL, and a rounded bottom.

Each test included the use of a new gear set, which demonstrated the three stages of machine wear — wear in, steady wear and rapid wear out phases. The tests were concluded once the oil, wear debris and vibration analysis techniques indicated that severe wear was occurring. This was also confirmed by visual inspection of the gear teeth surfaces. Detailed specifications of each test performed using the spur gear test rig is discussed in Chapter 4.

Failure of gearboxes can be attributed to either operational or installation related causes. Operational related failures can occur due to the overload or over-speed of the equipment, and environmental conditions where corrosive or abrasive substances enter the gearbox resulting in an increased wear rate. In order to collect MCM data on this array of possible faults, the experimental test rig was operated under controlled fault conditions, including overload, contamination, inadequate lubrication, and bent drive shaft operation. The overload test was performed by operating the rig at 125 % rated load. This value was chosen as it represents an overload that may be imposed unintentionally by minor machine modification using non-OEM components. This scenario may occur when replacing the motor with a slightly larger unit due to availability or to simplify spare parts inventory, and an operator running the machine at maximum throughput.

Contamination is a common operating condition that is common encountered in the mining and material handling industries. The corresponding wear test was conducted by adding a 3740 ppm concentration of silicon dioxide particles to the lubricating oil, which is a common constituent of dust [89]. Although typical dust contamination can lead to lubricant silicon dioxide concentrations of about 50 ppm, the higher concentration was chosen as other contaminants would be present with the dust, resulting in a significantly higher total contaminant concentration than 50 ppm. One objective of this test was to analyse the effects of contamination by sharp abrasive particles, under controlled concentration. The silicon dioxide particles have a high hardness value compared to the steel gears, and tend to fracture with sharp edges, thereby representing contamination of sharp hard particles, such as hard rocks and crushed ore. The size range of the silicon dioxide particles were determined to be 8 to 50 microns.

Typical installation related causes of failure can be linked to either component damage due to rough handling during storage or installation, or unsatisfactory maintenance practices where contaminated or incorrect lubricants were used. The improper lubrication condition was achieved by filling the gearboxes with a lower viscosity lubricant than required to operate in elestio hydrodynamic lubrication. Another installation fault condition studied using the spur gearbox test rig was bent drive shaft operation. This condition can occur due to the installation of a faulty component, which may have been salvaged from a wrecked gearbox previously subjected to severe overload. High interference fits between the shaft and supporting bearings on shafts with high length to diameter ratios may also result in bent shafts due to rough installation practices. In order for each test to be operated independently to the other tests, all wearing components including gear sprockets, bearings and seals were replaced between tests.

3.2.1.3 Worm Gearbox Test Rig

The worm gearbox test rig was designed to allow the impact of various operating conditions on worm gear wear modes and rates to be investigated. In order to facilitate the equipment to be positioned in the laboratory, as well as keep the cost associated with each test to a minimum, a relatively small gearbox was selected. As the selected gearbox is a commercially sourced product, the entire gearbox is replaced for each test.

The test rig was constructed so that the gearbox is mounted in the centre of a circular water trough, and rotates a water paddle as a load dissipation device. Energy input is via a 0.37 kW 3 phase electric motor and variable speed drive to allow the speed, and hence transmitted power to be varied. The transmitted power can also be varied by the water level in the tank. Detailed specifications of the test rig are summarised in Table 3.2, while a photo depicting the test rig is shown in Figure 3.2. The fluid stirrer in a circular tank allows smooth power transmission through the gearbox and for the entire rotation of the stirrer. As the paddle is rigidly connected to the output gear — one rotation of the paddles is equivalent to one rotation of the gear — smooth loading of the paddles is essential for even gear loading and wear.

The worm was made from an alloy steel with a ground finish, while the pinion gear was manufactured from a shell cast high-strength phosphor bronze. The worm was case hardened to a depth of 0.2 mm, with a hardness value of Rockwell C58/60.

The power transmitted through the gearbox can be determined by using a strain gauge fitted to the gearbox housing, and measuring the torque transmitted by the motor. Loosening the bolts of the flange mount between the gearbox and motor facilitates the strain gauge to be activated. To aid with oil sampling of the otherwise sealed gearbox housing, three ports were installed into the housing comprising a filler, oil sampling, and oil drain port. Apart from the addition of oil ports, accelerometer mounting positions were installed at the top rear and front of the worm, as well as at each output shaft support bearing. These mounting positions allowed the acquisition of vibration data from the front and rear of the worm including the supporting bearings, and at both sides of the pinion gear and bearings. Due to the confined design of the

Table 3.2: *Worm gearbox specifications.*

Item	Specification
Motor Power Rating (kW)	0.37
Number of Poles	4
Gearbox Manufacturer & Model No	Bonfiglioli VF-44
Gearbox Power Rating (W) at zero safety factor	250
Gear/Worm Material	Bronze/Steel
Reduction	28:1
Recommended Oil Grade	ISO 320 synthetic
Lubricant Used	Shell Tivela S 320 (321cSt@40°C)
Type of Synthetic Oil	PAG
Oil Capacity	65 mL

gears within the housing, good circulation of the oil through the gears is maintained throughout the gearbox operation.

The worm, pinion and bearings operated within the oil, while the upper drive bearing was splash lubricated, with no provisions for cooling or filtering. The sampling point of the gearbox was located at the front of the gearbox, mid way on the pinion gear. The oil filler was positioned at the top of the gearbox which allowed the oil to be filled to capacity, with excess running out of the same tube doubling as a breather hose. The oil samples were taken while the gearbox was in operation, and the position of the sampling port enabled oil to be extracted directly above the pinion gear.

3.2.2 Data Collection and Preparation

The data collection of wear tests conducted as part of the correlation investigation involved the monitoring and storage of vibration, oil and wear particle analysis information. This sampling of data must be performed at suitable operating time intervals, which coincided with the accelerated rate of wear experienced by the test rig. Sampling

Figure 3.2: *Photo of the worm gearbox test rig. Note that the water level is not at operating level, and the strain gauge is not connected to the wheatstone bridge at the time of the photo.*

intervals that allow approximately 10–12 samples to be obtained between the commissioning and de-commissioning of the gearbox test rig were selected, as this provides sufficient resolution to detect the wear-in, normal operation, and wear-out stages of the gearbox, and allowed the fault detection of each MCM technique to be evaluated. This sampling strategy has been based on analytical analysis of the gearbox as well as previous wear tests. The effective lifetime of the gearbox can be considered to be the operating time until the primary fault can be detected with accuracy. Analytical analysis of the gearbox with respect to the load, lubrication regime and operating speed was used to estimate the effective lifetime of the gearbox, using literature on EHL and boundary lubrication theory. The operating time to the onset of gear tooth fatigue or scuffing was therefore determined, and used as a guide in planning the duration of the individual wear tests.

Sampling of the spur gearbox was performed using a single use plastic pipette, and plastic sampling bottles. The regular sampling size was 5 mL of oil, which is sufficient for filtergram analysis. A larger oil sample of 16 mL was taken every second interval, in order to perform particle count and size distribution analysis. Four samples were collected in the initial 24 operating hours, with sampling intervals then extended to every 24 hours.

Data collection of the worm gearbox was performed similar to the spur gearbox, with four vibration and oil samples collected during the first 24 hours of operation, and then extended after this period. Due to the slower operating speed of the worm gearbox compared to the spur gearbox, sampling intervals were correspondingly longer. The regular sample size was 5 mL of oil, with 60 mL being collected during oil changes.

The data acquisition for vibration analysis includes the collection of time, frequency and demodulated frequency domain spectra, at a suitable frequency bandwidth that allows all desired faults to be detected. Typically, a suitable frequency bandwidth for condition monitoring of a gearbox would allow the detection of 3 times the gear mesh frequency. The data was collected by mounting the accelerometer to the specified mounting points on the gearboxes, and allowing the vibration analyser to sample and store the emitted frequencies. As the data acquisition was performed by the vibration analyser, numerical data preparation was performed automatically, which involved demodulation of the spectra scan, and an FFT on the time domain data to obtain the frequency domain spectra. Manual data analysis would also require the spectra to be graphed, which was performed automatically by the vibration analysers PC software.

Oil and wear particle analysis rely on the collection of an oil sample, which is representative of the bulk fluid. This means that the sample should contain similar concentrations of the wear particles found throughout the oil, and should therefore be withdrawn at a location where the oil is subject to sufficient turbulence and mixing. The oil sample must also contain sufficient volume to allow all desired tests to be performed. For this project, the requirements by each test include: wear particle analysis — 1mL, particle counter — 10 mL, and viscometer — 10 mL. Once the oil sample had been collected, the preparation included the production of a filtergram for microscopic wear particle analysis, and the analysis of oil using the particle counter and viscometer. Microscopic analysis of wear particles was used to reveal both the physical dimensions of the wear particles, as well as the particle colour. The physical dimensions of wear particles were obtained by scanning individual wear particles using a Laser Scanning

Confocal Microscope, and performing digital image processing techniques. Numerical descriptors such as length, angularity and surface roughness [27] were obtained in this process, yielding quantitative data that allows further processing.

3.2.3 Data Processing and Fault Diagnosis

Maintenance programs require an efficient methodology for using available machine condition information for fault detection and diagnosis. This typically involves the manual analysis of vibration spectra and oil analysis results data by experts. In order to verify the existence of complementary interaction between vibration, oil and wear particle analysis, manual analysis of the collected data was performed together with post test visual inspection of the test apparatus.

The data processing and fault diagnosis is an important step in the machine condition monitoring operation, as the hints in the collected data are combined in order to detect existing and developing faults. The techniques of data analysis as discussed in Chapter 2 need to be applied to the collected data for fault detection. Vibration analysis was performed by using knowledge from literature, handbooks, as well as consultation with experts in the vibration analysis field. Similarly, oil analysis was performed by consulting literature and standards such as the draft ISO/TC 108/SC5 standard [102]. Wear particle analysis was performed by evaluating the filtergram microscopic slides using an optical microscope and comparing the wear particles to images from a wear particle atlas and 3D wear particle analysis techniques developed in [27] to categorise the particles. All of the information was then analysed together, and the overlap in fault detection evaluated.

The data collected for each experiment consisted of four components, including oil analysis, wear debris analysis, vibration analysis, and visual inspection of the wearing surfaces. The oil analysis was conducted on a CSI Oil View 5200 Trivector Analyser, which provided particle count, size distribution data and viscosity. Wear debris analysis was conducted using the filtergram method for slide preparation. This included the dilution of 1mL of oil sample with solvent, and passing this mixture through a 3 micron filter patch. Curing of the patch on a glass slide to render it transparent was followed by image acquisition using a LSCM, resulting in particle images at 0.05 micron height increments. The images were compiled into a single 3D surface morphology image using Matlab, which allowed the surface roughness values to be calculated. The use of numerical descriptors like surface roughness improves the reproducibility of wear debris analysis, by reducing the reliance on subjective operator judgements [22, 27].

Vibration analysis was conducted by analysing both time and frequency domain data, of the input and output gearbox shafts. Visual inspection of the gear teeth was performed during the oil changes, and after each test had concluded. This allowed the determination of the actual type and extent of damage that had occurred, and the degree of accuracy of the oil, wear debris and vibration analysis techniques.

Data processing as described here is the typical procedure that is followed for the respective analysis of vibration, oil and wear particle analysis. While these techniques are used for the purposes of MCM, the difficulty in correctly assigning each abnormal operation with the appropriate fault has been a primary reason why a correlation analysis has not been performed until now. The correlation investigation focused on using all indicators of abnormal machine operations provided by the three techniques, and linking the indicators of each technique that signal the same faults. This differs considerably from conventional analysis, where each technique is applied for fault detection individually, and correlation is not performed. This effectively means that not all of the information supplied by each technique is used, limiting the accuracy and reliability of the resulting machine health report.

3.2.4 Comparison of Diagnostic Results

The comparison of diagnostic results obtained from the individual condition monitoring techniques presented the major step in the correlation investigation. While the three analysis reports can be used to approximate the machine condition, a case study type investigation for each performed test is crucial to observe the possible links between the techniques. Post test machine component inspection was also conducted to aid with assessing the fault detection ability of each technique.

The diagnostic results obtained from each technique were compared on a detected fault basis. Each technique was used individually to diagnose two types of faults — component defects, and general fault indicators. Component faults included those faults where the technique could identify the faulty component or component type directly from the collected data. General fault indicators incorporated faults where an abnormal condition was detected, but could not be used to identify a particular component. The correlation investigation focused on both of these fault categories, as directly detected faults reveal the overlap in fault detection by the three techniques, while the general fault indicators were used to assess the possibility and potential benefit of correlation. When the techniques are used individually to assess a machines condition, only the direct detectable faults are identified. The general fault indicators are essentially discarded as these cannot usually be used with sufficient accuracy to make maintenance conclusions. It was therefore concluded that the success of correlation lies in correctly linking up of the general fault indicators, using the post test inspections to verify the reasoning.

3.3 Development of AI Systems for Fault Diagnosis

Condition monitoring of fixed plant operating in the mining, mineral processing and manufacturing industry sectors is commonly performed using vibration, oil or wear particle analysis techniques, or a combination of these. The information obtained by each technique differs where vibration analysis can detect imbalance and looseness type situations, oil analysis provides the lubricant status, while wear particle analysis provides an insight into the prevalent wear modes, cleanliness and component wear. Studies, and the work done in Section 3.2 have shown that the techniques therefore generally complement each other [1, 2], which has led to the adoption of hybrid condition monitoring programs. Due to contamination being a common occurrence in the targeted industries, oil analysis has typically been included in the condition monitoring programs, while vibration analysis is often used for general fault detection.

The correlation of vibration, oil and wear particle analysis techniques would therefore enable a comprehensive machine condition report to be obtained, using the various fault indicators provided by the individual techniques. The potential benefits of this approach would be earlier component fault detection, and the ability to treat root failure causes such as contamination or imbalance before causing excessive secondary faults. More accurate condition monitoring information also allows better management of maintenance resources by mitigation of typical failure modes and developing faults due to improved fault detection ability.

The research project therefore focused on the construction of artificially intelligent (AI) systems utilising these three techniques, in order to investigate how the analysis results can be correlated into a comprehensive machine condition report. While the analysis methods are typically performed manually by trained maintenance staff, the use of AI systems was included in the project to allow the analysis to be executed in an objective approach thus reducing reliance on the operator. The benefit of an AI system is that once the individual analysis of each technique is performed, the AI system has all the results in the required digital format to continue to perform the correlation analysis.

As the use of hybrid condition monitoring programs is becoming more widely adopted, an AI system capable of a correlated analysis of machinery condition could be implemented easily. While oil and vibration analysis can be automated, these are generally chosen by maintenance departments and laboratories. Development in the automation of wear particle identification may make this effective technique commercially viable, and further increase the accuracy of condition monitoring. The use of an AI system for routine machine condition utilising a correlated technique approach would be a valuable tool for any maintenance department, especially those with large machine inventories.

3.3.1 Selection of Artificial Intelligence Systems

Artificially intelligent systems encompass a large group of software designs and algorithms designed to allow computers to interpret data using human expert like reasoning. The forms of artificial intelligent systems considered in this project include neural networks, gray systems, and expert systems. Neural networks are very useful for relating a trend in the input data with a certain outcome or result. This type of operation is often referred to a black box, where a direct relation between input and output was initially unknown, and established by the AI system. Gray systems are useful for implementing mathematical models, thereby relating output to the system inputs. These systems have been used successfully to identify wear particles according to shape and surface morphology characteristics [27, 73]. This AI system for particle characterisation can be used as a pre-processing step for the AI system developed in this project, thereby allowing quantitative wear particle identification.

The type of data analysis performed in machine condition monitoring utilises well proven rules to diagnose machine faults using distinctive features of the input data. Black box and mathematical model type AI systems are therefore not required for data analysis, as the links between input and output are already well defined, and widely used by experts in the machine condition monitoring field. The type of AI systems well suited for this application are expert systems, which follow predefined reasoning logic in order to relate features in the input data to the possible outputs. Expert systems are categorised into the transparent type of AI systems, as the relation between input and outputs is clearly defined, as opposed to neural networks and gray systems. The AI system chosen for this project are expert systems, as these simulate the data analysis performed by human experts.

3.3.2 Development of Integrated Expert Systems

The development of expert systems for the correlation of vibration, oil and wear debris analysis will be undertaken by designing separate expert systems for each analysis technique, such that a third expert system can be used to correlate the two condition reports into one comprehensive report. This approach was selected to allow the development of each expert system to be thoroughly tested, before proceeding with the analysis of the integration expert system. The thorough testing of each expert system, designed to operate as an individual module, ensures the integrity of the development.

The principal of this data processing procedure is shown in Figure 3.3. This methodology allows the design and testing of the expert system for each technique, while also

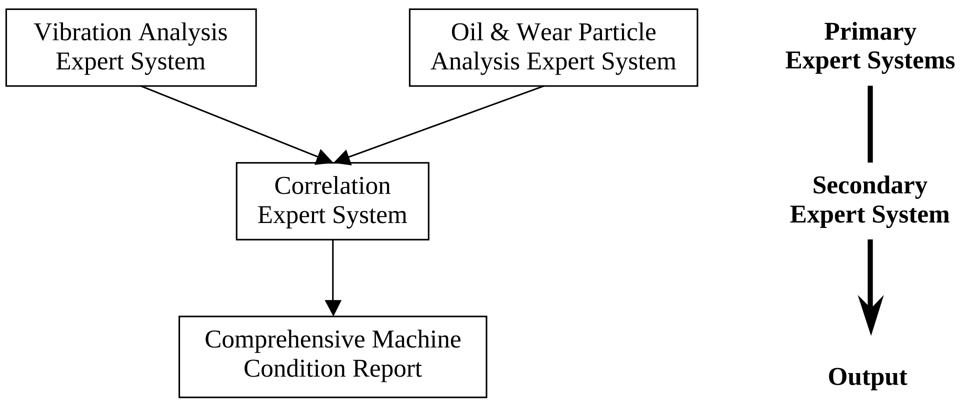


Figure 3.3: *Data process flow chart of the expert systems.*

providing the ability to diagnose machinery faults when only vibration or oil and wear particle analysis data is available. The individual vibration, and oil and wear debris analysis expert systems will operate so that each expert system analyses the respective data independently. The results from each expert system can then be correlated by the third (secondary) expert system.

The fault detection ability of the vibration analysis, and oil and wear particle analysis techniques differ significantly, resulting in the two analysis reports complementing each other, especially for weak or developing faults. The secondary expert system is therefore required to correlate all the detected faults of each analysis technique in the final condition monitoring report.

The vibration analysis knowledge base was developed by compiling a list of all possible component faults that can be diagnosed and are relevant to machinery found in mining and processing industries. Once all of the relevant faults were identified, the detection strategies using tri-axial frequency spectra and demodulated spectra, as well as amplitude-time spectra were compiled to construct the knowledge base. This fault oriented approach was also used during the knowledge base development for oil and wear debris analysis. The included detection techniques are oil viscosity, water and dust concentration, ISO cleanliness code, wear particle type and colour, and elemental analysis. These techniques have proven success for diagnosing wear conditions in gearboxes and hydraulic systems. The knowledge base was constructed by compiling the results obtained from each oil analysis technique, and formatting the reasoning logic into one integrated knowledge system.

The developed knowledge bases were implemented in software code as expert systems, featuring quantitative analysis of the input data according to the compiled reasoning logic rules. The aim of the integrating expert system was to correlate the results of each of the two expert systems the vibration analysis, and the oil and wear debris analysis expert systems. The possible difficulties with integrating these techniques is well documented in literature, and are predominately concerned with the possibility of conflicting results from the individual expert systems. Extensive investigations of the results of the two techniques for various gearbox failures allowed three scenarios of conflicts to be identified. These include only one technique detecting a fault, both techniques detecting a fault but with differing severity, or both techniques detecting different (or numerous) faults. In these cases, the technique which has the lower uncertainty was used in the analysis if possible, while the more severe fault report was used in cases where the uncertainty is unavailable, such as the presence of water in oil. This strategy was also implemented for scenarios when the main fault is unknown as numerous faults have been detected. The fault with the lowest uncertainty was considered to be the predominant fault. However, this methodology does not indicate whether the predominant fault was actually the first fault to develop (the primary fault), or any information about the failure process. This kind of analysis can only be performed by a root-cause analysis.

The comprehensive diagnosis of machine faults obtained by the operation of the three expert systems allows the prediction of the chronological order of progressive failure. This type of analysis commonly called root-cause analysis, was included in the expert system, and involved the development of a dedicated analysis algorithm, by studying machine failure modes and construction of a knowledge base on the findings. Using root-cause analysis, faults can be categorised as either primary or secondary faults, depending on whether a fault was caused by another fault, or whether it is an individual failure mode. Faults resulting from individual failure modes including bearing and gear fatigue, bent drive shaft, lubrication faults and imbalance can be categorised as primary faults. Component faults that are the result of a primary fault occurring can therefore be categorised as secondary faults, such as misalignment resulting from a worn bearing or unacceptable installation practices. While some faults such as bent drive shaft can generally be considered primary faults, many faults could be grouped into either category depending on what other faults are present. Failure mechanisms were studied and organised in a table format to allow the categorisation of primary and secondary faults based on what component faults were detected. The results were arranged in flow charts as shown in Appendix Section E.

The development of the complete AI system concentrated on satisfying the research project objectives; to design an AI system capable of correlating vibration, oil and wear particle condition monitoring data using a software package that can be used as a prototype in a commercial setting. The expert system structure proposed above allows the AI system to process and interpret vibration, oil and wear particle data in a logical sequence, then correlate the preliminary results to obtain one machine condition report. The inclusion of additional features such as a root-cause analysis algorithm, and maintenance recommendations enabled the system to be operated by general technical staff rather than highly trained staff. The development of a dedicated user interface allows the expert system analysis algorithms to be used in a commercial environment, thereby satisfying the design objectives.

3.3.3 Interface Development

The user interface is an important component of the project development, as it enables the developed knowledge base and AI system to be used in a commercial application. As this is an industry linkage project, contribution to industry in a practical way is of prime significance. The objectives relating to the interface development therefore focus on the ease of use, compatibility with Microsoft Windows type operating systems, and reduction of operator interaction.

In order to meet the user interface objectives, a graphical type of user interface was used, as this has numerous advantages over text based systems. The interface development differed to the research and knowledge base development, as human interaction, visual appeal and predjustice must be taken into account, apart from efficient operation from an analytical perspective. A graphical interface (GUI) with a Microsoft Windows style operation was therefore deemed most appropriate as it allows operators familiar with Windows to navigate the interface using intuition. This helps reduce operator training time as well as provide an easy to use system. The GUI also allows the placement of strategic help menus and active mouse cursers (help message pops up when mouse is hovered over object) at strategic positions to provide the operator with the required information.

The required reporting standards used to present the results were developed by considering the required operator input for each machine analysis, and information flow within the different departments within an operation. As machine maintenance and condition records are a valuable tool for maintenance departments, text file based reporting was selected over on-screen reports. In order to reduce operator time, the expert systems were designed to report pre-defined text messages into the text file, thereby compiling a ready-to-use output report.

The input information required for the expert systems to operate consists of the raw data, machine specifications, and analysis specific information. As the machine specifications and analysis information do not change for each machine, it was decided that two data input menus would be used, and each menu would be able to save the information to text files for future re-use. The raw data of vibration analysis is available as an exported data file, while a data input menu was required to allow oil and wear particle analysis data to be saved as a text file. The use of text style data files for all input information simplifies the analysis menu, as only browse buttons are required to select the appropriate data files.

While the data input mechanisms were designed to be menu driven and text file based, a text file only output for individual expert systems, and a menu only output for the combined analysis expert system was deemed most appropriate. The text file outputs allow these to be used in analysis reports or to be archived for future reference, while the on-screen menu style output permits the results to be presented in a logical and simplified manner. It was considered important to give the operator a quick overview of the health of the machine, with the details being available by selection of an additional menu button called Details. Similarly, the results from the root-cause analysis and analysis recommendations can also be accessed from the overview menu. As this layering is not possible in a text file, it was decided to only offer an on-screen display for output.

3.3.4 Testing Criteria of AI System Developments

The project relies on the correct implementation of analytically developed knowledge bases into software code, in order to achieve an AI system capable of meeting the stated project objectives. A testing strategy needs to be in place to verify that the completed AI system performs as planned, as well as verifying the conducted analytical research. These two goals were used when deciding on the testing strategy.

The initial testing of the AI system developments was performed to ensure that the operation coincided with the knowledge base, including data processing, fault detection, result reporting, and interface operation. Testing of this phase was performed by assessing the correct operation of all If-Then-Else loops, by manipulating the input data and testing for the corresponding outputs. As the expert systems were developed in sequential order, the performance of each system could be verified before proceeding with further development. This simplified the software code error checking and testing process, as small sections of code can be de-bugged easily, and subsequently saved development time.

Once each expert system operated as planned, real machine condition data from the laboratory tests and industry were used to verify that the correct machine condition conclusions were reported. The criteria used to assess the success of analysis was to test whether the reported faults coincided with the faults detected by manual condition analysis, and post-test visual inspection of the laboratory rigs. The laboratory data obtained from the spur gear wear tests described in Section 3.2.1.2 was used for the verification purpose, as well as data from industrial reduction gearboxes sourced through collaboration with BHP Queensland Nickel. This rigorous testing phase therefore included the verification of each of the conducted laboratory test rig wear investigations, each analysed as a case study. The conclusions of the developed integrated analysis expert system were compared to the results of the manual condition analysis, and verified using the post-test visual inspections.

3.4 Summary

The development of data analysis and interpretation techniques was a main component of this research project. These range from the initial design of experiments to obtain machine condition monitoring data, to the comparison between vibration, oil and wear particle analysis data, the development of a user interface, and the development, testing and verification stages of the analysis algorithms. The methodologies discussed in this chapter were used throughout the project, and hence relate to the developments of the successive chapters.

Chapter 4

Experimentation and Results

4.1 Introduction

The acquisition of condition monitoring data from laboratory testing equipment was an important component of the project, as it enabled the investigation into the complementing abilities of vibration, oil and wear particle analysis. Data obtained from laboratory equipment as opposed to machinery used in industry has the advantage that abnormal operating conditions can be imposed individually and under controlled conditions, providing more accurate diagnostic information for the particular failure mode investigated. This single fault condition specific machine condition information allowed the identification of sequential component failures, which was compiled into a root-cause analysis knowledge base. The experimental data was also used to verify the correct operation of the developed expert systems, in terms of fault detection and diagnostic ability.

4.2 Spur Gear Tests

The test rig utilised to run the experiments was a single reduction spur gearbox and centrifugal pump arrangement, powered by an electric three-phase motor. The abnormal conditions imposed onto the gearbox were selected to correspond to those frequently encountered in industry, and capable of significantly reducing the service life of the gearbox. The conditions leading to gearbox failure investigated in this project were constant and cyclic overload, contamination, and bent gear mounting shaft operation. These tests were selected by studying common gearbox failure modes as well as based on the experience of Industrial and Technical Services, the industry partner of this project.

The experiments were conducted using a set method, which consisted of the wear-in of the components prior to imposing the abnormal operating condition. The only test which did not undergo this step was the bent drive shaft test, as this shaft was installed during the gearbox overhaul. Once the overhauled gearbox was fitted to the test rig, the strain gauge amplifier was zeroed, so that the load cell output voltage could be recorded throughout testing. The experimental rig was started and initial voltage readings were recorded from the digital multimeter. The motor shaft speed was measured using a digital tachometer. Throughout testing, vibration data, motor characteristics, oil temperature, and ambient temperature were recorded at regular intervals. Oil samples were also taken during data collection. After each data collection, the vibration data was uploaded into a PC, while all temperature and motor speed values were entered into a spreadsheet. The operating time of each test varied, depending on the severity of the wear experienced by the gearbox, and resulting operating time at the normal wear to wear-out transition. The transition from wear-in to normal operation was monitored using trend information of wear particle concentration and size.

4.2.1 Normal Operation

The aim of this test was to study the lifetime of the gearbox and inherent failure modes when operating the gearbox at 80 % load rating, as well as identify the transitions between wear-in and normal operation, and normal operation to wear-out stages. During the test which consisted of 120 hours of continuous operation, 11 slides in total were taken with data collected at the initial 6, 12, 24 operating hours, with a 24 hour interval for the remainder of the test. The analysis of the test data was performed using each technique individually, thereby evaluating the machine health using vibration analysis, and oil and wear particle analysis.

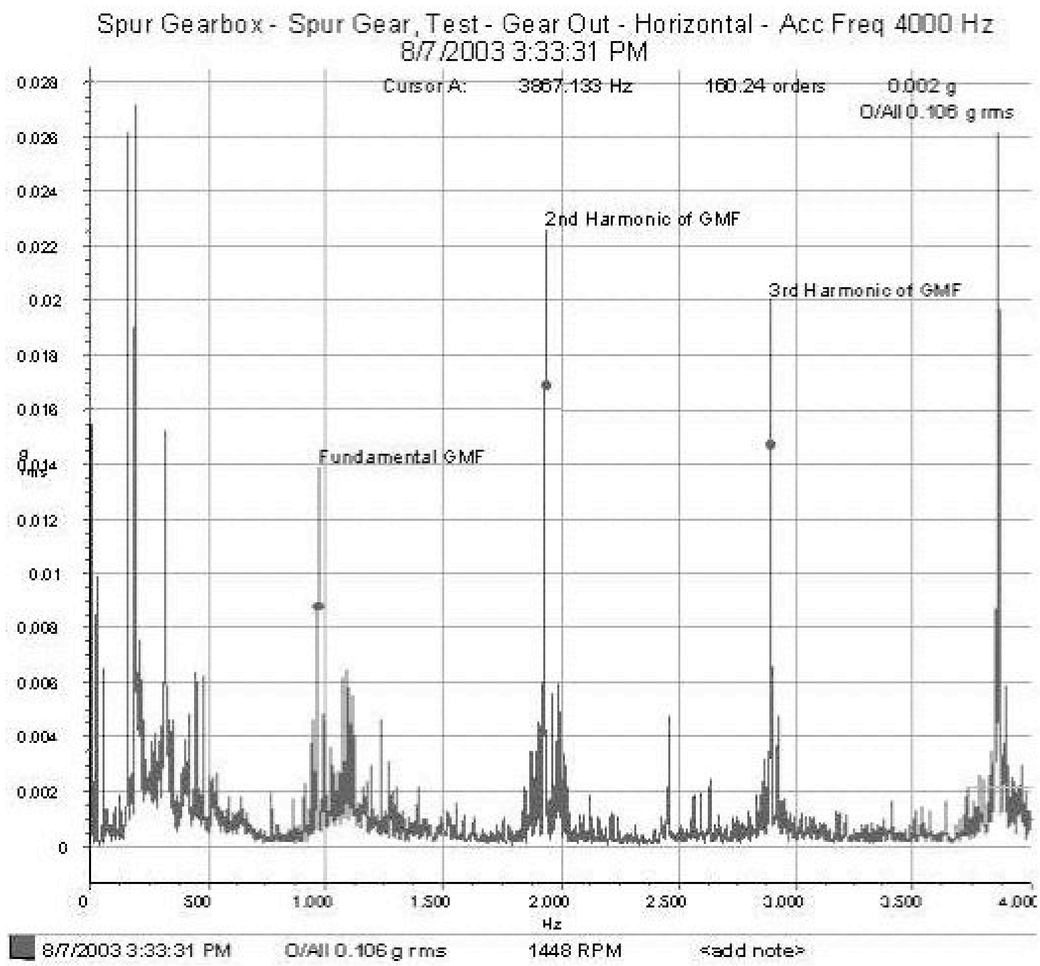


Figure 4.1: *Acceleration-frequency spectrum at the output side of the gearbox.*

4.2.1.1 Vibration Analysis Results

Figure 4.1 shows the acceleration-frequency plot for 0 – 4000 Hz taken on the output side of the gearbox. This plot distinctly shows the fundamental gear mesh frequency and its harmonics. The frequency amplitude for each of the gear mesh frequencies is extremely low which represents smooth initial operation of the system.

Some associated sideband activity can also be seen around these frequencies but is representative of the gears running-in stage. Figure 4.2 shows the velocity-frequency spectrum for the region 0 – 400 Hz at the gearbox input. It can be seen that there is a distinct peak at 1X, which may be an indicator of imbalance or eccentricity. This vibration feature however, is common for a normal operating system. From this plot, there is

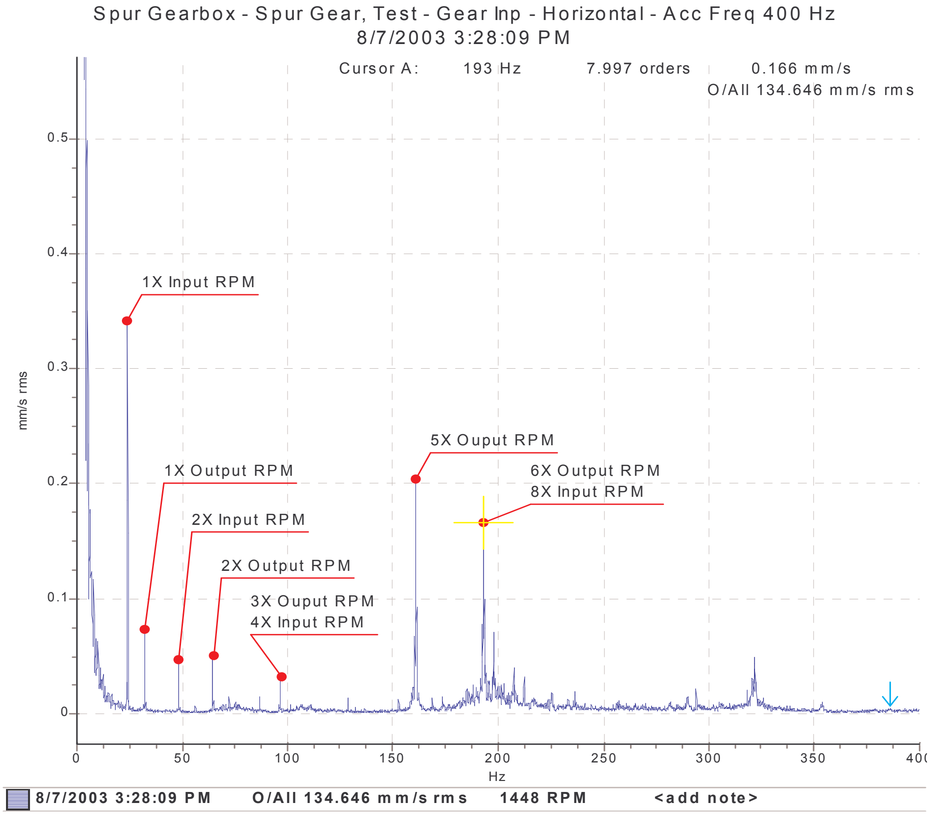


Figure 4.2: *Velocity-frequency spectrum at the input side of the gearbox.*

no evidence of bearing defects, misalignment or imbalance, and the only peaks are due to running speed harmonics that show low levels of velocity amplitude. Examination of a waterfall plot on the input side of the gearbox (as shown in Figure 4.3) indicated that the vibration levels throughout the normal testing of the gearbox remained fairly constant.

4.2.1.2 Oil and Wear Particle Analysis Results

Microscope slides were prepared using the filtergram method, which involved the dilution of 0.3 mL of the oil sample in a solvent followed by passing through the 3 micron filter patch. After curing of the slide to make the patch transparent, it was examined and the following results recorded. The large concentration of rubbing wear particles is common for the wear-in period of a gearbox. The small number of fatigue and severe

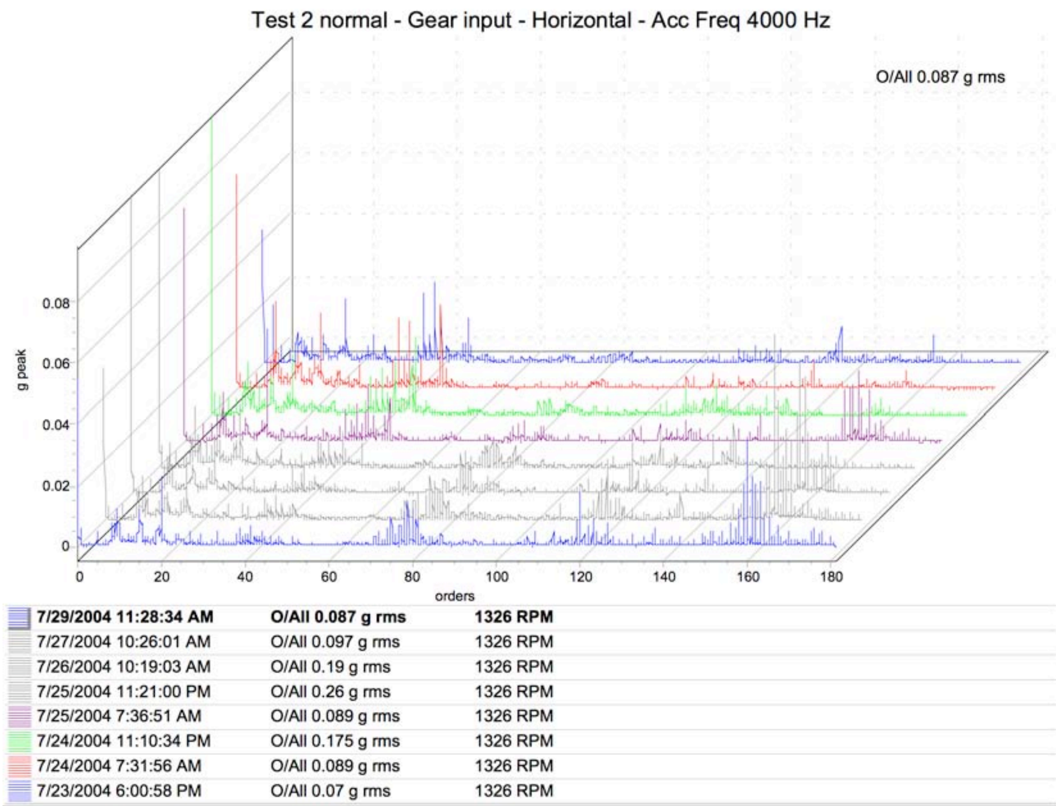


Figure 4.3: *Waterfall plot of 4000 Hz acceleration at the input side of the gearbox.*

sliding particles are indicative of the asperities present on the gear surfaces being worn down.

As shown in Table 4.1, the elimination of fatigue and sliding wear particles which appeared in the first oil sample indicates that these were produced as a result of the wear-in process and not due to a gearbox fault developing. Slides 3 to 6 feature a decrease in quantity and size of the laminar particles, typical for the transition to normal operating regime, as demonstrated by the little change in wear debris features during slides 7 to 10.

In slides 3 to 6, the size and quantity of the rubbing particles remained fairly constant through this interval. The quantity and size of laminar particles decrease through this interval of the wear-in process of the gears. In slides 7 to 10, the quantity and size distribution of both the rubbing and laminar particles remained fairly constant over this interval. This indicates that the gears have entered the normal operating

Table 4.1: *Wear debris analysis of the normal operation test.*

Slide	Operating Time (hours)	Wear Debris Features
1	6.5	85 % rubbing wear particles, 10 – 13 % laminar particles, <1% fatigue and severe sliding particles
2	12	90 % rubbing wear particles, 15 % laminar particles
3 – 6	24 – 60.7	Decrease in quantity & size of laminar particles
7 – 10	72.75 – 108.75	No significant change in particles present, concentrations and size
11	120.3	Increase in quantity & size of laminar particles

region. A very small amount of fatigue particles were still present. Finally, in slide 11, the rubbing particle quantity and size distribution remaining constant. There was a slight increase in the quantity and size of laminar particles relative to slide 10. This observation has been confirmed using a particle analyser. Figure 4.4 shows a laminar particle found in slide 1. Rubbing wear particles are similar to laminar particles in shape, but are smaller in size.

The laser scanning confocal microscope (LSCM) was used to confirm surface roughness values for representative wear particles during the wear-in, normal and wear-out operation stages of this test. This is an advanced technique of wear particle analysis, allowing quantitative wear particle identification. Seven laminar particles were analysed from slides 1, 5 and 9, to represent the wear-in, transition and normal operation stages. The results of the surface roughness values, Ra, for the laminar particles are given in Table 4.2. The results from Table 4.1 show that the surface roughness for the laminar particles decrease over the duration of the test. This trend demonstrates that

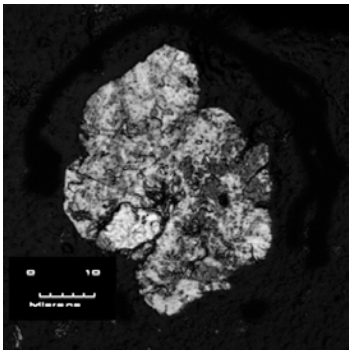


Figure 4.4: *Laminar particle generated during the normal operation test.*

Table 4.2: *Surface roughness values for wear stages of the 5 tests.*

Test Number	Start of Test (μm)	Middle of Test (μm)	End of Test (μm)
Normal Operation	0.247	0.244	0.220[b]
Constant Overload	0.166	0.130	0.173
Cyclic Overload	0.191	0.207	0.262
Contamination	0.110	0.085	0.080
Bent Shaft	0.051	0.035	0.074

[b]End of Test 1 was still in normal operation, with no significant change in value observed.

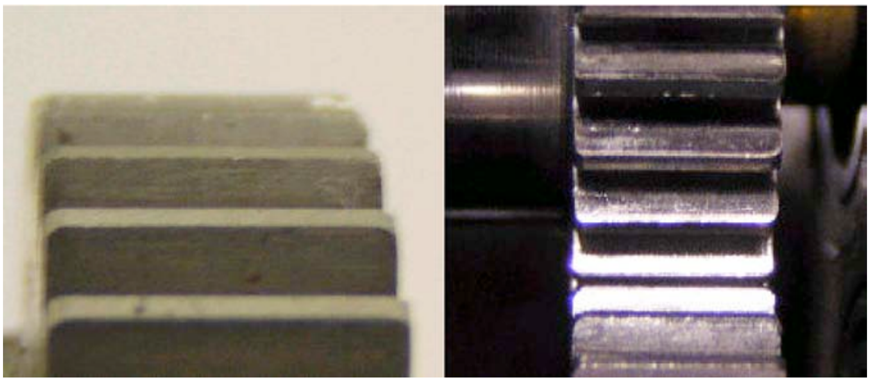


Figure 4.5: *Gear tooth surfaces before (left) and after (right) the normal operation test.*

the surface roughness of the laminar particles is decreasing during the wear-in period.

This test monitored the wear debris resulting during the wear-in period of new gears, and demonstrates the change in wear particles and size distribution in the transition from wear-in to normal operation. Figure 4.5 shows the gear wear surfaces before and after the test. Wear debris analysis revealed that the wear modes present during the transition was rubbing wear. This coincides with the rolling contact of the meshing gear teeth, and no major faults have been detected.

4.2.1.3 Correlation of Vibration, Oil and Wear Particle Analysis

The wear debris and vibration analysis techniques both exhibited evidence for a decreasing wear rate as is typical for the running-in to normal operation transition. The reduction of laminar particles, and presence of limited quantity of small fatigue particles found by wear debris analysis demonstrate good correlation with the findings of vibration analysis: a decrease in vibration amplitude, and low amplitude of gear mesh harmonic frequencies and sidebands. Post test inspection confirmed the conclusion drawn from the correlated wear debris and vibration analysis approach. The results of this test verified that the gearbox operates satisfactorily with little wear rate when no initial seeded faults are triggered, and the transmitted load is limited to 80 % of the rated transmission power. Machine faults during the test were not detected by either analysis technique, while the wear-in stage was characterised by a general decrease in vibration amplitudes, a reduction of fatigue and sliding wear particles, as well as a decrease in surface roughness of laminar particles.

4.2.2 Constant Overload

The overloaded operating condition was imposed onto the gearbox by operating the test rig at an input motor speed that resulted in the centrifugal pump absorbing the desired amount of power. The transmitted power was determined by measuring the motor torque using a strain gauge, and noting the motor shaft speed. The duration of the wear-in process of this test was observed for the first 133 hours of operation, and an oil change was completed after the first 108 hours of operation. Once the gears were operating in the normal regime, the 125 % overload condition was initiated, and the gearbox operated for another 109 hours.

4.2.2.1 Vibration Analysis Results

Three spectra ranges were sampled during this test consisting of a broad scan at 4000 Hz, mid range of 1000 Hz, and another to 400 Hz. The resolution of the data was 3200 lines for the spectra, and 4096 samples for the time domain data. The vibration data taken for this test revealed that a number of defects existed throughout the duration of the test. The low frequency velocity spectra indicated the presence of a loose fit between the gearbox output shaft and bearings, while a demodulated and high frequency acceleration spectra gave evidence of gear looseness, and eccentricity on the output gear.

The overloaded condition of the gearbox could be identified by vibration analysis using historical spectra for normal operation, as the higher load resulted in an increased amplitude of vibrations. The increase of sidebands around the harmonics of gear mesh frequencies towards the end of the test indicated that a gear meshing fault had occurred and that the gears were wearing severely. However, the type of gear mesh fault and wear mechanism could not be diagnosed using vibration analysis. Figure 4.6 shows a trend in vibration of the gearbox input frequency spectra to 4000 Hz, with an increasing time axis being out of the page. The gear mesh frequency and the first two harmonics at 40, 80 and 120 orders respectively, indicate that misalignment possibly due to excessive looseness may have developed.

4.2.2.2 Oil and Wear Particle Analysis Results

Oil samples were taken when the vibration measurements were made, with wear debris analysis being performed using computerised image analysis techniques, while a particle counter was also used for particle concentration and size distribution analysis. The wear debris obtained from this test was analysed using the filtergram method for slide preparation, and an optical microscope. The wear particles were analysed for size and size distribution, shape, and surface roughness. The initial wear-in period of the

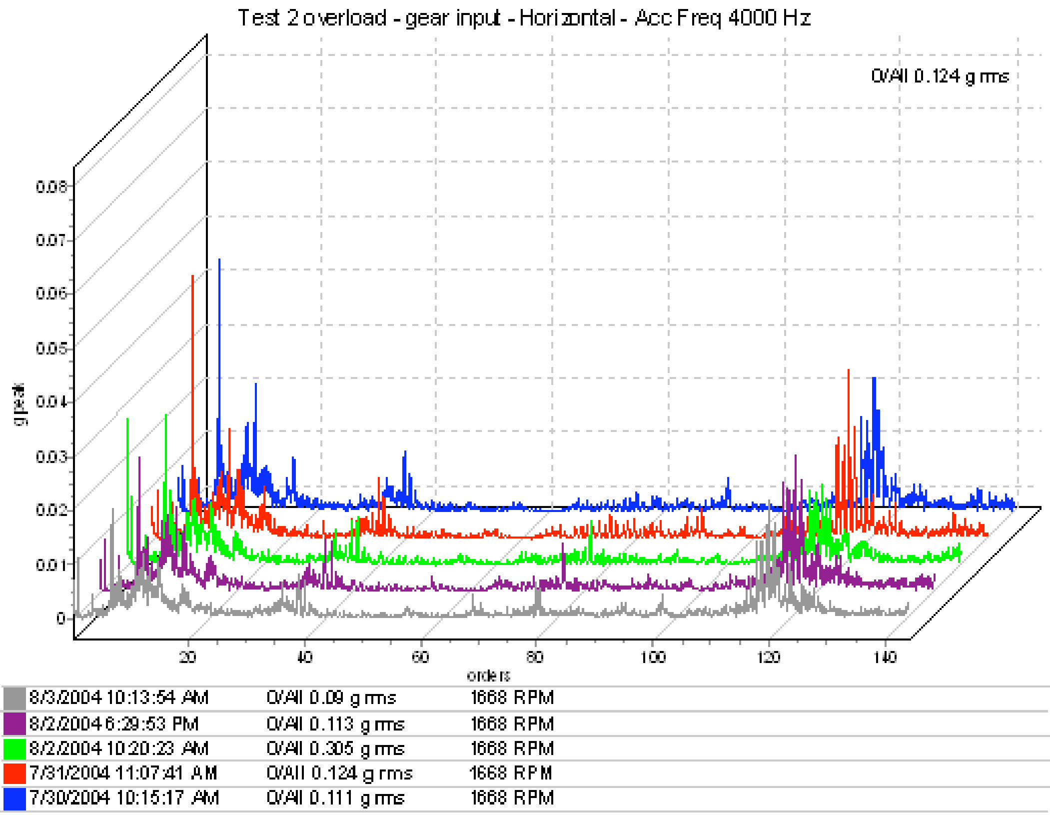


Figure 4.6: *Trend of input gear frequency spectra (normalised to input gear speed).*

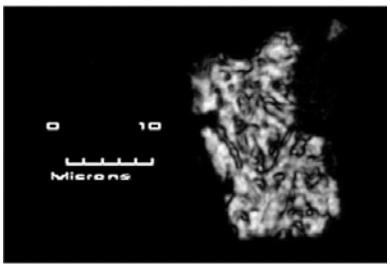


Figure 4.7: *Fatigue particle generated during the constant overload test.*

Table 4.3: *Fatigue particle concentrations on filtergram microscope slides.*

Slide	Operating Time (hours)	% Concentration
1 - -3	18	55
4 – 6	41	60
7 – 8	60	60
9 – 11	133	70
12 – 14	204	70
15 – 16	242	70

gearbox was characterised by a decrease in the generation of laminar particles and an initial increase in larger rubbing particles.

The wear particles generated during the overload period exhibited a continuous increase in fatigue particles for the initial 70 hours of operation, followed by a rapid increase in fatigue particles during the final 50 hours of operation (the wear-out phase) as shown in Table 4.3. Figure 4.7 shows an image of a fatigue particle, found in slide 12. Rubbing and laminar particles were found to represent around 30 and 10 percent of particles respectively, with the size of laminar particles decreasing from 20-50 microns to 20-30 microns. The roughness values of the laminar particles is listed in Table 4.2. The increase in fatigue particles was accompanied in a large increase in particles in general, which was shown by both particle count information as well as visual inspection of the lubricant colour during the wear-out phase. The surface of the fatigue particles was found to be significantly rougher than of the laminar particles.

The fatigue particles were suspected to originate from the gear teeth surface by the pitting wear mode, due to their generally smooth surface with holes and presence of straight edges. Numerical surface roughness data for fatigue particles of this test using the LSCM were not obtained as these only appeared in the wear-out stage of the test, and trending was thus not possible. However, the surface roughness trend of the laminar particles shows that the particle surface became smoother during the wear-in to normal

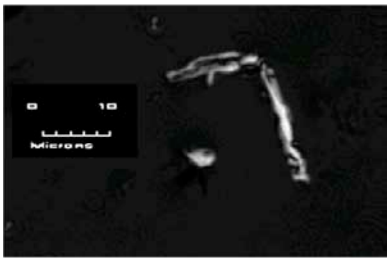


Figure 4.8: *Cutting wear particle generated during the constant overload test.*

operating stage, and then increased again during the wear out stage. Although sliding wear particles were not observed during the duration of this test, a small number of cutting particles were noticed at the end of the test, as shown in Figure 4.8. This could be an indication that gear looseness had developed which resulted in gear misalignment.

The conclusion that can be drawn from the wear debris analysis is that the gears were wearing out due to surface fatigue (pitting). As the operating hours of the test are known, the presence of fatigue particles at low operating hours suggests that an overload condition may have caused the gears to fail prematurely. In an industrial application where gear hardness data is not obtained during overhaul, the wear debris data could also have suggested that the gears were too soft for the imposed load.

4.2.2.3 Correlation of Vibration, Oil and Wear Particle Analysis

The effects of the overloaded condition relating to gear wear were identified by both analysis techniques. While vibration analysis detected a gear mesh fault with increasing severity, wear debris analysis revealed fatigue particles suspected to originate from pitting. This diagnosis was confirmed when the gearbox was dismantled and inspected. The majority of gear teeth showed the onset of pitting, caused by high localised surface stress. Other wear modes such as sliding wear were not present, as shown by the otherwise smooth gear tooth surfaces in Figure 4.9.

Of the wear particle analysis techniques, particle shape and morphology inspection allowed the detection of an increase in pitting fatigue particles approximately 24 hours before particle counting revealed a significant increase in the number of particles. Simi-

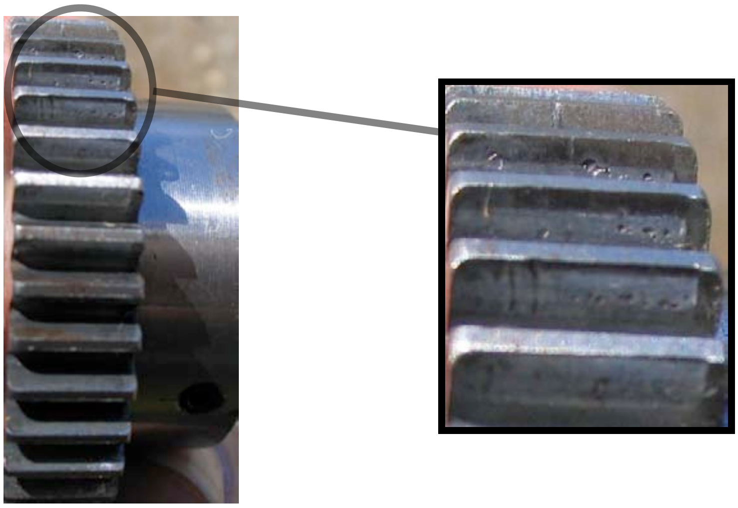


Figure 4.9: *Photo of gear teeth after constant overload test.*

larly, vibration analysis showed an increasing sideband activity of gear mesh harmonics throughout the overload test.

The wear evidence given by vibration analysis can be used for root-cause analysis, as it is possible to diagnose other machine faults including gear misalignment and looseness. While the chronological order of these fault being detected can be used for root-cause analysis, the detection of wear modes can also verify this information. The nature of oil analysis however requires a fault and resulting component damage to occur before the coinciding wear particles can be detected. Given a case where both analysis techniques can detect a fault condition, vibration analysis would therefore be expected to yield the first discovery.

4.2.3 Cyclic Overload

This test was conducted to allow the effects of a cycling load on a spur gearbox to be investigated. This condition may be imposed to industrial spur gearboxes working in material handling due to varying material feed rates or different operator shifts. The overload range for this test was set at 120 to 160 % of the rated power transmission of the gearbox. This was achieved by operating the test rig at a line frequency of 75 Hz, resulting in gearbox input and output shaft speeds of 2125 and 2833 RPM respectively. The test was operated for a total duration of 80 hours, during which 8 oil and vibration data samples were taken.

4.2.3.1 Vibration Analysis Results

The vibration data of this test indicated that the sidebands of gear mesh harmonic frequencies increased over the duration of the test. Although the cyclic load condition could not be detected directly, the consequent developing gear mesh fault was thought to be responsible for the increased sideband activity of gear mesh frequencies.

The presence of gear eccentricity and slight misalignment, indicated by the harmonics of the gear mesh frequency was also detected, as shown in Figure 4.10. Installation defects including bearing defects, shaft misalignment and imbalance were not detected in the low frequency velocity spectra. The low frequency velocity spectra was not shown as no faults were detected in this region.

The vibration analysis data therefore suggests that one of the present wear modes occurring in the gearbox is sliding wear, resulting from the misalignment. Other wear modes may also be present, but cannot be identified using the available vibration data.

4.2.3.2 Oil and Wear Particle Analysis Results

The wear debris analysis of this test revealed that both rolling as well as sliding wear was occurring, and increased in severity for the duration of the test. The wear particles from slide 1 were composed of around 75 % of rubbing wear particles, 20 % laminar (the roughness values of the laminar particles is listed in Table 4.2) particles and the remainder being shared by fatigue and sliding wear particles. At slide 6 (60 hours of operation), the quantity and size of fatigue and sliding wear particles present increased significantly, which was also accompanied by an increase in the quantity and size of laminar particles. One of the sliding wear particles is shown in Figure 4.11.

The results obtained by wear particle analysis using an optical microscope were also confirmed by a particle count and particle surface roughness values for particles of slides 1 and 8 (80 hours). The wear debris analysis resulted in the conclusion that pitting

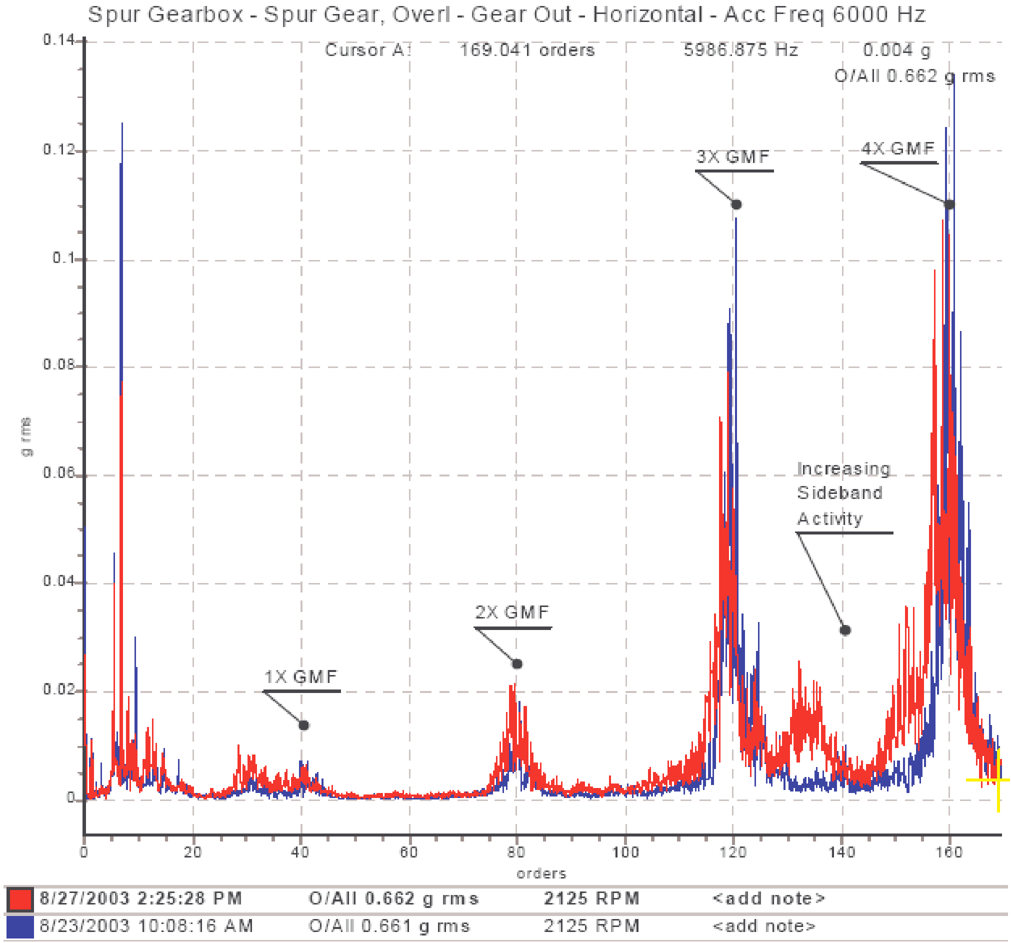


Figure 4.10: *Vibration spectra of output gear collected during the cyclic load test.*

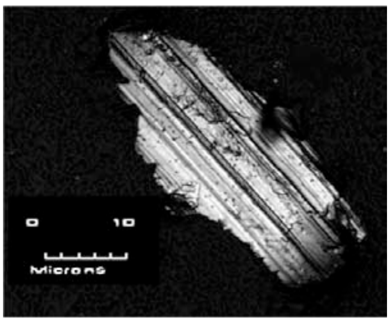


Figure 4.11: *Sliding wear particle collected during the cyclic load test.*

of the gear teeth had occurred due to the presence of fatigue particles, combined with scuffing and/or scoring which resulted in the production of sliding wear particles. The trend in surface roughness of laminar particles shows a significant increase during the wear-out phase, indicating that the gearbox no longer operated in the normal stage. The numerical surface roughness of laminar particles therefore confirms that a gearbox fault exists, as diagnosed by visual wear debris analysis.

4.2.3.3 Correlation of Vibration, Oil and Wear Particle Analysis

Both the wear particle and vibration analysis techniques were unable to detect the root-cause of failure, that a cyclic loading condition was occurring. However, both techniques detected the resulting damage of the gears wearing out. Wear particle analysis provided evidence that both gear fatigue (in the form of pitting) and sliding wear modes were occurring, and increasing in severity towards the end of the test. Vibration analysis added to the evidence by indicating that while a gear mesh fault was developing, bearing faults did not exist. This supports the conclusion of wear debris analysis that the fatigue particles originated from the gears. Vibration analysis also complemented the wear particle analysis in the detection of misalignment which could have resulted in the gears not meshing at a constant centre distance, thus creating sliding wear particles. Post test inspection of the gears proved that both pitting as well as scuffing and scorching wear did indeed occur, as shown in Figure 4.12, as predicted by both analysis techniques.

The three tests demonstrated that both wear debris and vibration analysis techniques complement each other, by correlating of the faults determined by vibration analysis with the wear modes detected by wear debris analysis.

4.2.4 Contamination

The contaminant selected for this test was silicon dioxide, to allow the study of hard particle abrasive wear while also being a common constituent of dust [89,103]. A silicon dioxide concentration of 3740 ppm was used in the tests, to allow the gearbox to wear severely within the expected normal lifetime of the gearbox, and to account for other

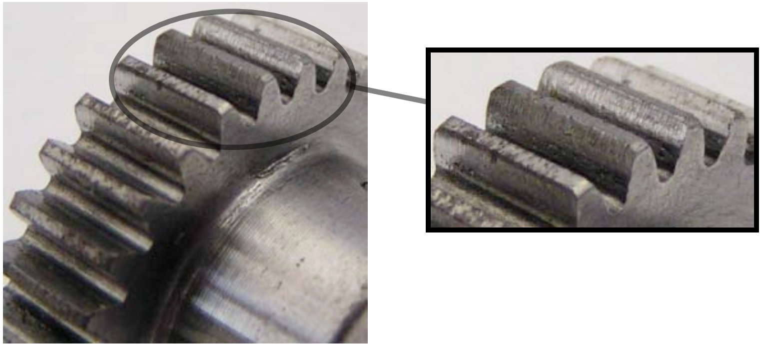


Figure 4.12: *Photo of gear teeth after cyclic load test.*

contaminant which would generally be present had contamination of dirt occurred. This test was conducted for 162 hours of continuous operation, at the conclusion of which both vibration, oil and wear particle analysis indicated that the gearbox was operating in the wear-out stage. The load imposed on the gearbox was adjusted to 80 %, which conformed to the condition of the normal test. During the test, 10 oil samples and vibration scans were taken, in order to monitor the gearbox condition and developing faults.

4.2.4.1 Vibration Analysis Results

The vibration analysis indicated that the gearbox underwent wear-in and normal operation stages during the initial 89 hours of operation before the contaminant was added. Although the audible noise emitted from the gearbox decreased for the first few hours after contaminant addition, an increase in bearing and gear looseness could be detected, as well as a gear backlash fault and misalignment were detected within 7 hours of operation. These defects were easily recognisable after 24 hours of contaminant operation. At the conclusion of the test, 73 hours of contaminant operation, all defects mentioned had progressed to advanced stages, while detectable bearing faults consisted of ball fault, and inner and outer race faults. Figure!4.13 shows a waterfall plot of the acceleration spectra over the test duration.

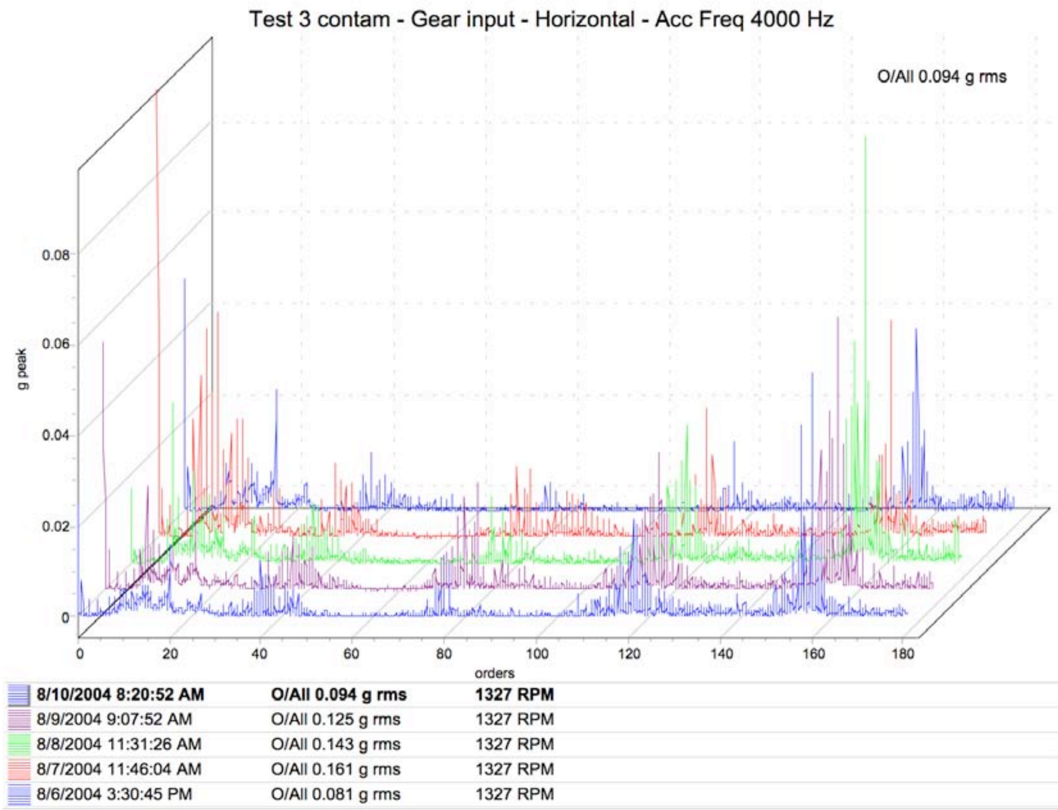


Figure 4.13: *Waterfall plot of acceleration spectra from the contamination test.*

4.2.4.2 Oil and Wear Particle Analysis Results

The wear particles found during the wear particle analysis indicated that the gearbox was operating in the normal stage at 89 hours running time. After the addition of contaminant, rolling element fatigue particles appeared at approximately 20 % concentration, which increased to 30 % during the test. Cutting wear particles (approximately 5 %) also appeared during the same time, and increased to 15 % concentration after 52 hours of contaminant operation. Examination of the cutting particles revealed that the size was generally smaller than 5 microns in length. This indicates that the dominant wear mode resulting in the cutting particles may be due to a grinding process involving the silicon dioxide particles. This claim has been further confirmed by the results of the numerical analysis of the laminar particles. The average surface roughness values were 0.110, 0.085, and 0.080 μm for wear-in, normal, and wear-out operation respectively. This indicates that the particles became smoother during the test. Towards the end of the test, both rolling element and gear fatigue particles dominated, while the general particle size decreased. This could be due to larger particles being modified and broken into smaller ones by the wear process.

Particle count and concentration confirmed that particle concentration of all sizes doubled during the initial 28 hours after addition of contaminant. The concentration of particles smaller than 25 microns in size doubled again during the final 10 hours of the test.

After the test, the gearbox was dismantled and the parts inspected visually for wear. It was found that both gears had experienced severe wear from the tooth tip to approximately a third down from the tip, and had a definite wear mark at the tooth pitch line. The pitch line had a fine polished appearance with no apparent pitting, scuffing or scoring damage, as shown in Figure 4.14. Gear wear was found to be more severe on one side, indicating that misalignment had occurred. The drive shafts showed signs of scoring and localized spalling at the bearing seats, which confirmed the presence of bearing looseness. An oil leak had also occurred towards the end of the test, due to worn seals and the misaligned shaft.

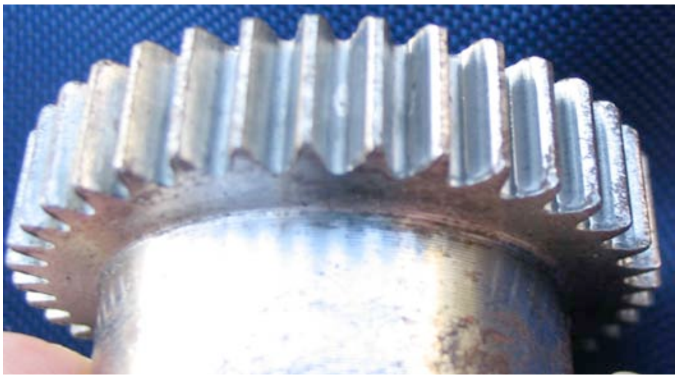


Figure 4.14: *Photo of one of the gears from the contamination test.*

4.2.4.3 Correlation of Vibration, Oil and Wear Particle Analysis

The result of a high concentration of sharp abrasive material in lubricating oil is rapid gear wear, which was detected by both oil and wear particle analysis. Wear particle analysis indicated that a bearing surface fatigue fault had developed, and that cutting wear was occurring. The cutting wear is an indicator of excessive looseness, caused by worn bearings. This hypothesis was confirmed by vibration analysis, which detected looseness, gear backlash and a misalignment fault.

The severity of gear faults were monitored by vibration amplitude, sideband activity and baseline level using vibration analysis, and particle concentration using oil analysis. Wear particle analysis was becoming complex at detecting wear particles due to the large number of particles in the oil, and high occurrence of wear particle modification by numerous passes through wear zone. Examining the trend of changing particle size and surface morphology assisted in detecting wear particle modification.

The high occurrence of wear particle modification was also confirmed by the average roughness trend, which indicated that particles were becoming smoother with less jagged edges. The effect of particles being broken into a number of other particles could have been aided by the grinding processes occurring within the gearbox.

The benefits of using both wear debris and vibration analysis in this test are twofold. Firstly, oil analysis was able to detect the large number of small contaminant particles, which lead to the increased wear rate. Wear particle analysis was again able to detect the wear modes present as cutting wear, and fatigue particles generated from bearings. Secondly, vibration analysis was able to confirm the secondary faults predicted by the wear debris analysis. The combined use of analysis techniques therefore allows primary and secondary faults to be identified, allowing the gearbox condition to be determined with a high level of confidence.

4.2.5 Bent Shaft

The bent shaft was installed into the driven gear, which resulted in the majority of the gear teeth not meshing at the pitch line. Due to the inward and outward movement of the gear, sliding wear would be expected to occur. This phenomenon was verified by both wear debris analysis and visual inspection of the gear teeth. The test was operated for a duration of 293 hours, representing one of the longest operating tests. The wear severity of the bent shaft can therefore be contrasted to the duration of the other tests, such as overload. The bent shaft test was conducted at 80 % power rating of the gearbox.

4.2.5.1 Vibration Analysis Results

Vibration analysis of collected data revealed the presence of a bent output shaft, as well as gear looseness and misalignment. Trending of vibration data as shown in Figure 4.15 revealed evidence of the gears wearing in during the first 84 hours of operation, followed by a period of normal wear, and then wear-out. The wear-out region was identified by significant sideband frequency components around the gear mesh frequency. The severity of bearing looseness and outer race defect were also found to increase towards the end of the test. Figure 4.16 illustrates the faults detected on one of the frequency spectra generated from this test. The bearing looseness and gear misalignment are evident by the haystack, and high 1 times peak respectively.

4.2.5.2 Oil and Wear Particle Analysis Results

The oil analysis depicted a general trend of increasing concentrations of small particles (smaller than 10 microns) throughout the test. Particles in the 10 to 50 micron range

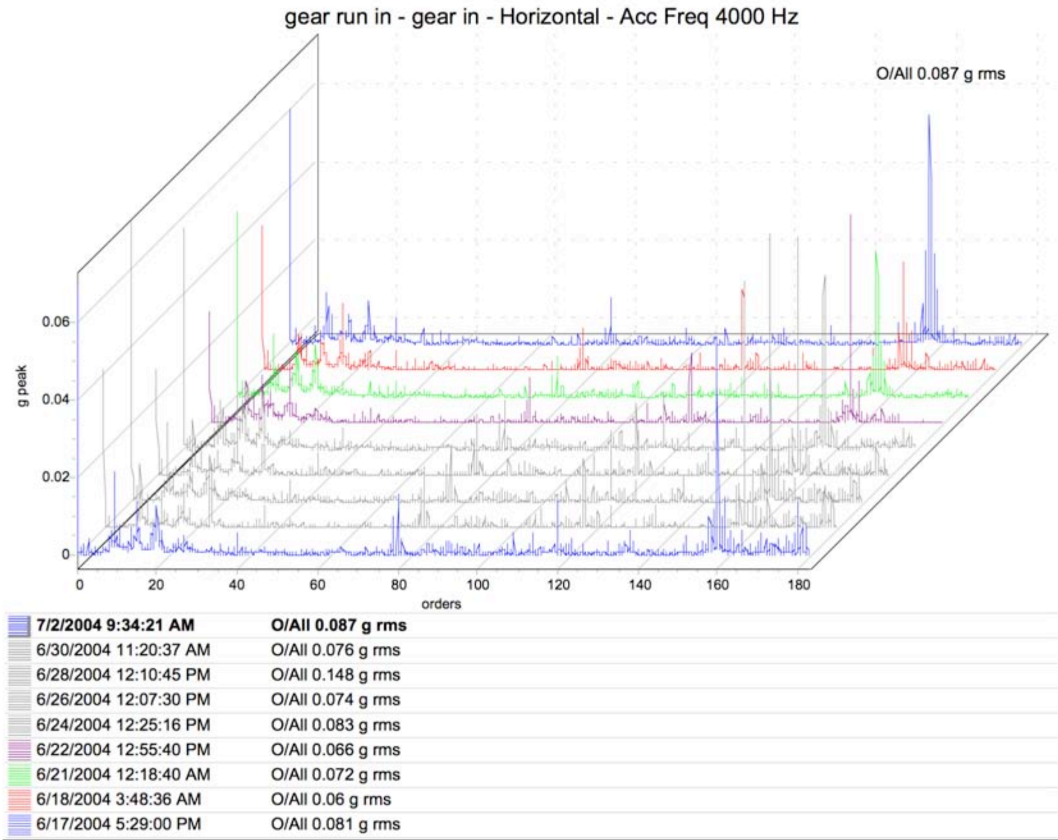


Figure 4.15: *Waterfall plot of 4000 Hz acceleration at the input side of the gearbox, for the bent shaft test. The rotational speed of the input shaft was 1327 RPM, the 4000 Hz corresponding to 180.9 orders.*

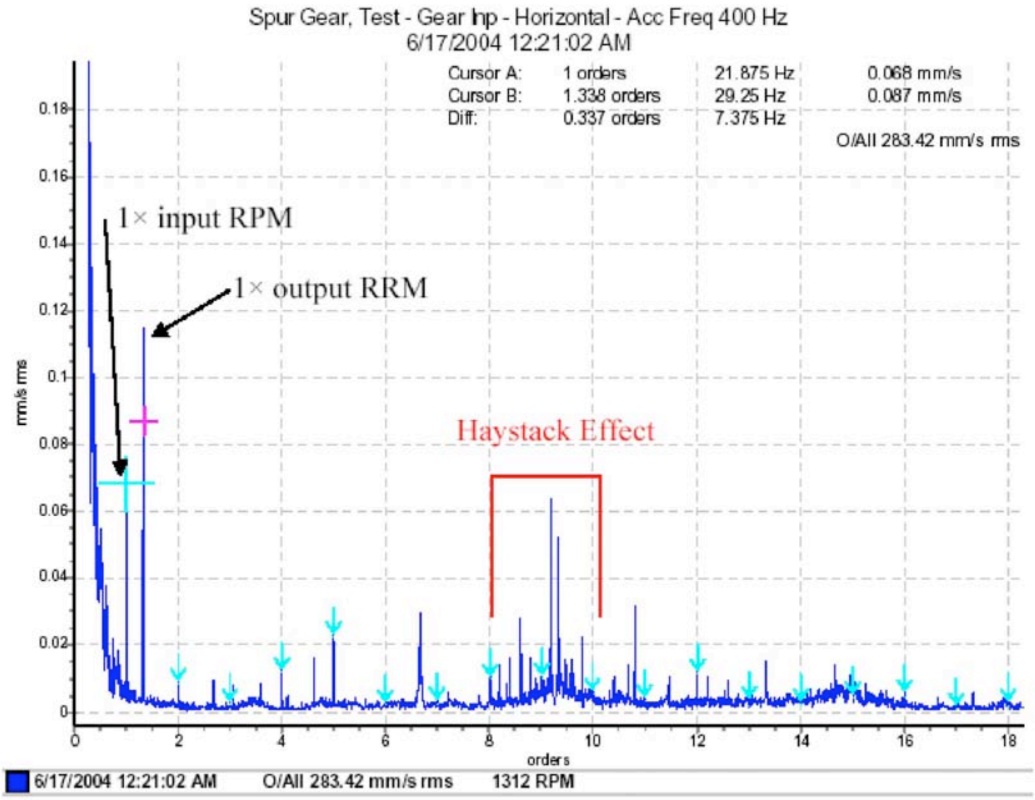


Figure 4.16: *Frequency spectra of input gear (frequency normalised for speed of input gear) for bent input shaft test.*

were found to increase in concentration during the wear-in phase, and then continuously decrease for the remainder of the test.

Throughout the test, rubbing and laminar wear particles were present, as well as rolling element fatigue particles. The rolling element fatigue particles were diagnosed as an outer race defect using vibration analysis. Severe sliding particles were first noticeable after 45 hours of operation, at approximately 20 % of particles present. The concentration of severe sliding particles increased gradually to 55 % by the end of the test, at 290 hours of operation. The surface striations and roughness increased during the final 100 hours of operation. Cutting wear particles were present at approximately 5 % during the initial stages of the wear-in phase, and again during the normal operation and wear-out phases.

Numerical analysis of the laminar particles was conducted from oil samples corresponding to wear-in, normal, and wear-out operation. The average surface roughness values for each stage were 0.051, 0.035, and 0.074 μm respectively indicating that the particles became smoother during the wear-in to normal operation, and then significantly rougher.

4.2.5.3 Correlation of Vibration, Oil and Wear Particle Analysis

The results obtained from this experiment demonstrate that the wear particle, oil and vibration analysis techniques correlate well in both detecting the fault, a bent drive shaft, as well as monitoring the severity of damage that has occurred. As the imposed fault is of the mass imbalance type, it is directly detectible with vibration analysis. Wear particle analysis did however detect severe sliding wear after only 45 hours of operation, corresponding to only 16 % of the test.

The transition between the wear-in to normal operation, and normal to wear-out operation was judged by monitoring the gearbox using oil, wear particle and vibration analysis. Vibration analysis displayed a decrease in amplitude at the gear mesh frequency (GMF) at the onset to the period referred to as normal operation, and a significant increase in amplitude at the GMF at the wear-out transition. The three operating periods have been used for comparison to machine wear stage and the other test, although the gearbox did not undergo a true normal operation due to the imposed fault being present for the entire test.

The data from the numerical wear particle surface morphology analysis indicates that while the particles became smoother during the wear-in stage, the Ra increased significantly during wear-out. This trend corresponds to the surface roughness of the gear teeth, which start off with a machined surface, gradually becoming smoother during the wear in phase. Once surface fatigue commences, the surface roughness again increases due to the arbitrary removal of material. The surface morphology of wear particles is therefore an indicator of the surface roughness of the gear teeth.

The use of wear debris, oil and vibration analysis allowed all faults of the gearbox to be detected, as well as classified into primary and secondary faults. The primary fault in this test was the bent shaft, as detected by vibration analysis. The resulting wear modes were severe sliding wear and cutting wear as detected by wear debris analysis after 45 and 117 hours respectively. The sliding wear was due to the gear teeth meshing at varying pitch centre distances, while the cutting particles were generated from misalignment caused by gear and bearing looseness. The excessive looseness was also detected by vibration analysis. Oil analysis revealed an increase in the total number of particles towards the end of the test, which is generally a sign of rapid wear occurring in a machine.

The benefit of utilising wear debris analysis as well as vibration analysis for this test is that faults present in the gearbox can be detected with greater confidence. Wear particle analysis allowed the detection of wear modes present within the gearbox, which confirmed the gear looseness and suspected misalignment faults identified by vibration analysis.

4.3 Worm Gear Tests

Worm gearboxes differ in wear modes to spur gearboxes, by inherently relying on predominately sliding wear as opposed to rolling wear of spur gears. Due to the high sliding component, gearbox designers often select differing worm and pinion materials, with very different hardness properties. The design and operating differences of worm gearboxes, including the slow operational speeds common with worm gear reductions, result in significant differences in machine condition monitoring data obtainable from this style of gearbox when compared with that from spur gearboxes. Although the expert systems developed in Chapters 5, 6, and 7 are for spur and helical type gearboxes, the worm gearbox tests discussed in this section were used to verify the ability to correlate the vibration, oil and wear particle analysis techniques for gearboxes other than spur gears.

The output shaft of worm gear reductions is generally significantly lower than the input shaft, resulting in the vibration analysis data of the output shaft generally being of low frequency. This can make the early detection of bearing faults difficult. The generated wear debris can include rubbing and sliding wear particles, as well as particles from the usually softer pinion gear (bronze in the case of the test gearbox). Apart from these differences to spur gears, the vibration, oil and wear particle analysis techniques are used successfully for worm gear condition monitoring.

The worm gear test rig discussed in Section 3.2.1.3 was used to conduct 3 tests, consisting of a normal operation test, contamination, and low oil viscosity with iron particles. The normal operation test was used to observe the wear-in and wear-out stages of the gearbox, and to obtain the vibration, oil and wear particle data during these stages. The other two abnormal operation tests were used to establish the ability of each technique to detect the resulting faults, as well as assess the degree of correlation of these techniques.

4.3.1 Normal Operation

The normal operation test was conducted over a duration of 4 weeks, comprising of approximately 664 hours of operation. Oil samples and vibration data were taken after every 166 operating hours, after which the lubricating oil was replaced with Shell Tivela S320, the recommended lubricant.

The vibration analysis trending was used to monitor the transition from wear-in to normal operation, with a general decrease in vibration amplitude. The wear

Table 4.4: *Surface roughness of the worm gearbox normal operation test.*

Sample	1	2	3	4
Surface Roughness, Ra (μm)	0.235	0.252	0.208	0.170

particles found during this test included laminar, rubbing and cutting wear particles. The concentration and size of wear particles was observed to decrease during the test, which is the typical results for the wear-in to normal operation transition. Quantitative wear particle analysis was also performed, and the trend of surface roughness was observed to decrease during the test, as shown in Table 4.4.

4.3.2 Contamination Test

The contaminant test was conducted by operating the gearbox for 166 hours, with oil and vibration samples taken every 48 hours. The contaminant chosen for this test was the same as used in the spur gear contamination test — silicon dioxide power, with an average particle size range of 8 to 50 microns. The contaminant was mixed to the recommended lubricant at a concentration of 15000 ppm (w/v), which corresponds to a severe contamination condition. The oil was changed and the gearbox dismantled and cleaned at every oil sample.

4.3.2.1 Vibration Analysis Results

The vibration analysis consisted of 1000 Hz frequency domain spectra at each accelerometer mounting position on the gearbox, as discussed in Section 3.2.1.3. The peaks detected in the spectra shown in Figure 4.17 consist of 1 times (1X) running speed, line frequency, 2 times line frequency, and outer ball pass frequency.

The line frequency and harmonic result from motor induced vibrations being transmitted to the gearbox due to the close coupled mounting arrangement, and is a common component of vibration spectra of electrical machines. The 1 time running speed and BPFO are gearbox vibrations. The BPFO indicates that bearing damage has occurred due to the high contaminant concentration.

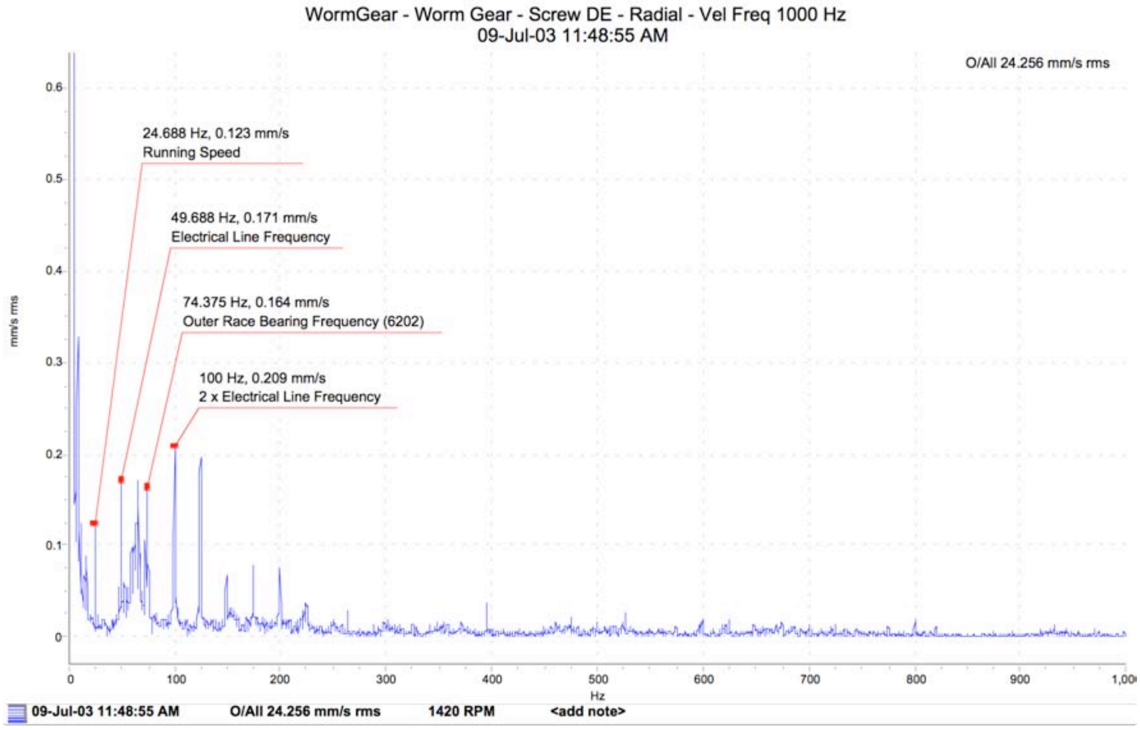


Figure 4.17: *Velocity-frequency spectrum at the drive end of the worm gearbox for the contamination test.*

Table 4.5: *Surface roughness of the worm gearbox lubricant contamination test.*

Sample	177 Hrs	402 Hrs	495 Hrs
Cutting Wear Particle Surface Roughness (avg), Ra (μm)	0.395	0.391	0.470
Rubbing Wear Particle Surface Roughness (avg), Ra (μm)	0.619	0.571	0.615

4.3.2.2 Oil and Wear Particle Analysis Results

Wear particle analysis consisted of optical microscopy and quantitative wear particle analysis. Optical microscopy revealed that the generated wear particles were of cutting and rubbing types, which is typical from an abrasion type of wear mode. Approximately two thirds of the generated particles were bronze particles, originating from the soft pinion gear when compared to the hardness of the worm or bearing metal. The surface roughness values of the cutting and rubbing wear particles was found to decrease slightly initially, after increasing significantly during the end of the test, as shown in Table 4.5. The increase in surface roughness of the wear particles indicates the increase in surface roughness of the abrading gear surfaces.

4.3.2.3 Correlation of Vibration, Oil and Wear Particle Analysis

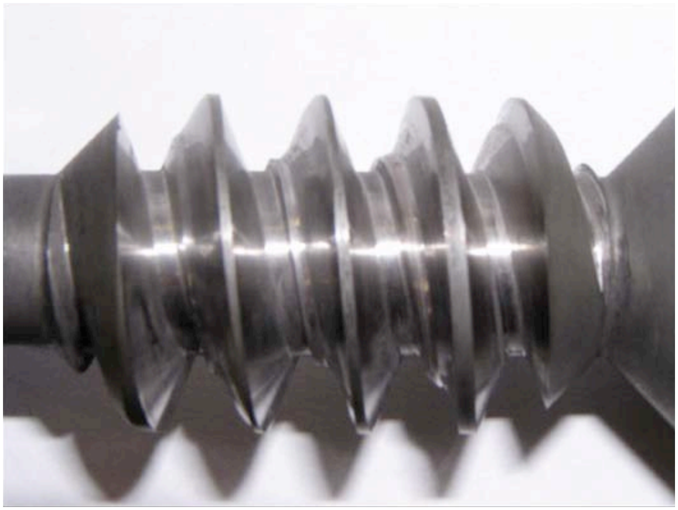
The conclusions drawn from this test are that vibration analysis was able to detect a bearing fault, while oil and wear particle analysis could detect the contamination directly. However, due to the large quantity of particles, bearing wear particles were not detectable. It is therefore evident that the two analysis techniques to not overlap at all, but rather complement each other for this contamination case.

Post test inspection of the gearbox components confirmed the severe wear that had occurred, with a significant part of the worm and pinion gear worn away. Figure 4.18 shows the worm before and after the test, while Figure 4.19 shows the pinion gear prior to and after the test.

4.3.3 Inadequate Lubrication

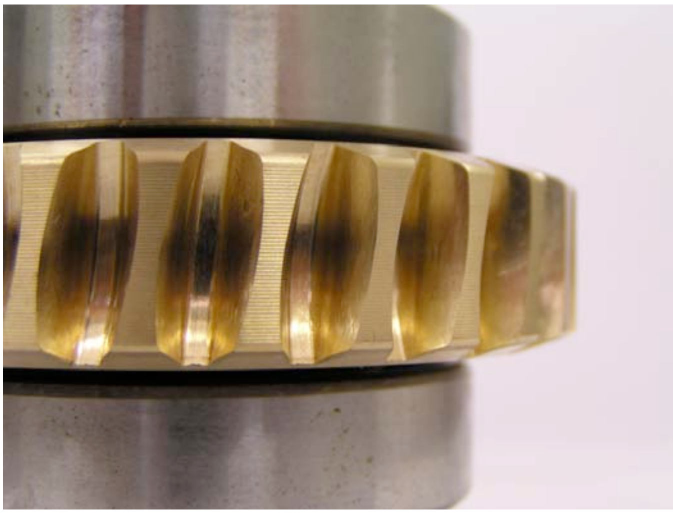
This test was performed to simulate a lack of lubrication condition achieved by the use of an oil with low viscosity. The oil used was Shell Tecoma 68, an ISO 68 grade mineral lubricant without anti-wear and extreme pressure additives. The aim of this test was to study the efficiency of MH300.29 iron particle powder as possible anti-wear additive, by suspending it in the lubricating oil at a concentration of 15000 ppm (w/v), which corresponded to 1.0 gram into the sump capacity of 65 mL. This test was conducted

(a)

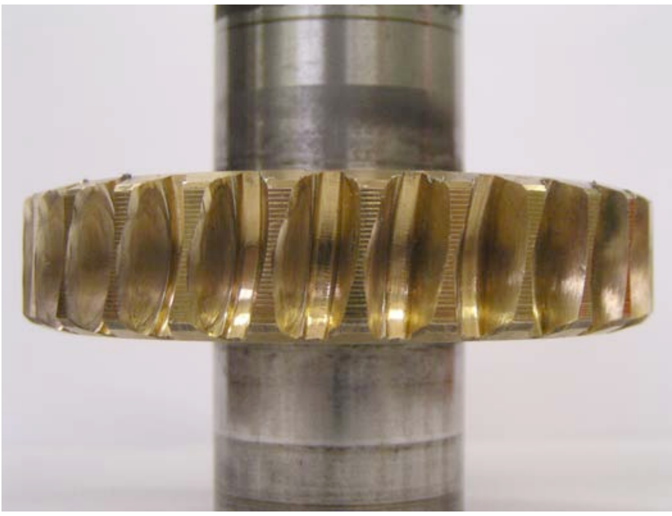


(b)

Figure 4.18: *Worm gearbox — worm (a) before contamination test; (b) after contamination test.*



(a)



(b)

Figure 4.19: *Worm gearbox — pinion gear (a) before contamination test; (b) after contamination test.*

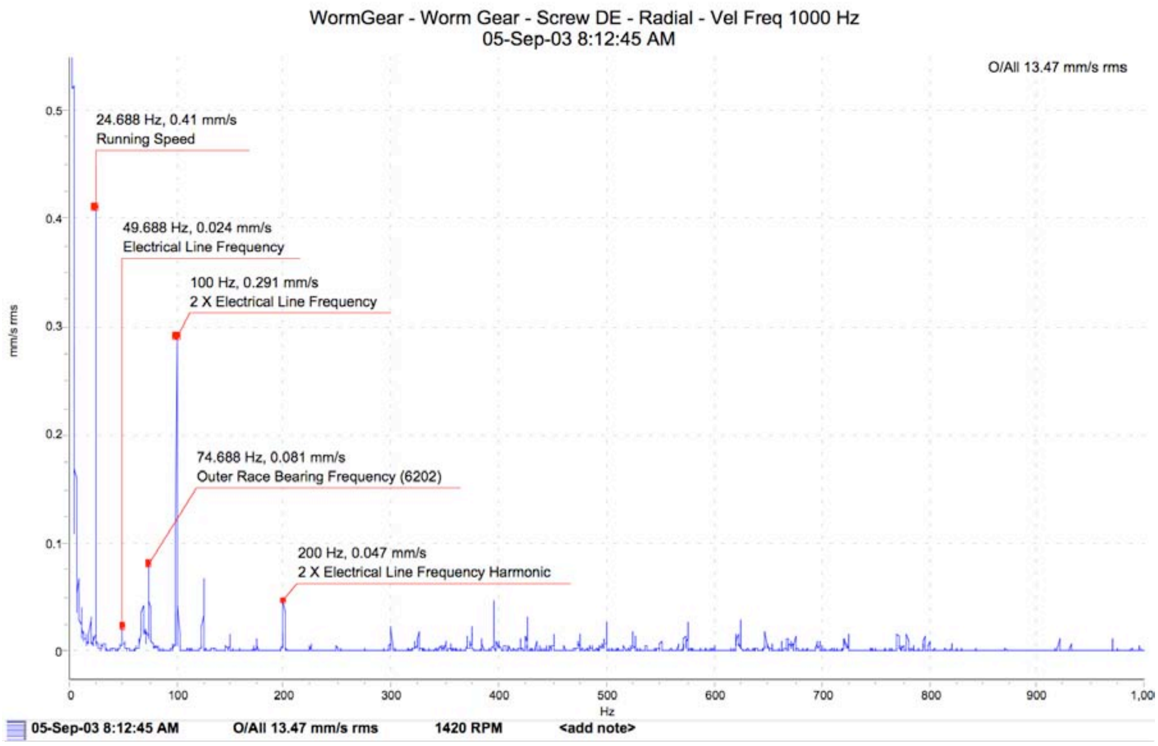


Figure 4.20: *Velocity-frequency spectrum at the drive end of the worm gearbox for the lack of lubrication test.*

over a 4 week period (approximately 470 hours), with vibration data and oil samples taken on a weekly basis (approximately every 168 hours). No oil change was performed during the operating period of the test.

4.3.3.1 Vibration Analysis Results

The vibration analysis detected the electrical line frequency and the 2 times harmonic, which may be characteristic or indicative of an electrical fault of the test rig motor. The gearbox relating faults detected was a BPFO peak, indicative of a bearing fault in the input shaft. Due to the tight clearances within rolling element bearings, the iron particles may have been responsible for causing high surface pressure at the roller–race interface when entering the load zone [85, 104]. The low viscosity oil would have caused the lubricating regime to shift from an elasto hydrodynamic (EHL) towards a boundary lubrication regime, and resulting in an increased wear rate. Figure 4.20 shows the velocity-frequency spectra of the worm at the driven end accelerator mount.

4.3.3.2 Oil and Wear Particle Analysis Results

The inspection of filtergram slides revealed that five types of wear particles were present throughout the test, which included laminar, rubbing, cutting, sliding and fatigue. The low viscosity oil resulted in significant volumes of wear particles being present on all slides. The cutting particles were found to increase in size, indicating that wear was becoming more sever. Sliding wear particles are generally the result of a breakdown of the shear mixed layer, which would be expected due to the low viscosity oil and resulting boundary lubricating regime. The breakdown of the sheer mixed layer would explain the absence of fatigue particles at the end of the test.

Wear particle analysis using an optical microscope revealed that the soft iron particles added to the lubricant were decreasing in size during the test. This means that the anti-wear ability was decreasing, as evident by the increase in cutting wear particle size. The surface roughness of the laminar wear particles was observed to decrease slightly over the test from 0.191 at the beginning (45 hours) to 0.178 at 402 operating hours.

4.3.3.3 Correlation of Vibration, Oil and Wear Particle Analysis

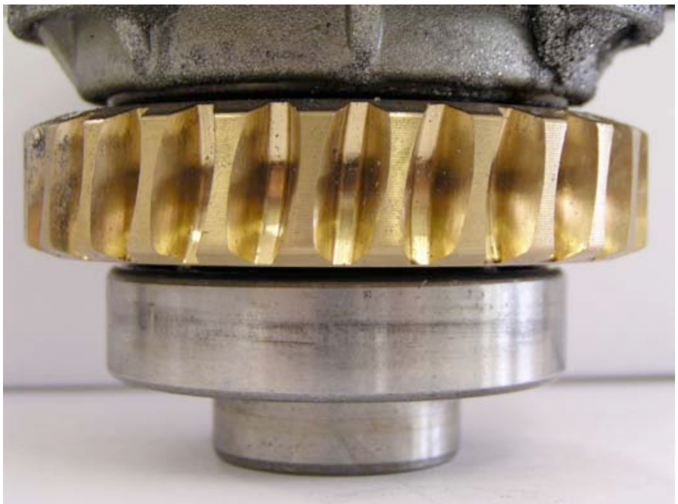
The wear and lubricating conditions of this test were more complex than the contamination test case, due to the varied effect of the mild anti-wear iron particles and prevalent low viscosity oil. Vibration analysis again demonstrated that individual faults can be detected, as illustrated by the bearing outer race fault detected in the worm support bearing. The low rotational speed of the output shaft made output shaft bearing fault diagnosis difficult however. Oil and wear particle analysis complemented vibration analysis well by detecting cutting and sliding wear particles, indicative of abnormal wear and shear mixed layer breakdown respectively. Although not performed, a viscosity analysis would have detected the low oil viscosity directly, and is a routine test in general oil analysis performed in industry.

Post test inspection revealed that while both the worm and pinion gear had sustained wear, the total worn volume was not as great as the contamination case, as shown in Figure 4.21. It is therefore evident that low oil viscosity and the mild anti-wear agent is not as critical an operating condition as severe contamination. The gradual deterioration of the shear mixed layer demonstrates that the soft iron particles did indeed act as a mild anti-wear agent. However to ensure continued anti-wear performance, the concentration of suitably sized particles would need to be maintained as small particles were found to be less efficient in reducing wear.

4.4 Summary

The test rig specifications, procedure and types of operating regimes used to obtain laboratory testing data were outlined in this chapter. The generated data was used to investigate the fault indicators of the vibration, oil and wear particle analysis techniques, made possible as the test gearboxes were operated with only one fault condition. This data was also used for the verification of the expert systems discussed in detail in Chapters 5, 6 and 7.

(a)



(b)

Figure 4.21: *Worm gearbox components after test (a) worm; (b) pinion gear.*

Chapter 5

Vibration Analysis Expert System

5.1 Introduction

Vibration analysis is a commonly used machine condition monitoring technique for fixed-plant rotating machinery, due to relatively fast data collection and interpretation when compared to other available off-line techniques. Since the data is collected as digitally sampled time domain signals, the vibration analysis technique has allowed further manipulation using computers. The development of transforms, such as the fast Fourier transform (FFT) [61], have allowed the conversion of the time domain data into frequency spectra with ease, as the data was already stored in a digital format. This contrasts to oil and wear debris analysis techniques, which often rely on extensive chemical analysis [3] and data interpretation by experienced/trained analysts.

Artificially intelligent systems have been applied to a large range of technical problems, in order to automate an otherwise tedious or complex analysis algorithm. Of the artificially intelligent methods, expert systems are well suited for the vibration analysis technique, as a known set of rules are used to diagnose various machine faults. The rules were developed by relating the physical fault condition to the frequencies emitted by the machine, and analysing the vibration data for the unique fault signatures, which can be high amplitude peaks at a characteristic frequency or several frequencies, depending on the fault. This type of analysis is typically performed by experienced maintenance engineers by manually examining the vibration time histories and frequency domain spectra.

The use of computers for digital signal processing (DSP) has allowed the implementation of filters and signal enhancing calculations to be performed on the vibration data for improved noise reduction and signature detection. This technology has enabled vibration analysis to be used for monitoring road vehicles, which inherently have a high noise component in the raw vibration data. Many of the DSP algorithms have been included in the data acquisition units, which feature time to frequency domain conversion using FFT, demodulated spectra acquisition, as well as coupling with a tachometer to allow the analysis of variable speed machinery.

Despite the use of computers for manipulation of vibration data, the interpretation of the vibration spectra and diagnosis of machine faults has generally remained the job of highly trained experts. The difficulty of building a knowledge base from human experts, and implementing the expert system for a broad range of possible faults are common drawbacks of artificially intelligent systems [92].

Although artificially intelligent systems have been developed for vibration analysis, they have been developed for a particular machine component, including rolling element bearings [105], and transformers [106, 107]. One expert system was recently developed to analyse frequency domain vibration analysis data for general machine condition monitoring, using decision table and decision tree techniques [99]. This development demonstrated that expert systems can be useful for analysing vibration data and can successfully diagnose faults of rotating machinery. While this expert system is useful in application, expert analysts typically employ tri-axial as opposed to single axis frequency domain analysis, as well as demodulated frequency spectra which allows better fault frequency detection in the selected region. Time domain analysis is also still commonly used by analysts to detect faults such as imbalance and gear tooth cracks. An expert system that truly incorporates the techniques used by maintenance engineers for high accuracy fault detection of vibration data has not yet been developed.

The expert system development discussed in this chapter focuses on establishing a knowledge base, peak detection algorithm and user interface to analyse tri-axial frequency domain, demodulated frequency domain, and time domain vibration data. The objective was to develop an expert system to analyse vibration data with similar accuracy as an expert maintenance engineer in an automated software package allowing high analysis throughput, and hence suitable for commercial condition monitoring laboratories or on-site use. The ultimate goal is to develop a first artificially intelligent system for fault diagnosis and machine condition monitoring using integrated analysis of vibration, oil and wear debris analysis technique.

5.2 Expert System Development

The design of an expert system to analyse vibration condition monitoring data was considered the first step in the development of the integrated artificially intelligent system using vibration, oil and wear debris analysis techniques. The development objectives were to interpret vibration data of fixed plant using proven techniques, provide an easy to use interface for stand-alone operation, and output results in a way that can be used for further processing by the comprehensive analysis expert system discussed in Chapter 7.

The expert system was developed to be used for high throughput condition monitoring laboratories of fixed plant, common in mineral processing and manufacturing industries. Due to the requirement to operate in a commercial environment, the efficient use of human resources is of prime importance. This was achieved by using proven analysis techniques, allowing operators familiar with manual fault detection to use the expert system with minimal training. Many new vibration analysis techniques operate by black box methodologies, and do not provide the operator with transparent fault detection.

The expert system was developed in a number of stages, coinciding to the design of the constituent sub components. The development stages were comprised of the design and development of the knowledge base, analysis algorithm, and menu structure. The knowledge base includes all of the logical rules for the vibration data analysis, and forms the core of the analysis algorithm, which is the software code that executes the knowledge base rules. The user interface makes the analysis algorithm accessible to the operator by enabling data input via a dedicated software environment, while also providing additional useful features.

5.2.1 Machine Information

The vibration analysis technique for machine condition monitoring is concerned with relating the discrete frequencies emitted by a machine to the motion of the components. Components emit vibrations when a fault enters the load zone, such as the meshing gear teeth or load carrying rollers of a roller bearing for example. As the vibration frequency is a function of the rotational speed of the element, as well as the number of rotating elements (number of gear teeth, or rollers), the frequency emitted by a certain component operating at a certain rotational speed can be calculated. The frequencies detected in a frequency spectra can therefore be diagnosed to a fault in a certain component.

In order for frequency spectral analysis to be performed, the typical frequencies emitted by faulty components (called fault frequencies) must be known, as well as the number and types of components present on the machine. This information is accessed by the expert system by reading of a text file, which contains the required data. In order to simplify the construction of the text file, as well as to prevent accidental mistakes in data entry, a dedicated user interface menu was constructed to perform this task. Apart from easy data entry, the machine information menu also includes data checks to help preserve data integrity.

Machine information is required by the Vibration Analysis Expert System (called VES) in order to calculate component fault frequencies as well as scan for characteristic faults. The information is entered in the machine information menu, as shown in Figure 5.1. This menu guides the operator through the process of determining the mechanical components found on the machine, including bearings, coupling, pump, gears and belts. Interference frequencies can also be entered, which could arise due to other rotating equipment being close to the machine. The bearings, spur gears, belts and interference frequencies include an additional menu, where specific component information is entered. The additional bearing menu allows the operator to enter the fault frequencies of each bearing, running speed and whether it is of rolling or ball design. This information must be entered for every bearing that is either of different design, or operating at different speeds and thereby creating dissimilar fault frequencies.

The additional spur gear information menu prompts the operator to enter the number of teeth and rotational speed of the input and output gears for each gear set, while the belt input menu includes pulley diameters and rotational speeds, and whether the belt is of the cog type.

Once all the relevant information has been entered, the data is saved to a text file. Since machine components are rarely changed, this information only needs to be entered once for the particular machine. However, should a change in operating conditions such as running speed be undertaken, the text file can either be edited in the machine setup menu, or a new file can be created.

5.2.2 Knowledge Base Development

The development objectives of VES were to diagnose common machine faults of fixed plant, as commonly found in minerals processing and manufacturing industries, using proven vibration analysis techniques currently used by maintenance engineers in these industries. The expert system is composed of a knowledge base for fault detection and diagnosis, and a peak detection algorithm that is used to scan the data file and determine the frequencies where peaks are positioned. The knowledge base was constructed to detect the faults associated with mechanical systems typically used in fixed plant, including roller and journal bearings, spur gears, belt drives, couplings, and centrifugal pumps. Fault charts for each component type were constructed using tri-axial frequency spectra, demodulated spectra and time domain techniques from handbooks and literature [56, 108], outlining the detection algorithm. The faults associated with each component type are summarised in Table 5.1, and the relationship with the knowledge base shown in Figure 5.2.

The developed flow charts were discussed with three independent experts, working

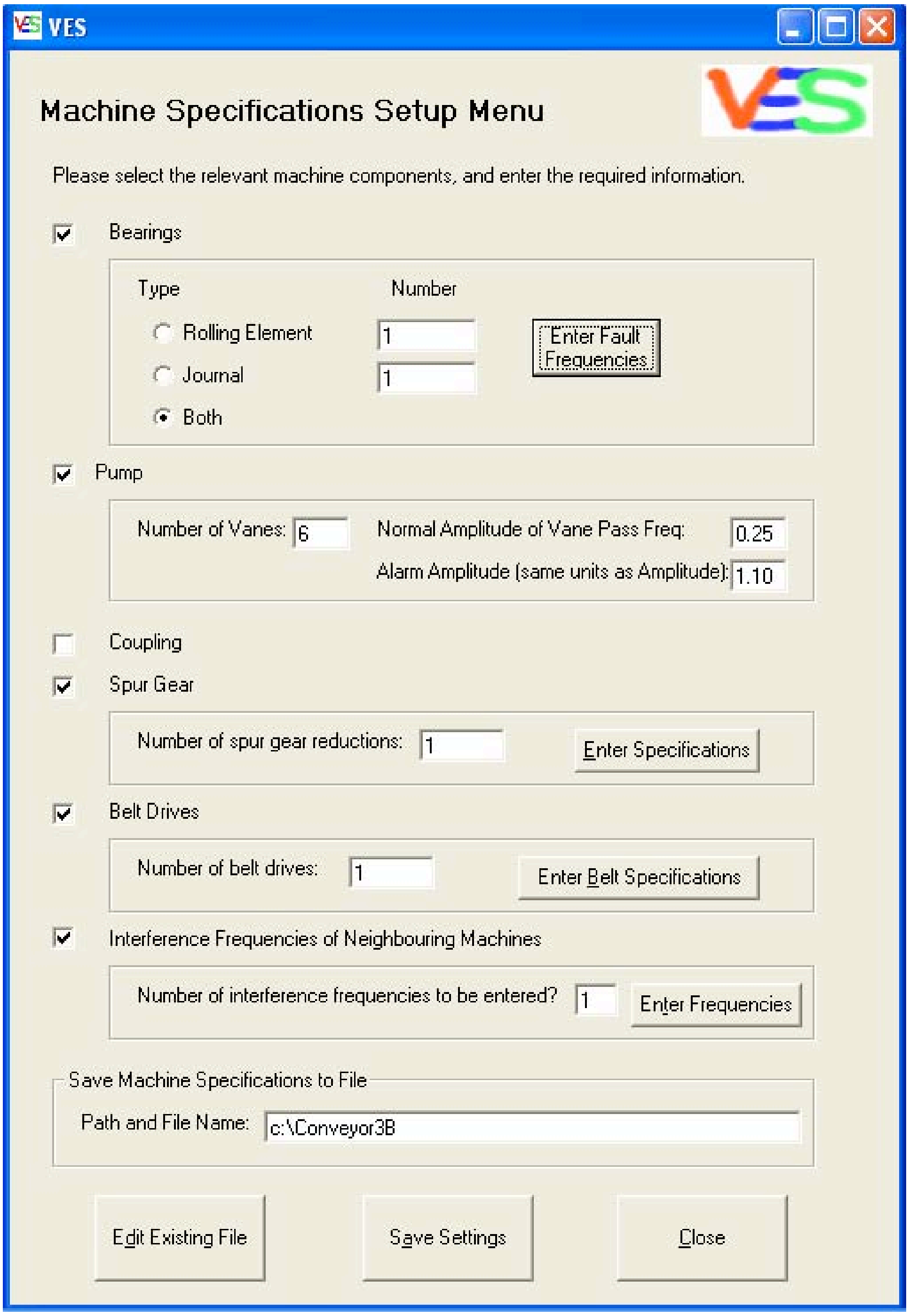


Figure 5.1: *The VES Machine Specification menu, for the analysis by amplitude threshold peak detection (see Section 5.2.2.2 for details).*

Table 5.1: *Possible faults of machine components.*

Machine Component	Fault
Roller Bearings	Cage Fault or Cage Loading
	Ball or Roller Fault
	Race Defect
	Inadequate Lubrication
	Installation Fault
	Bearing Loose in Housing
	Bearing Turning on Shaft
Journal Bearings	Excessive Clearance (and Looseness)
	Oil Whirl
	Oil Whip
Coupling	Misalignment
Pump/Fan	Hydraulic related pumping problem
Spur Gears	Input & Output Gear Looseness
	Input & Output Gear Eccentricity
	Misalignment
	Bent Shaft (Input & Output)
	Backlash or Oscillating Gears
	Broken, Cracked Chipped or Pitted Teeth (Input & Output Gear)
	Gear or Pinion Fault (due to Manufacture or Mishandling)
	Preferential Wear
Belt	Worn, Loose or Mismatched Belts
	Belt / Sheave Misalignment
	Eccentric Sheaves
	Belt Resonance
General	Imbalance
	Bent Drive Shaft
	Looseness

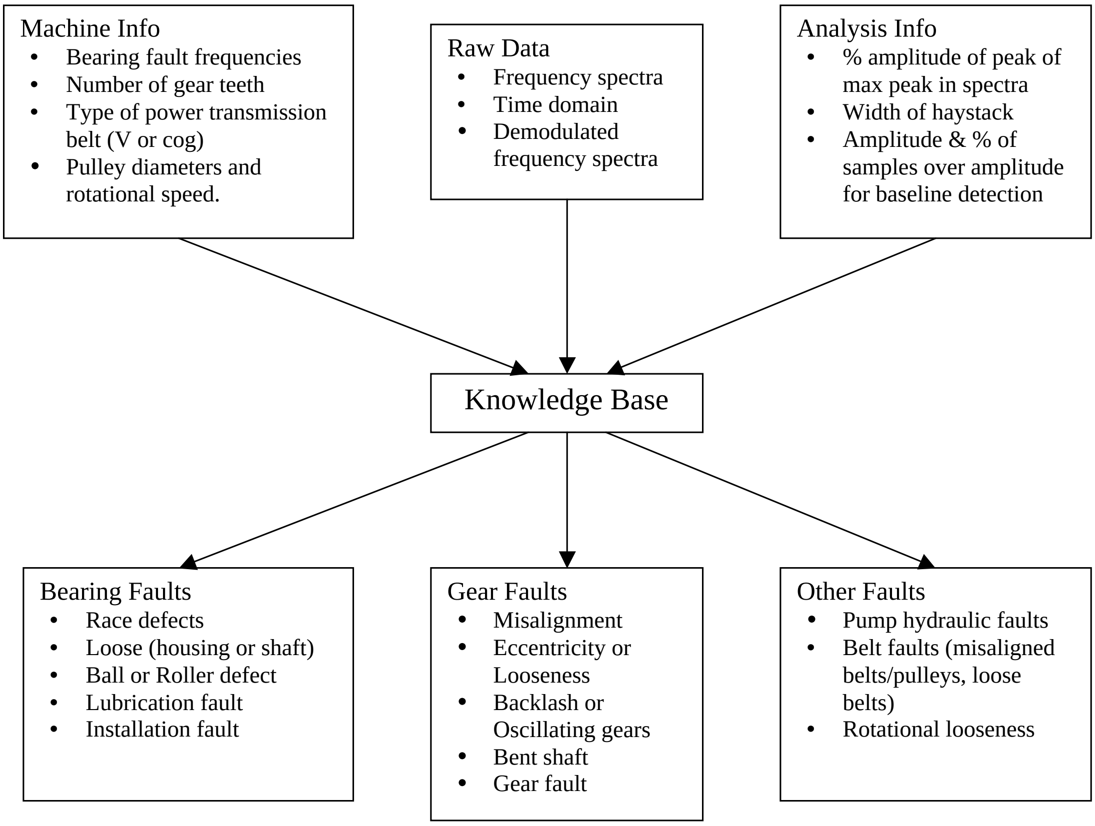


Figure 5.2: *Flow chart of knowledge base inputs and outputs. Note: refer to Table 5.1 for a complete list of all detectable faults.*

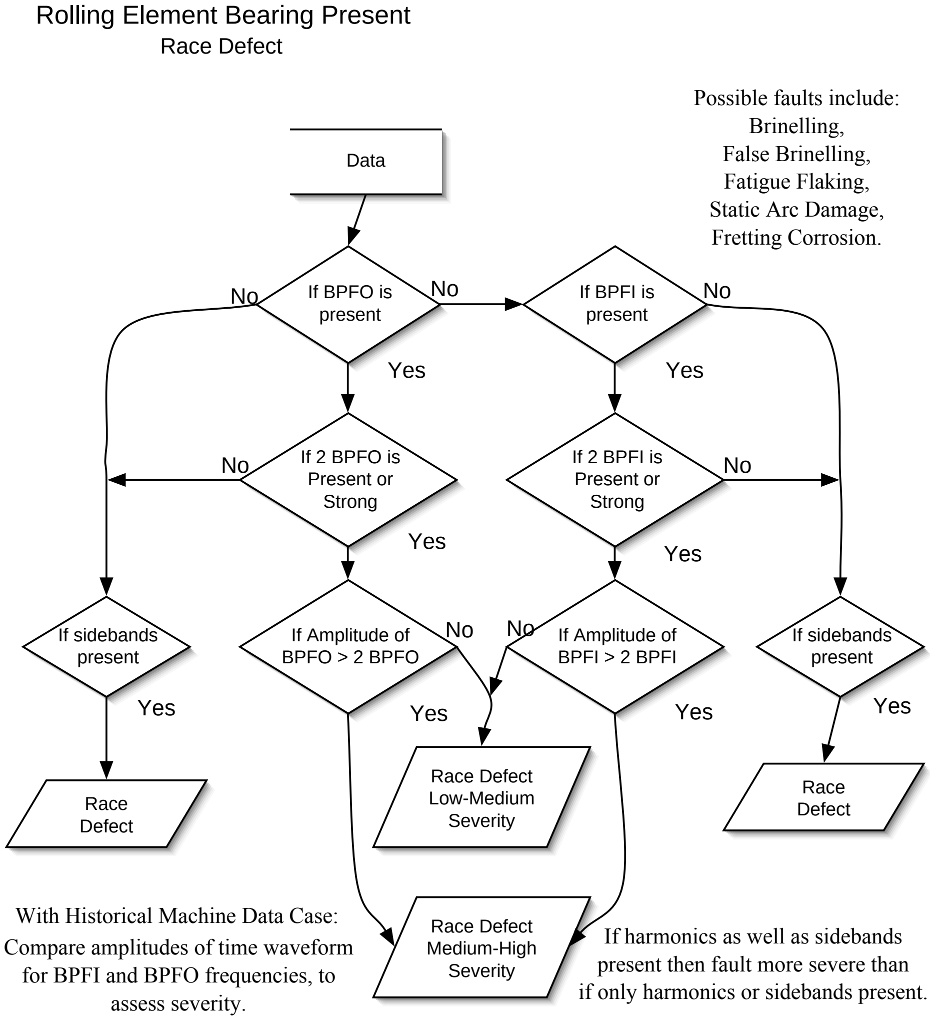


Figure 5.3: *Knowledge base flow chart for bearing race defect diagnosis.*

in the vibration analysis condition monitoring industry. The flow charts were compiled into one set of reasoning algorithms, and implemented in Microsoft Visual Basic software code. Microsoft Visual Basic was selected for implementation due to the requirements of the user interface, allowing ease of use including on-line help screens. The implemented flow chart of detecting a roller bearing race defect is shown in Figure 5.3, including fault severity assessment.

The expert system incorporates 75 rules implemented in If-loop type statements as outlined in Appendix Section C, in order to diagnose 54 different machine component faults shown in Table 5.1. The pseudo code used to implement the flow chart of

```
If (Amplitude of BPFO or BPFI is above Alarm Threshold) then
    If (Amplitude of 2 BPFO or 2 BPFI is above Alarm Threshold) then
        If (Amplitude of (2 BPFO < BPFO) or (2 BPFI < BPFI)) then
            Race Defect — Moderate-High Defect Severity
        Else If
            Race Defect — Low-Moderate Defect Severity
        End If
    End If
Else If (Sidebands present on BPFO or BPFI peaks) then
    Race Defect — Low-Moderate Defect Severity
End If
```

Figure 5.4: *Pseudo-code for bearing race defect diagnosis.*

Figure 5.3 is outlined in Figure 5.4.

Data and analysis integrity checks have also been included in the expert system, to reduce the likelihood of analysis errors occurring. In the event that the loaded vibration data spectra file is of insufficient range to detect higher frequency fault peaks, an error message is displayed to the operator advising to load a data file with higher frequency range.

The VES analysis algorithm utilises nine operator defined variables to determine the peak detection sensibility, which the operator can edit using the Analysis Setup menu. The variables have been categorised into three groups, depending on whether the variables are required for analysis by amplitude ratio, amplitude threshold, or both. In order to improve software usability for operators, the analysis modes were designated according to whether alarm amplitudes are available for machinery, or whether a spectra is to be analysed purely by peak pattern recognition.

Peak detection in frequency domain spectra is performed by searching for the highest peak within a frequency window around the target frequency. The frequency window allows for measurement inaccuracies, where the particular peaks can be several Hertz

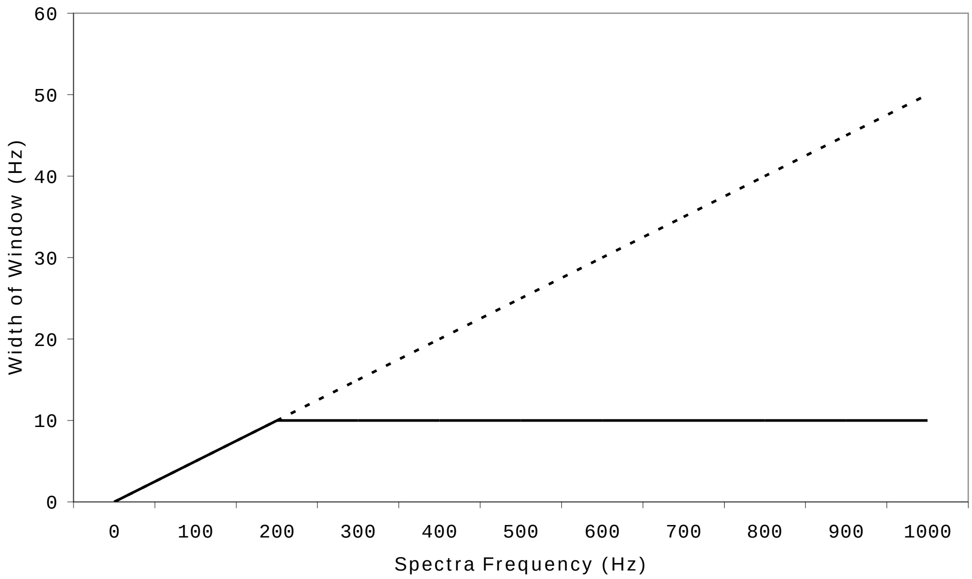


Figure 5.5: *The influence of the percentage deviation and maximum size in Hz factors on the frequency window used to detect peaks in frequency spectra. Solid line is window size limited by both factors, while dotted line shows window size without maximum size limit. In this figure, the 'percent deviation' is 5 %, while the 'maximum size in Hz' frequency window is 10 Hz.*

off their theoretical frequency. The frequency window size is calculated using two user defined parameters that relate to the percentage deviation of the target frequency (Percentage Deviation variable), as well as to a maximum window size in Hertz (Frequency Limit variable). These two factors allow the operator to define a window size that is suitable for the spectra sampling rate and scanning range (which together define the spectra resolution). As shown in Figure 5.5, the percentage deviation factor is useful for limiting the window size at low frequencies, while the finite maximum window size limits the deviation for high frequencies.

5.2.2.1 Peak Detection Algorithm — Amplitude Ratio

The analysis algorithm relying only on relative peak amplitudes was developed to allow the examination of machines without knowledge of their condition and typical fault amplitude alarm levels. The algorithm is especially useful for analysing machines that are new to a plant, or that have been obtained from companies that are unable to provide detailed vibration specifications. The objective was to develop an algorithm that would detect characteristic fault signatures in amplitude-frequency spectra. Since amplitude could not be used as a fault detection indicator, detection sensitivity was achieved by normalising all peaks with respect to the highest peak in the spectra, and only considering peaks above an operator defined amplitude ratio.

The analysis algorithm operation can be summarised into a three step process. Firstly, the vibration data files are read into memory. The second step involves the calculation of fault frequencies for the particular machine, which are calculated using the machine specifications data file, and scanning the data in memory for the fault frequencies. Each fault frequency is categorised either as strong, present, or not-present depending on its amplitude ratio, and the operator defined high and low normalised alarm threshold values. This principle is demonstrated in Figure 5.6. The third step is concerned with compiling two output data files to report the analysis results to the operator, as well as for further expert system analysis.

The user interface guides the operator through the analysis process, by prompting for the location of the vibration analysis data files as well as the machine specification and analysis setup files, as shown in Figure 5.7. While the vibration spectra file is mandatory, the analysis of a time-domain and demodulated frequency spectra files are optional. For each vibration data file, the number of lines and frequency or time range need to be specified, to allow the data to be read into memory and associated to the correct frequency. The file format of the data files was set to be two columns of data corresponding to frequency and amplitude respectively for the spectra files, and time and amplitude for the time domain file.

The text based results output file reports all faults in the order of increasing component number, ordered by component type. This file allows the operator to view the results of the expert system, and is useful when the expert system is used for stand-alone data interpretation. If certain fault analysis could not be run as the frequency of the fault was higher than that contained in the vibration data file, a warning message is

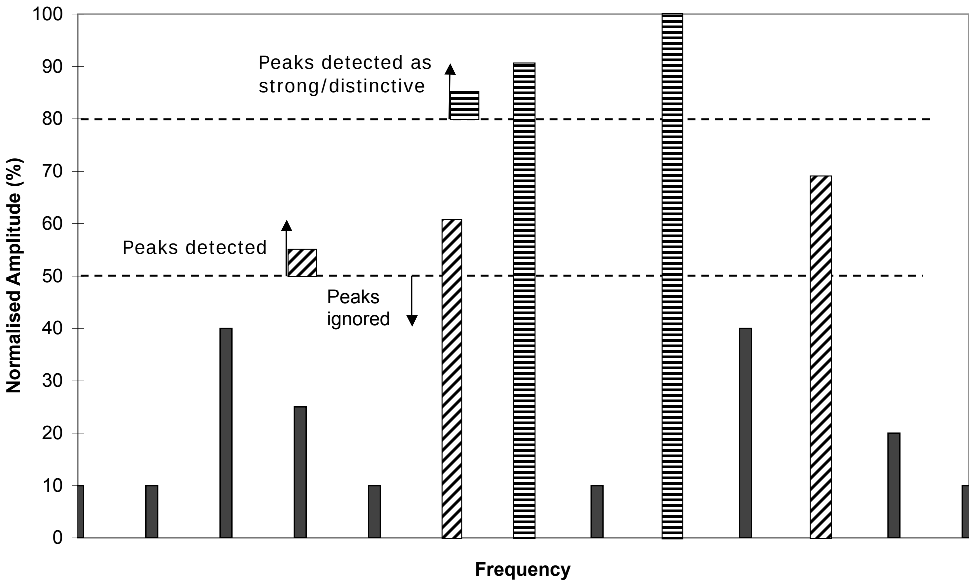


Figure 5.6: *Normalised amplitude peak detection principle. The low and high normalised alarm threshold values are operator defined, and in this case set at 50 % and 80 % respectively.*

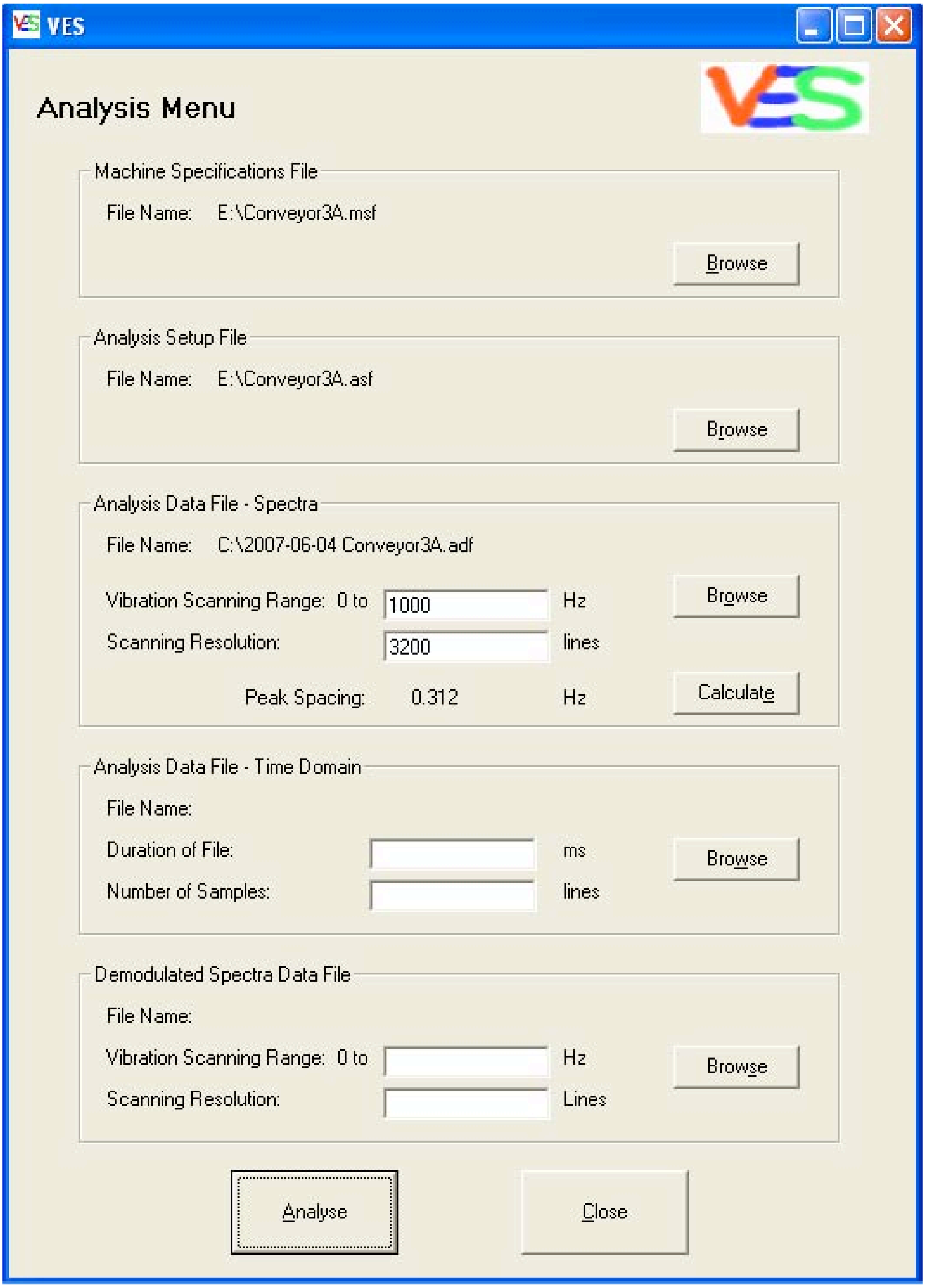


Figure 5.7: *The VES Analyse menu.*

written into the output file. The message states which faults could not be scanned for, and the required frequency range of the data file to scan for these faults. This enables the operator to select the correct spectra when analysing another Analysis Data file, in order to scan for the missed faults. The end of the output file contains information about the analysis, including the file names and paths of each of the selected files, the values of the variables contained in the Analysis Setup file, as well as the test specific information which is entered in the Analyse Menu (the frequency range of the selected Analysis Data file, and the scanning resolution). This information allows the operator to check which files were selected for the vibration analysis, and the values of the changeable variables. The second output file also contains the analysis results, but in a numerical format. This file is compiled to deliver the analysis results to the combined analysis expert system discussed in Chapter 7, which combines the output of VES with those from the oil and wear debris analysis expert system.

5.2.2.2 Peak Detection Algorithm — Amplitude Threshold

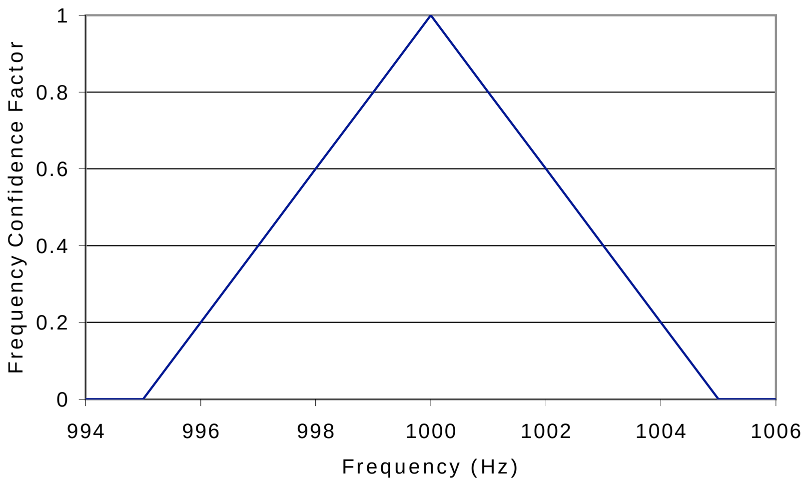
The analysis procedure using fault detection by amplitude alarm limit is similar in operation to the analysis based on amplitude ratio. However, instead of normalising the peaks of the frequency spectra, each fault frequency requires an alarm amplitude to be set up as part of the machine specifications setup menu, which is used in the analysis operation. Fault detection sensitivity is therefore done by setting a threshold amplitude which acts as an alarm trigger. A second threshold can be set to recognise a strong peak amplitude, and alert the operator for a severe fault condition. These two amplitude threshold levels allow the peaks in the spectra to be classified as strong, present, or not-present. The analysis based on amplitude alarm thresholds allows the VES software to be easily implemented by industry, as these thresholds have already been established for plant currently monitored using vibration analysis.

The categorisation of detected fault frequencies with respect to their amplitude allows the calculation of a confidence factor, determined by fuzzy logic relation to the threshold limits, shown in Figure 5.8(b). The frequency calculation process is also used to calculate a confidence interval using the relation of how close the detected peak was to the theoretical peak position, shown in Figure 5.8(a). Both confidence factors are calculated to be between zero and 0.5, and are summed to obtain a final confidence factor between zero and one. This confidence factor allows the operator to gain an insight into how closely the detected peak resembles the frequency and amplitude characteristics of the theoretical fault peak.

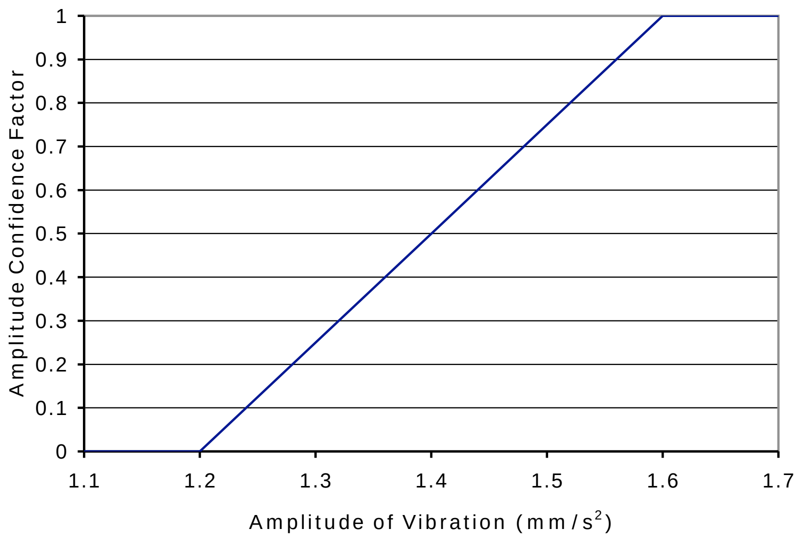
The use of threshold type fault detection has the advantage over amplitude ratio detection, that the effect of interference vibration on the vibration spectra can be evaluated. If an interference peak happens to be in the vicinity where a fault frequency may exist, the analysis algorithm takes into account the typical amplitude of the interference peak and hence will trigger an alarm only if the detected peak is greater than the typical interference peak amplitude. The threshold type analysis is therefore recommended for reliable fault detection of plant, such as routine condition monitoring applications.

5.2.3 Interface Development — Input

The requirement of the user interface is to successfully portray the operation mechanism and data entry modules of the expert system to the operator. The graphical layout and menu structure is an important component of the user interface, to ensure that data entry and analysis can be performed in a manner that is intuitive, thereby minimising accidental data integrity errors or misinterpretation [93]. Appendix Section H.4 shows the structure and menu screens of the user interface. The design objectives for the VES user interface focused on operator usability and efficiency, by minimising the operator time per machine analysis. The objectives were to minimise the required training time of new operators, and allow rapid data analysis by reducing the amount of information that needs to be entered for each analysis. The design goals were implemented by the use of a user friendly interface, programmed in the Microsoft Visual Basic 6 programming language, featuring quick help comments throughout the VES program. The input data layout of the interface was designed so that analysis specific information, and machine specific information is entered in dedicated data input menus, which include relevant data integrity checking. During the analysis process, the only operator



(a)



(b)

Figure 5.8: *Principle of confidence factor calculation using linear fuzzy logic. (a) Frequency confidence factor for frequencies where the target frequency is 1000 Hz, and the allowable frequency deviation is 5 Hz; (b) Amplitude confidence factor for amplitudes between Alarm and Severe Alarm thresholds, set at 1.2 and 1.6 mm/s^2.*

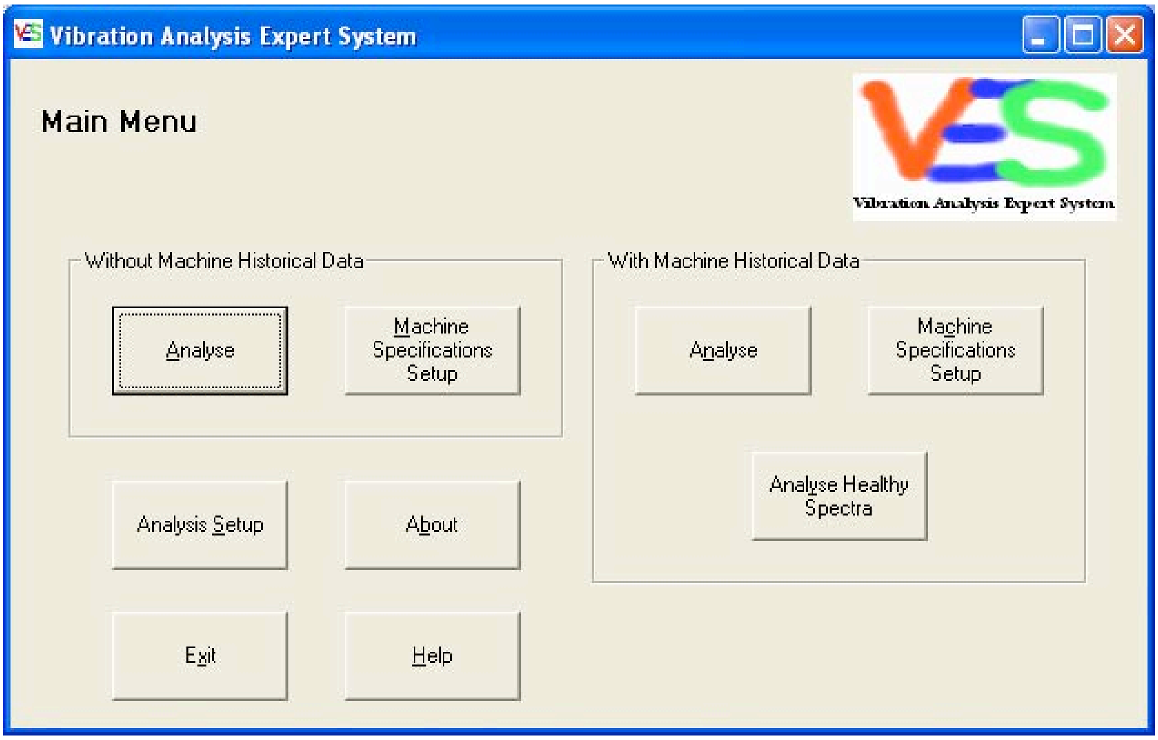


Figure 5.9: *The VES Main menu.*

input required is the selection of the relevant analysis and machine specification files. As the analysis and machine specification variables are not changed frequently, high machine analysis throughput is possible.

The menu layout has been constructed so that the choice of data input or analysis can be made at the main menu, as shown in Figure 5.9. The selection buttons for machine specification and analysis has been duplicated for the two types of analysis processes, as the menu content differ slightly depending on which analysis process is chosen. In the case of machine specification menu, alarm threshold values need to be entered if analysis by amplitude threshold (with historical data) is selected.

Other functions accessible from the main menu include the Help, and Analyse Healthy Spectra menus. The Help menu contains instructions on program operation, frequently asked questions, and detailed specifications of variables. The text of the help menu is shown in Appendix Section I.3. The Analyse Healthy Spectra menu allows the analysis of a spectra file in terms of baseline amplitude, as well as the amplitude of a specific frequency. The baseline amplitude function is useful for obtaining the amplitude at which a certain percentage of peaks are below or equal to. When this amplitude and percentage is entered in the Analyse Setup menu, a raised baseline can be detected in the spectra. The second function in the Analyse Healthy Spectra menu allows the operator to find the amplitude of a peak at a certain frequency. Again, this information is useful for entering the healthy amplitude of frequencies in the Machine Specifications Setup menu (selecting the button in the With Machine Historical Data frame from the Main menu). The alarm amplitudes can then be calculated using the healthy amplitudes and guidelines of the ISO 10816 standard [46]. This menu is discussed further in Section 5.2.5.

Another design criteria of the VES interface is the ability of the analysis to be performed while the menu is hidden, and used by another expert system. This requirement was important in the development stage, as the VES is only one expert module of the combined analysis expert system that was developed later.

High analysis throughput efficiency has been achieved by structuring the interface such that machine specific information and analysis setup variables are saved to a text file once, requiring the operator to only select the appropriate file during the analysis process. This saves time as redundant information does not need to be entered for every spectra analysis. The machine specific information is entered in the Machine Specifications Setup menu, while analysis variables are entered in the Analysis Setup menu. This arrangement enables the VES program to be used in a commercial situation, as many vibration spectra can be evaluated quickly, and the output file comments incorporated in a report for customers.

5.2.4 Interface Development — Output

The analysis results of the expert system are displayed in the form of two text files. One text file lists the detected faults by selecting one of 75 pre-defined comments for each machine component. The results are ordered by machine component type and number, starting with general misalignment and imbalance faults, roller and plain bearings, spur gears, pumps, and finally belt and pulley faults. The layout of the file, including full text comments, allows it to be used directly as an analysis report for customers, or easily incorporated into a comprehensive report using cut and paste. The second text file was designed to allow the results to be saved for further processing by the comprehensive analysis expert system. The file format is therefore purely numerical, with data arranged in a fixed format.

5.2.5 Other Functionality of Developed Expert System

The interface was developed with additional features to improve the versatility. Apart from a detailed help menu, a menu for spectra file peak detection analysis was developed. The objective of this menu was to enable an operator to assess the amplitude of a particular frequency, and analyse the spectra baseline using the peak detection algorithm of the expert system. The menu is shown in Figure 5.10.

The frequency detection menu was designed to help the operator to establish amplitude alarm thresholds, by monitoring the fault frequencies manually of a machine which has a developing fault. The algorithm searches the tri-axial spectra file and lists the amplitude of the desired frequency in each axis. This feature is useful as it allows the operator to use the peak detection algorithm rather than having to manually look at the spectra and calculating the amplitude.

Apart from distinct peak detection, the detection algorithm also features an algorithm for raised baseline detection, as well as haystack detection. The Average Baseline Amplitude and Percentage variables are used in detecting a raised baseline, as is often the case for severe looseness type faults. The raised baseline detection algorithm operates by counting the number of sampled peaks that have an amplitude equal to or below the operator defined 'average baseline amplitude' variable. If the percentage of peaks equal to or below the 'average baseline amplitude' is less than the value defined in the 'percentage of peaks with an amplitude below or equal to the average baseline amplitude' variable, a raised baseline condition is triggered.

The haystack detection algorithm has been developed to scan for regions of consecutive peaks of detectable amplitude (peaks classified as 'Present' or 'Strong' using the amplitude ratio analysis method). The minimum width in frequency of such a region

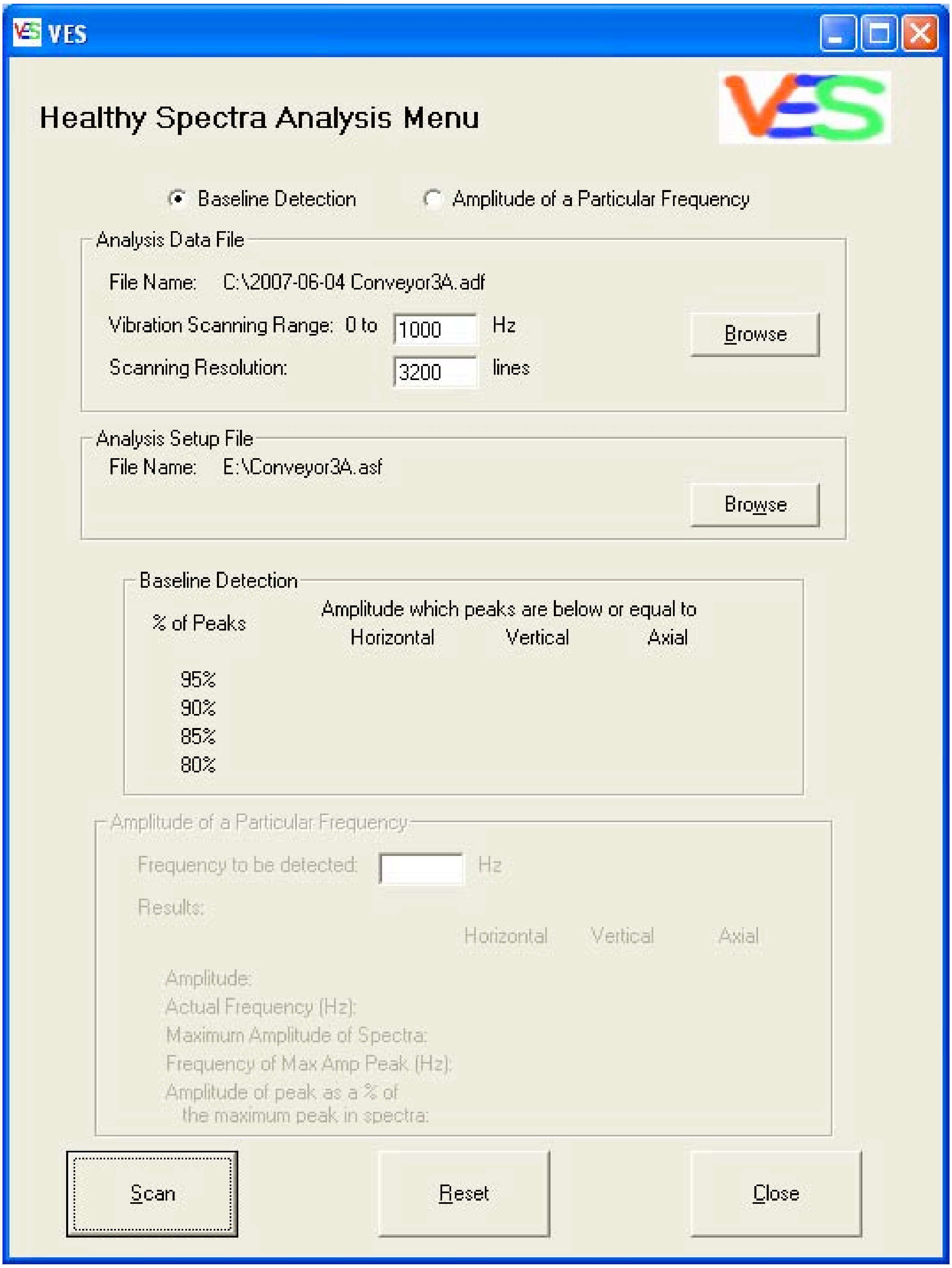


Figure 5.10: *The VES Healthy Spectra Analysis menu. This menu allows (a) Amplitude detection of a particular frequency (selected in figure), (b) Baseline analysis.*

before it is categorised as a haystack is defined using the Min Haystack Width variable. The haystack detection algorithm can be applied over the entire frequency spectra, or be used to detect a haystack around a particular frequency. The Haystack Search % Run Speed variable can be used to adjust how far on each side of a specific frequency the algorithm searches for a haystack. In order to reduce the likelihood of a one times running speed harmonic being mistakenly detected as a haystack, this variable allows the width of spectra which is searched to be limited to a percentage of the running speed.

5.3 Expert System Testing

The VES software was thoroughly tested using vibration data obtained from a laboratory single reduction spur gear test rig, as well as a spur gearbox connected to a grain auger. The operating conditions analysed for the system testing phase consisted of bent output shaft, overload, and contamination. Three tri-axial vibration spectra of 400 Hz, 1000 Hz, and 4000 Hz were analysed, as well as a 400 ms time domain file. The sampling rates for the vibration spectra were 3200 lines, while the time domain file was 4096 lines. Two sets of spectra were obtained, one on the input shaft of the gearbox, and another at the output shaft.

The alarm amplitude limits were determined from spectra taken when the gearbox was overhauled and in good condition, and increasing the amplitudes by approximately 30 %. The gearbox condition was confirmed using oil and wear particle analysis techniques. Each spectrum was then analysed using the analysis by normalised amplitude, and amplitude alarm threshold options. For the peak detection by normalised amplitude, peaks smaller in amplitude than 5 % of the largest peak in the spectra were disregarded. This setting corresponds to high sensitivity fault detection, as even small peaks are recognised.

The VES detected the bent output shaft condition in all output shaft spectra, for both analysis modes. The 1000 Hz horizontal spectra is shown in Figure 5.11. The high amplitude peak at low frequency causes the remaining spectra to appear quite small.

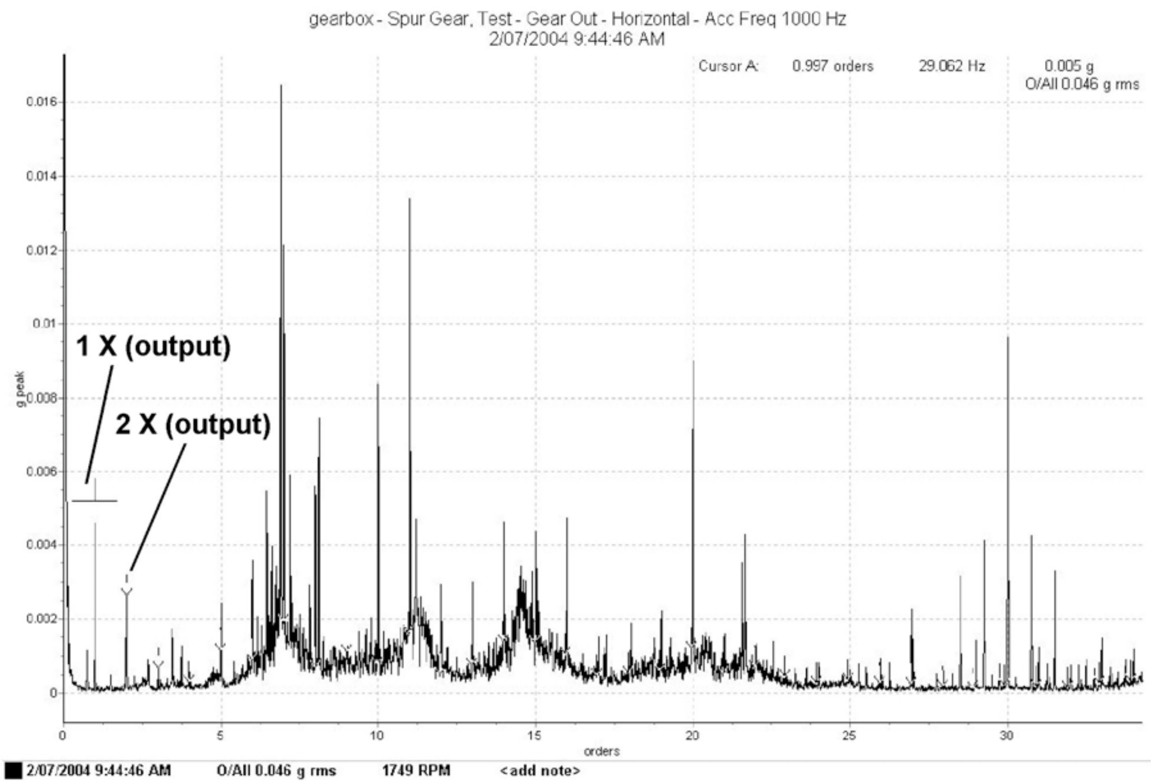


Figure 5.11: *1000 Hz horizontal acceleration spectra (at output gear) of worn spur gears with a bent output shaft.*

This high amplitude spike at the low frequency region of the spectra is believed to be due to operating limit of the accelerometer used to obtain the data.

The overloaded operating regime of the laboratory gearbox resulted in the gears showing signs of mild gear looseness and backlash, as well as surface fatigue pitting, scuffing and misalignment. The gear looseness and backlash were detected, as was a low severity input shaft bearing race fault, and a medium to severe output shaft race defect. The bearing faults, gear looseness and misalignment faults were detected by both analysis modes of VES. Other detected bearing faults include a loose fit between the bearing, shaft and housings. Inspection of the gear teeth revealed that although the gears were pitted and showed scuffing marks, the teeth profile had not changed significantly.

The contamination laboratory test resulted in the gears becoming severely worn by a polishing action, causing excessive looseness and a misalignment secondary fault.

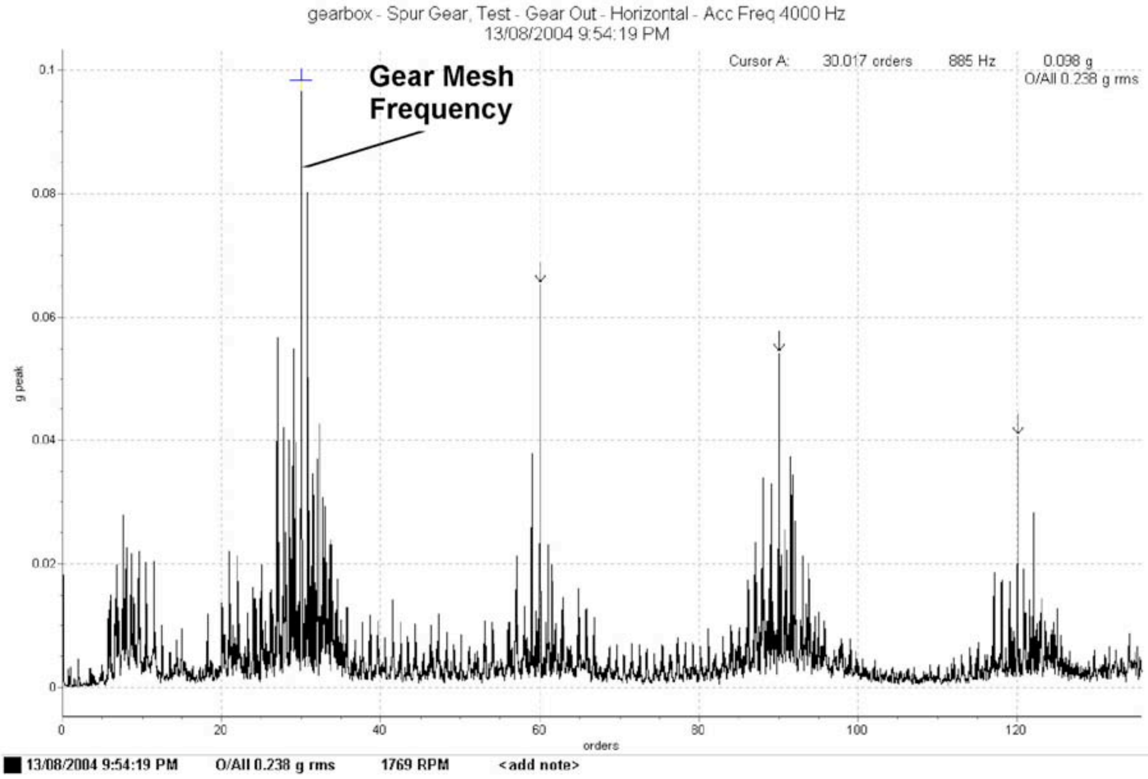


Figure 5.12: *4000 Hz horizontal acceleration spectra of the contamination test.*

The looseness was found to be a combination of the worn gear teeth as well as the worn bearings and shafts. The VES analysis revealed that one or both input and output bearings developed ball faults, as well as gear misalignment and backlash. The horizontal 4000 Hz spectra is shown in Figure 5.12. Evidence of loose and eccentric gears was also detected. The gear eccentricity may have come about due to preferential wear of the laboratory gearbox, as the gears have a greatest common divisor higher than 1.

The capability of the expert system to assess the condition of a multistage-reduction gearbox operating in an industrial environment was determined by analysing the data obtained from a two-stage reduction spur gearbox operating in the agricultural industry. The gearbox was powered by a 0.55 kW four pole flange mount electric motor, and used to operate a grain auger of 50 mm diameter. All 4 gears were of the spur gear design, with consecutive reduction ratios of 3.33:1 and 1.44:1, giving an overall reduction of

(a) (b) (c)

Figure 5.13: *Wear marks on the output gear of reduction 1. (a) wear on side of gear teeth, typical for misalignment, (b) wear extending across whole of width of gear teeth, (c) wear marks of neighbouring pinion gear, indicating looseness.*

4.8:1. The intermediate and output shafts were supported in brass plain bearings, while the input pinion was mounted directly to the motor shaft. Data from two gearboxes was collected, in order to obtain amplitude levels of a gearbox in good condition and of a gearbox in the wearing out stage. The operating hours of the two gearboxes were approximately 300 hours and 3000 hours respectively. The faults detected by the expert system were:

- Reduction 1: Loose output gear, misalignment, preferential wear.
- Reduction 2: Possible eccentric pinion and output gears.
- Possible lubrication problem of bearings, or other machine resonance.

Dismantling and visual inspection of the gearbox components confirmed the loose output gear, misalignment and preferential wear of reduction 1. The loosening of the

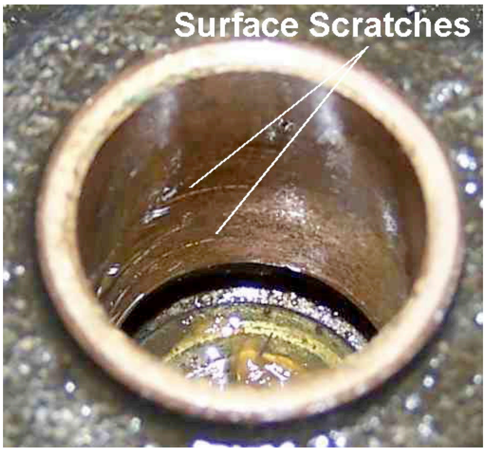


Figure 5.14: *Scratched surface of brass bush supporting intermediate drive shaft.*

press fit between the gear and shaft resulted in the gear looseness and misalignment, as shown in Figure 5.13. The looseness of the output gear is evident by the rubbing marks of reduction 2 pinion on the side of the gear. Possible gear eccentricity of the reduction 2 gears could not be confirmed by visual inspection, as the gears had not worn sufficiently to show typical wear marks. The plain bearings were found to have a worn and scratched surface, which resulted in a polished shaft, as shown in Figure 5.14. The bearing wear may have been caused by a low oil level, as the gearbox had a leaking input oil seal.

5.4 Summary

An expert system was successfully developed for the condition monitoring of fixed plant, using proven industry analysis methods traditionally performed in a manual manner. The developed vibration analysis expert system (VES) has been specifically designed to allow it to be integrated into a planned comprehensive analysis expert system, which will be used to analyse vibration, oil and wear debris analysis data and provide a single correlated condition report. The interface and data handling operations of the software therefore reflect this goal.

The development of the expert system has allowed the verification of vibration analysis techniques commonly used in industry, including tri-axial spectra, time domain, and demodulated spectra, for machine condition monitoring. The VES analysis algorithm has been tested using laboratory data collected from a single reduction spur gearbox, and a two-stage reduction spur gearbox operating in the agricultural industry. The robust fault detection algorithm of VES successfully identified the gear faults that occurred, which included bent output shaft, continuous overload, contamination, as well as loose and misaligned gears [109]. The successful completion facilitates the design of a comprehensive machine condition monitoring expert system utilising oil, wear debris and vibration analysis techniques, discussed in Chapter 7.

Chapter 6

Oil and Wear Debris Analysis Expert System

6.1 Introduction

Oil and wear particle analysis has become a popular technique in machine condition monitoring for detecting wear related faults of gears, bearings and hydraulic components operating with oil lubrication [2, 14, 19, 110]. Analysing the used oil and constituent wear particles of a machine allows the condition of both the machine and lubricant to be assessed, using wear particle analysis and oil analysis respectively. Wear particle analysis is concerned with identifying wear modes and severities by the size, shape and surface morphology of the wear particles. Elemental analysis of the wear particles can also be useful in diagnosing wearing components by relating high element concentrations to unique elements in the component alloys. Oil analysis conversely is concerned with the physical and chemical properties of the oil including viscosity, chemical index and total acid number (TAN)/ total base number (TBN). Apart from assessing the machine condition, oil analysis also provides information as to the performance of the machinery protection systems including oil filtration, oil cooling and water desiccators on breathers.

Oil analysis data is interpreted by comparing the physical and chemical properties of the used lubricating oil to new oil specifications, and identifying those properties which are not acceptable based on standards such as ISO 4406 [11] or ISO/TC 108/SC5 [46]. Similarly, wear particles can be characterised by their physical properties including shape, size, angularity, surface roughness, and hence linked to wear mode responsible for the particles. The identified wear modes can be associated with the typical failure modes of the machine components, as well as other condition monitoring information such as elemental analysis, in order to diagnose the component and specific fault occurring.

Oil and wear particle analysis techniques are commonly used for machine condition monitoring, and are carried out by either dedicated laboratories or on-site maintenance departments. While oil analysis utilises quantitative data, wear particle analysis is generally performed qualitatively using optical microscopy, where the percentages of wear particles are judged by the operator. This analysis procedure therefore requires extensive experience to identify the correct particle percentages with acceptable repeatability using this subjective process. Additionally, the use of wear particle percentages to diagnose machine faults is also performed manually, resulting in the complete wear particle analysis process being subjective and time consuming.

The data analysis of oil and wear particle analysis can be performed using artificial intelligence, such as an expert system, by simulating the reasoning logic used by a human expert. The input parameters for the expert system include all of the possible test results that are commonly performed for oil and wear particle analysis. The output parameters consist of the possible machine component faults associated with oil lubricated gears and bearings. As the input parameters for the possible outcomes (output parameters) are known, an expert system type of AI is well suited for this type of data analysis.

Due to the high throughput of oil samples common for large plants, an expert system for data interpretation and reporting would allow more human resources to be directed at operational and design changes to improve machine lifetime and reliability. An additional benefit could be obtained when wear particle analysis technology advances further to allow numerical characterisation parameters to be performed by automated analysis equipment. These parameters could be input directly into an expert system, and hence enable wear particle to be performed in an objective manner, without subjective requiring operator expertise.

This section is concerned with the development of an expert system for machine condition monitoring using the oil and wear particle analysis techniques. The development stages include the design of an analysis algorithm that is capable of analysing data as supplied by oil laboratories, the development of a user interface to allow stand-alone operation, and the testing phase of the completed package using laboratory and industry derived machine condition monitoring data.

6.2 Expert System Development

The design objectives of the expert system developed for oil and wear particle analysis were to interpret oil and wear particle analysis data using logical reasoning processes to diagnose machine faults as well as lubricating oil contamination and deterioration. The expert system would accept input parameters corresponding to those commonly tested by oil analysis laboratories, and the ability to interpret wear particle analysis.

The design objectives of the expert system require the analysis algorithm to interpret the oil and wear particle analysis data taking into consideration the machine and analysis information, in order to compile a list of possible machine faults. Another design objective of the expert system is that it would be suitable for use in a commercial situation for routine condition monitoring. In order to meet this goal, the expert system structure as well as the user interface were designed so that machine specific and analysis information would only need to be entered once for each machine. The user interface was designed such that the data entry for laboratory raw data, machine information and analysis information is entered in separate menus, and saved to text files. These text files are then retrieved during the analysis process, as shown in Figure 6.1. The analysis algorithm contains the developed knowledge base on how oil and wear particle analysis is carried out, and is used to interpret the input data in order to diagnose machine faults which are reported to the operator. The conclusions by the expert system are also saved to a text file, which allows the report to be archived for future reference.

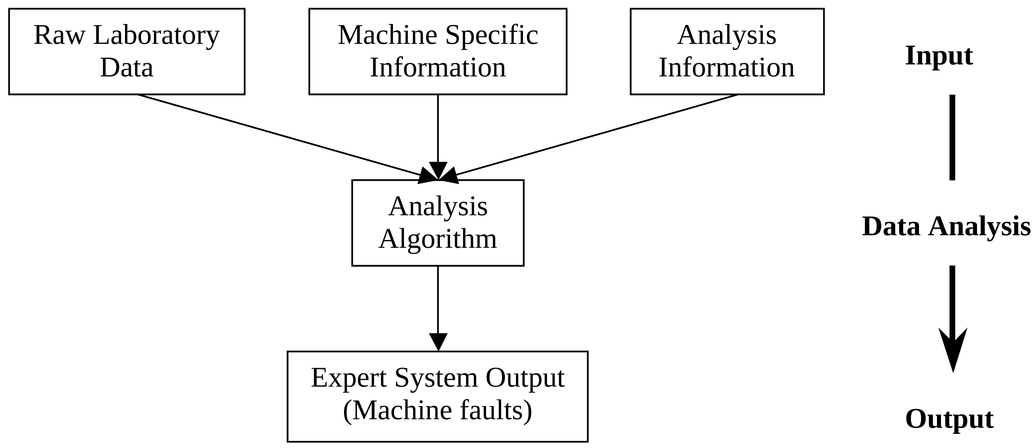


Figure 6.1: *Expert system input & output data flow.*

6.2.1 Information required for condition monitoring

The input parameters for the expert system are composed of the raw oil and wear particle analysis input data, the machine related information, and factors that relate to how the expert system executes the analysis algorithm. The raw input data consists of the information provided by the oil analysis laboratory, in the form of numerical values of tests used to determine the condition of the oil, and concentrations of wear particles and constituent elements. In order to diagnose machine faults, an expert analyst would need to know the type of components of the machine, including gears and bearings, as well as the alloy composition of each component. This type of information is machine specific, and has therefore been categorised accordingly.

The third type of input parameters relates to how the analysis algorithm is executed. Due to the numerical nature of oil analysis reports, the data interpretation typically consists of either monitoring a change in a parameter with respect to that of new oil, or a change between consecutive oil samples. Each parameter is therefore compared to either the new oil or previous sample, and if the difference is above a preset threshold, an alarm is triggered. The thresholds for each parameter are defined by standards including ISO/TC 108/SC5 [102]. In order for the oil and wear particle analysis data to be interpreted by the expert system, these threshold values must be defined.

The physical and chemical properties of lubricating oil typically tested by oil analysis laboratories include viscosity, dielectric constant, concentration of water present, TAN/TBN, and a particle count and size distribution according to ISO 4406-1999 [11]. Wear particle parameters generally included analysis reports includes the general colours of the wear particles and their relative concentration, as well as the type and concentration of wear particles present. The wear particles are categorised into Rubbing, Laminar (rough and smooth), Cutting ($<$15 μm and 20-100 μm), Fatigue chunk ($<$20 μm and $>$20 μm), Flat Fatigue, Fatigue Spall, Severe Sliding, and Spherical ($<$3 μm, 3-10 μm and $>$10 μm). A comprehensive report will also usually contain the concentrations of various elements detected in the oil, reported in parts per million (ppm). The common elements identified include iron, lead, tin, copper, aluminium, chromium, nickel, silicon, sodium, boron, calcium, magnesium, phosphorous, molybdenum, zinc, sulphur, antimony, manganese, silver and titanium.

The expert system interface was constructed using a central main menu, with all data input and analysis menus branching off the main menu. A schematic diagram of how the menus are accessible in the user interface is shown in Figure 6.2. This menu structure was chosen due to its simplicity, and easy negotiation between the various menus. This structure features the analysis menu being directly available from the main menu, saving operator time during machine routine analysis.

This expert system user interface has been designed to allow operators to enter laboratory data using a dedicated menu, rather than obtaining a text file with the information in the correct format. This additional menu has been added as laboratories have different report structures, and it cannot be assumed that a laboratory will make results available in the required file format.

6.2.1.1 Machine Information

The machine specific information required by the expert system analysis algorithm includes the type of components present on the machine, as well as their elemental composition. The machine information menu has been designed as part of the user

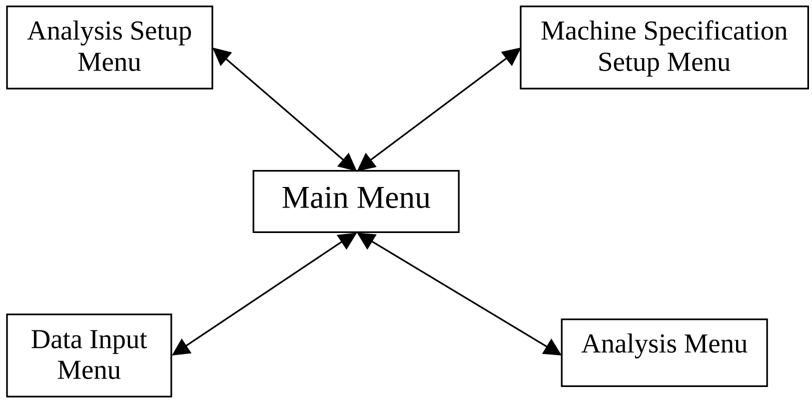


Figure 6.2: *Expert system menu structure.*

interface, to allow this information to be entered, and saved in the relevant file format.

The machine information menu was designed to input the type of machine components found on the machine, as well as a register of the elements present in the component materials. The menu has been adapted from the Vibration Analysis Expert System discussed in Chapter 5. Apart from the basic menu, an additional frame has been added to include elemental information of the machine components. The elemental information has been categorised into four component types, bearing materials, gear materials, drive shaft materials, and other materials. The appropriate elements contained in each material category can be selected from a list of commonly used elements, while the other materials category allows operators to also enter the appropriate component name. These elements are summarised in Table 6.1, including common applications.

The benefit of modifying the machine information menu designed for the vibration analysis expert system is that the machine information file can be used by both expert systems, eliminating redundant data entry. The file format has been designed so that the vibration analysis menu items are stored at the beginning of the file, while the elemental analysis of the oil and wear debris analysis expert system (called OWDES) are added at the end of the file. The file also contains a unique code, to allow the

Table 6.1: *Common machine elements and uses.*

Element	Components Typically Featuring Element
Iron	Gears, shafts, machine housings
Lead	Bearings, seals, solder
Tin	Bearings, thrust bearing bushes, solder
Copper	Bushes, washers, heat exchangers, gears
Aluminium	Spacers, washers, some bearings, heat exchangers
Chromium	Bearings, seals, cylinder rings
Nickel	Bearings, turbine blades
Magnesium	Machine housings
Molybdenum	Piston rings
Zinc	Seals, galvanised coatings, brass components
Antimony	Bearings
Manganese	Valves
Silver	Bearings, shafts, gears
Titanium	Bearings

expert system to test whether the selected file really is a genuine machine information file. This helps eliminate situations where an operator accidentally selects the wrong file, possibly causing a system crash.

6.2.1.2 Analysis Information

The information required by the expert system analysis algorithm to determine whether a parameter in the oil or wear particle analysis report is considered acceptable has been categorised as analysis information. This information includes the alarm thresholds, which define the change in magnitude of a monitored parameter compared to new oil or the last sample, that will result in an alarm condition to be triggered. While general guidelines exist [102], this menu of the user interface allows alarm thresholds to be changed easily if required. As the alarm thresholds define the deterioration of the oil or machine before a fault is detected, fine tuning of the thresholds for the particular machine and operating environment allow early detection of critical faults.

The alarm thresholds for parameter increases include laminar particle concentration, viscosity increase, and chemical index, while decrease thresholds include viscosity decrease, and TAN/TBN. Absolute alarm thresholds, not comparing to new oil or a previous sample, include wear particle concentrations, element concentrations, and the particle count cleanliness code according to ISO 4406-1999 [11].

The information input menu has been adapted from the vibration analysis expert system, similarly to the machine information menu. The analysis information file produced by this menu can therefore be used for both expert systems, and has been designed to simplify both the manual data input, as well as the operation of the comprehensive analysis expert system, discussed in Chapter 7.

6.2.2 Interface Development

The user interface was developed in a number of stages including needs analysis, planning, and implementation. The needs analysis was concerned with determining the requirements of the user interface in order to satisfy the design objectives of the broader expert system development. It was noted that the usability objectives related to how the operator interacts with the analysis algorithms through the user interface. The requirements of the interface were therefore to allow easy use of the analysis algorithms, data entry via a series of input menus, as well as analysis results output. During the planning stage, these design ideas were transformed into design specifications, ready to be executed in the implementation stage.

6.2.2.1 Input

The user interface is an important feature of the expert system, as it relates the analysis algorithm to the operator and hence determines the usability of the entire system. While the analysis algorithm performs all the data interpretation, it is the responsibility of the user interface to make the data input, analysis and data output stages available to the operator. This requires a menu structure and computer operating system platform that is appropriate for the application.

The design objective was to develop an expert system that could be used in a commercial laboratory environment to replace current manual data interpretation, in order to increase sample throughput and decrease the occurrence of reporting variation due to subjective operator judgements. As the computer running the expert system would be based in a laboratory, a locally run exe program type system was chosen over a web based application programmed in the java language. Due to the high market share of the Microsoft Windows type operating system, the Microsoft Visual Basic programming language was selected. The VB6 version of Visual Basic was used, in order to allow some backward compatibility for operating systems, back to MS Windows98.

The user interface was designed for maximum operator efficiency, ensuring that the appropriate menu could be selected quickly and allowing the operator to focus on the required data input. The data input menus consist of machine information, analysis information, and laboratory raw data input, all directly accessible from the main menu. The laboratory raw data input menu was designed to allow information contained in laboratory reports to be transferred to a text file of the format required by the expert system. The menu is shown in Figure 6.3. This menu allows all information commonly

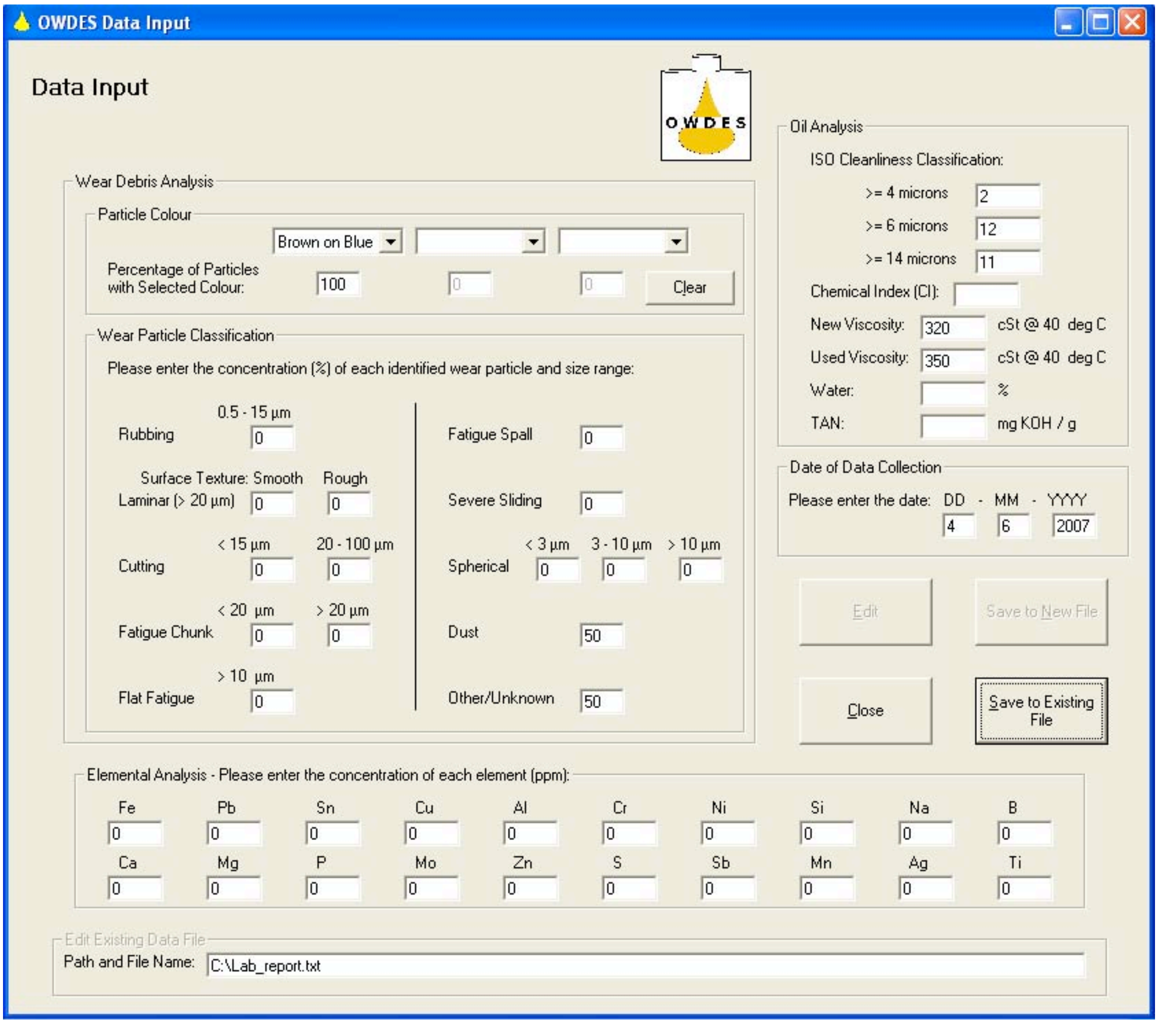


Figure 6.3: *Oil and wear debris analysis laboratory data input menu.*

contained in oil and wear particle analysis reports to be entered, most of which is optional. Mandatory fields required for analysis include the colour and concentration of wear particles, as well as the type and concentration of wear particles present in the oil. These data fields are contained in the Wear Debris Analysis frame of the data input menu. The user interface menus for the OWDES are shown in Appendix Section H.3. A help menu was also developed as part of the user interface, which is shown in Appendix Section I.2.

6.2.2.2 Output

The output user interface is responsible for portraying the results determined by the analysis algorithm to the operator in a suitable format. The possible formats include on-screen display of the results, text file type storage, or print out. Of these output formats, the text file storage medium was considered to have the most advantages in a commercial condition monitoring laboratory environment. As an analyst operator would rarely act on a set of results immediately, on-screen display is not really required, and opening of the text file can be achieved quickly. The output results file has numerous advantages, including the option of using the file directly or in part for a customer report, the ability to archive files as well as the ability to post the file onto a web site for customer viewing. The easy archiving ability was a major factor in the selection of the text file output mode, as a record of maintenance recommendations can be helpful for customer relations, including fine tuning of fault indicators, and consultation to improve machine lifetime.

The analysis algorithm has been developed to compile a text file using 45 preprogrammed messages for inclusion in the output file. The output file has been arranged to include all faults detected by oil and wear particle analysis at the top of the file, arranged into faults caused by contamination, lubrication, wear related or corrosion. The elemental analysis table has been positioned towards the end of the file, thus allowing operators to scan for detected faults, and then compare this the results of the elemental analysis. The defined analysis information used to interpret the data has been included at the end of the file, allowing the analysis to be examined in relation to the fault sensitivity variables, as defined in the analysis information menu. This is a useful feature for both fine tuning as well as allowing the analyst to manually trace the data interpretation.

6.2.3 Analysis Algorithm

The analysis algorithm constitutes the core component of the oil and wear debris analysis expert system. It is comprised of a knowledge base developed for oil analysis, wear particle analysis, and elemental analysis using literature sources [27, 102, 108]. The analysis algorithm operates by comparing the values of the laboratory data to the predefined alarm thresholds for each oil and wear particle parameter. Once a parameter is found to be out of specification an alarm for the particular parameter is triggered. The knowledge base was compiled into a number of flow charts that contain the reasoning logic of the data analysis. These flow charts are shown in the Appendix Section D. The knowledge base was then coded into a series of If-Then and If-Then-Else statements, which make up the analysis algorithm. This algorithm operates by relating the parameters in alarm state to possible machine faults, by considering the parameters both individually as well as in a comprehensive manner by correlating the various parameters in alarm state to a minimum number of faults.

6.2.3.1 Development of Oil and Wear Particle Analysis Algorithm

The analysis algorithm was developed to assess the condition of the lubricating oil in terms of physical and chemical properties, as well as detect typical machine failure indicators using wear particle analysis. The oil properties assessed by the oil analysis algorithm include those that are commonly tested by laboratories and have proven useful in machine condition monitoring. Wear particle analysis can diagnose the type of wear modes present in the machine, and is also generally reported in oil analysis reports. However, detailed interpretations of wear particle results are not generally performed by the oil analysis laboratories. This presents the need for an automated dependable approach to interpret oil and wear particle analysis data.

The objective of this algorithm was to interpret and diagnose machine faults using the data provided by typical oil analysis laboratory reports. It was therefore important to include a wide range of input data that may be available from the laboratory report. Three categories of input data were identified oil physical properties, oil chemical properties, and wear particle information. Although the input information available is dependent on the type of machine which is analysed, core elements had to be identified which would make up the minimum information to enable the algorithm to operate.

Wear particle types and concentrations were chosen to represent the minimum information required for the analysis algorithm to operate, as the output allows the wear modes to be identified the technique which has the greatest potential for fault diagnosis. While the physical and chemical properties of the oil provide useful fault indications, this information is more suited as supporting evidence. Oil properties were therefore considered as additional information for the analysis algorithm if available. The categorisation of input data as mandatory and optional satisfies the design objectives of utilising a broad range of input information, depending on the available data.

Apart from fault detection and diagnosis capabilities, two additional features were included in the algorithm. These included fault severity assessment where available, and a confidence factor of detected faults. While knowledge about the severity of a fault is useful for maintenance departments, fault severity cannot be diagnosed for all defects using only oil and wear particle analysis. However, the severity of faults such as bearing fatigue, scuffing and welding of surfaces can be diagnosed by the presence of related wear particles or particle colour.

The confidence with which a fault is detected is dependent on the concentration of wear particles or data value (in the case of oil analysis data) compared to the set alarm limit. Although the presence of a severe fault could be taken as an indicator that the particular fault has occurred, this is not the approach used during this project. Instead, the various severity stages of a particular fault are taken as individual faults, and the confidence factor derived from the data that was used to detect the fault. This method is less subject to erroneous results, as the source data is compared rather than comparing the faults (or severity stages) that have been detected. The principal used to determine the confidence factor is similar to that used in the vibration analysis expert system, discussed in Section 5.2.2. The confidence factor is zero if the detected percentage is below the alarm limit, and 1 if it is greater than the upper alarm limit. The mid range section is calculated using linear fuzzy logic, reporting the magnitude by which the set alarm limit is exceeded in a dimensionless variable.

The developed analysis algorithm allows the automated interpretation and fault diagnosis of oil and wear particle analysis laboratory reports, and thus fulfils the design objectives. The embedded knowledge base enables the algorithm to diagnose gear and bearing component faults as well as abnormal operating conditions and lubricant defects. This development represents a versatile and comprehensive tool for oil and wear particle analysis, both for maintenance departments or for integration in the combined analysis expert system as discussed in Chapter 7.

6.2.3.2 Development of the Elemental Analysis Algorithm

Elemental analysis has proven a useful tool in machine condition monitoring in order to provide the operator with a list of those machine components undergoing abnormally high wear, detectable through high concentration in the constituent elements [111]. In a case where each machine component contains at least one unique element, elemental analysis can be used to diagnose the actual component operating under a high wear condition. However, it is common that a single element cannot be used to uniquely pinpoint one component, or even component type, resulting in elemental analysis not able to diagnose a faulty component directly. In this case, elemental analysis can still be used to support the conclusions drawn from other indicators of oil and wear particle analysis. The operation of the developed elemental analysis algorithm is shown in Figure 6.4.

The design objectives of the elemental analysis algorithm were to provide an operator with a list of components that contain an element that was found in a critically high concentration. Since wear of a component manufactured of a certain alloy would result in most or all of the constituent elements to be detected in high or critical concentrations. For this reason, the results of the elemental analysis are sorted in decreasing order of the number of critical elements contained in each component. The components at the top of the list will therefore be those components correctly identified as operating under a high wear rate, and those components that are operating correctly but contain the same elements as the faulty component.

Elemental analysis is most effective in diagnosing faulty components when these are composed of differing materials. This would include a possible scenario of a gearbox where a steel worm (iron) drives a bronze gear (copper and tin), and the shafts are supported by roller bearings (apart of iron, also containing elements such as nickel, chromium, silver and/or titanium). If for example an abnormally high concentration of copper is found in an oil sample of this particular gearbox, elemental analysis would conclude that since the bronze gear is the only component containing copper, the gear is undergoing accelerated wear. In this scenario, a high tin concentration would also

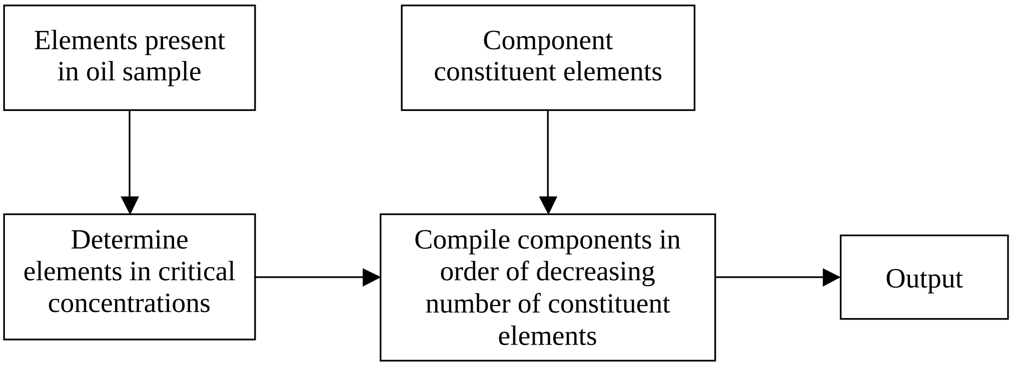


Figure 6.4: *Operation of elemental analysis algorithm.*

be expected, as this is the second constituent element of bronze. If the shafts were supported by brass bushes instead of roller bearings, and only a high copper concentration was detected, then bush or bronze gear wear would be predicted. However if copper and tin were found to be in high concentrations, the analysis algorithm would rank the bronze gear at first preference, as two of its constituent elements are in critical concentrations, and the brass bushes as second preference (one of the constituent elements are found in critical concentrations).

6.3 Expert System Testing

The developed analysis algorithm and user interface menus were strategically tested using hypothetical as well as industry data. The hypothetical data was used to verify the correct operation of all the encoded If-Then and If-Then-Else loops that make up the analysis algorithm. The input variables required to trigger each output variable were coded into an input file that was run sequentially, and the corresponding output checked for accuracy. Similarly, the user interface menus were tested to ensure that all data is correctly saved and retrieved from the corresponding text files.

The ability of the expert system to interpret real data was also verified using laboratory derived oil and wear debris analysis data. The oil samples were collected on a single reduction spur gearbox test rig, as described in Section 4.2. The gearbox was equipped with new bearings and gears, and was operated with a bent drive shaft. This operating condition resulted in the production of sliding, fatigue and cutting wear particles. The sliding wear particles resulted from the changing pitch circle diameter of the gears meshing, while fatigue particles were later identified to originate from the rolling element bearings due to overload. Post test inspection of the gearbox revealed that the cutting wear particles were a result of slight shaft misalignment as the drive shaft was not bent exactly at the centre of the spur gear. The output results of the expert system indicated that severe sliding wear and a bearing fatigue fault had occurred, and that gear misalignment may also have occurred. The confidence factors of the detected faults were 1 for the severe sliding and bearing fatigue faults, and 0.28 for the gear misalignment. As the confidence factors rely on the operator defining the lower and upper alarm limits which are used to calculate the confidence factors, these provide a dimensionless guide for fault comparison between different oil samples.

Once correct operation of the analysis algorithm were verified using laboratory data, industry data was also used in order to assess the ability of the expert system to correctly diagnose oil and machine faults. The data was collected from a process stirrer gearbox operating in a mineral processing plant. Routine oil samples were collected by the maintenance department, and sent to an external oil analysis laboratory for testing. Due to confidentiality of the plant operator, no photos or additional information could be included in this document. While the oil analysis laboratory offered crude conclusions, an expert team of the maintenance department interpreted the raw data and planned machine repairs accordingly. The raw data analysis results of the gearbox were transferred into an input data file, and analysed by the expert system.

The data presented by the oil analysis laboratory included oil viscosity, water concentration, elemental analysis, particle count according to ISO 4406 [11], and basic wear particle results. As the wear particles were only reported in the general particle types, it was not possible to determine whether the fatigue particles originated from a gear or bearing surface. In order to allow analysis when this information was not available, the concentration of fatigue particles reported by the laboratory data was entered for each of the flat, chunky and spall fatigue particles categories. This work around allows the expert system to perform an analysis, although all associated fatigue related faults will be triggered. This type of analysis coincides with the way an expert would analyse the data. The more information about the machine is provided in the laboratory report, the more specific conclusions the expert, and also the expert system can make.

The laboratory report included qualitative statements to describe wear particle concentration, such as fatigue particle concentration reported as low. These qualitative statements of the laboratory report were converted into quantitative particle percentages, by considering the alarm limits of particle concentrations. In the analysis information menu, the low alarm limit for fatigue particles in this gearbox was set at 5 %, while the high alarm limit was set at 15 %. The low category of the laboratory report was therefore correlated to a 6 % fatigue particle concentration. The laboratory report is shown in Appendix Section F.

The expert system results indicated that the oil was contaminated by particles, possible gear and/or bearing fatigue, possible oil dilution, as well as a concentration of silicon and sulphur. In the particular operating environment of the gearbox, both silicon and sulphur are contaminants external to the gearbox, verifying the high particle count. The contamination fault indicated by the expert system is therefore reasonable, and coincides with the conclusion by the laboratory. The possible oil dilution fault was triggered as the used oil viscosity is more than 10 % lower than the new oil, which could either be caused by solvent dilution or the use of the incorrect oil. As the concentration of fatigue particles was low, a confidence factor of 0.1 was calculated by the expert system for both gear and bearing faults. The correct interpretation of the laboratory report by the analysis algorithm indicates that the expert system operates according to the design objectives.

6.4 Summary

The design objectives of the expert system were to develop an artificially intelligent system that was capable of interpreting a comprehensive oil and wear particle analysis laboratory report for machine condition monitoring of gearboxes. In response to these objectives, an analysis algorithm was developed using parameters typically included on oil analysis laboratory reports, in order to assess both the lubricant and machine condition, as well as diagnose machine faults. The parameters as indicators for oil and machine condition include the physical and chemical properties of the lubricant, as well as the particle size distribution, and wear particle type and concentration.

The expert system was equipped with a graphical user interface, structured to allow all menus to be accessible from the main menu in order to reduce operator navigation time and net processing time per machine analysis. The analysis algorithm and menus were fully tested using hypothetical and industry oil analysis data. The successful testing procedure demonstrated that the expert system was able to satisfy the design objectives, by interpreting oil analysis laboratory data without relying on operator expertise. This development is therefore a useful tool for any maintenance department, allowing automated processing of machine condition data in a consistent objective manner.

Chapter 7

Combined Analysis Expert System

7.1 Introduction

Globalisation has forced many companies to improve their operating efficiency in order to remain profitable, and compete in their market segments. This has resulted in an adoption of improved maintenance programs featuring machine condition monitoring techniques, especially in machine intensive industries. Profit driven research by companies and research organisations has resulted in many significant improvements of vibration and oil analysis, the two most commonly used techniques for condition monitoring.

Machine condition monitoring programs generally feature either vibration or oil analysis, due to the very different equipment and expertise required to operate each technique. Shortcomings of each technique for early fault detection have led to the adoption of using both analysis techniques for health monitoring of critical machinery. Case studies of such machinery have allowed maintenance engineers to appreciate the benefit of using both vibration and oil analysis to complement each other [1, 2, 73, 74]. However, while some case studies reported of the two techniques complementing each other [1], others commented on how the techniques can also disagree in fault detection [2]. Due to the difficulties of successfully correlating vibration and oil analysis techniques, research has instead focused on improving the detection ability of the individual techniques.

The improvements of vibration analysis has been both in detection algorithms, as well as the use of artificial intelligence for faster and objective fault detection [99, 112]. Fuzzy logic, neural networks and expert systems have been used in many industries for data analysis and interpretation for condition monitoring of equipment, including transformers, gearboxes and longwall mining machinery [99, 105, 106, 113]. Similarly, oil analysis has been found to benefit from the use of information technology for both data management and fault diagnosis [114], and artificially intelligent systems for fault diagnosis [115]. While the use of artificially intelligent computational algorithms for automated fault detection and tracking is not unique to either vibration or oil analysis, the development of a procedure using a combined approach of vibration, oil and wear debris techniques is a totally new approach.

This chapter discusses the development of a novel expert system for the correlation of vibration and oil analysis techniques, incorporating a quantitative confidence factor to rate the detection success of the identified faults. This new development approach deviates from the previous case study approach, by using artificial intelligence and fuzzy logic for data analysis and reporting. An algorithm for root-cause analysis has also been developed, to allow operators to gain an insight into the possible failure progression.

Testing of the correlation expert system using both laboratory as well as industry data verified the successfully detection of the machine faults. The test cases again demonstrate the benefits of using both vibration and oil analysis techniques in a combined monitoring program, as suggested by Mathew and Stecki [73].

7.2 Expert System Development

The correlation of the vibration, oil and wear debris analysis techniques for gearbox fault detection has been achieved by analysing the machine using the techniques separately, and correlating the outcomes to obtain the complete condition report. This process requires the use of three expert systems, which have been categorised into primary and secondary expert systems. Two primary expert systems — one for vibration analysis (VES as discussed in Chapter 5), one for oil and wear debris analysis (OWDES as discussed in Chapter 6), are used to process the raw data, while the secondary expert system correlates the results of the underlying primary expert systems. The secondary expert system has been called the combined analysis expert system (hereafter referred to as CES).

7.2.1 Input Data Flow of Expert System

The primary expert systems were developed as stand-alone programs for machine condition monitoring, reporting results to a text file, as well as a numerical text file which contains the same data but in a numerical format. The text file allows the operator to read the expert system results, while the numerical file is read (input) by the secondary expert system (CES).

The development of the secondary expert system focused on the method of combining the results and conclusions of the primary expert systems into one machine condition report. This was achieved constructing a list of possible final results and correlating the outputs of the primary expert systems into these headings, as well as using a confidence factor to guide the operator on how likely a certain fault has occurred. An algorithm for root-cause analysis of faults was also developed to help the operator diagnose how machine faults may have occurred by examining and relating data from both vibration, and oil and wear debris analysis. Figure 7.1 illustrates the structure of the developed system and relationship between the three expert systems.

The software language chosen for implementation of the three expert systems was Microsoft Visual Basic, as this contains many features that allow a user friendly interface to be created, and thus the fulfilment of the usability design objectives. The user interface has been set up to allow each primary expert system to be used in a stand-alone configuration, or in a combined operation by performing the analysis via the secondary expert system. The menu structures and menu screens of all expert systems are shown in Appendix Section H, while the text of the help files is shown in Appendix Section I.

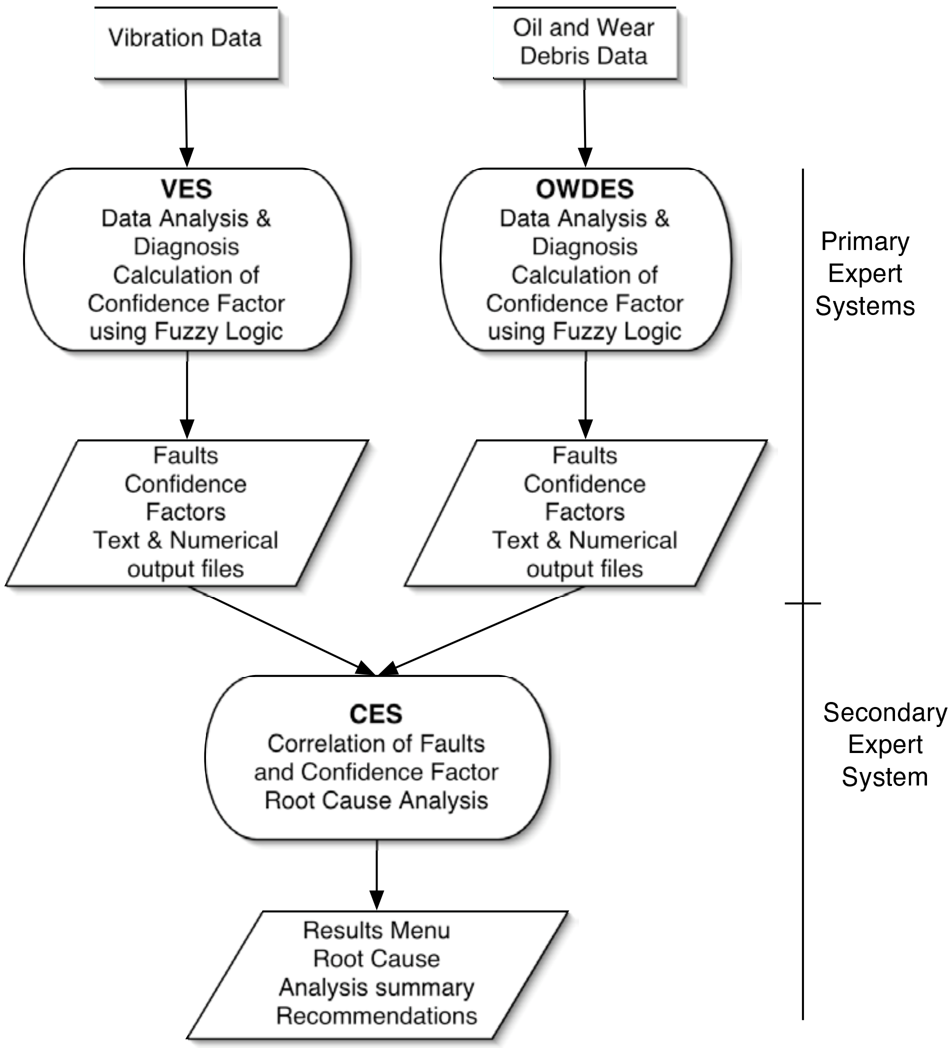


Figure 7.1: *Data flow between the vibration, oil & wear debris, and combined analysis expert systems.*

The expert systems were developed to process data in a similar fashion, as each individual expert system performs a similar operation on a different type of input data. Each expert system designed to utilise three core information components for analysis machine specific information, analysis information, and the data to be analysed. All three components are required in order to run the respective analysis algorithm, and are discussed below. The machine specific information and analysis information are concerned with information for the particular machine to be analysed, and will be operator programmable via individual menus of the user interface. The entered information of each menu will be saved to a respective text file, for use by the analysis algorithm. The advantage of using individual text files for data storage is that firstly, an individual file can be used for each machine, and secondly, the information can be used any number of times for regular routine machine condition analysis without the need to re-enter information.

The machine specific information category contains all the machine specifications, including the number and type of bearings and their fault frequencies, gear and belt ratios, material types of all components, as well as how the components are positioned in the machine, as shown in Figure 7.2. This information is required for the analysis code to calculate fault frequencies as is the case for the vibration analysis expert system, and for the oil and wear debris expert system to perform elemental analysis. The bearing types relate to the factors that influence their fault frequencies, such as bearing design and rotational speed. Therefore two bearings would need to be classified as two different types, if they are of different design, or two bearings of the same design but operating at different speeds.

The analysis information menu was designed to incorporate a set of variables that determine the fault detection sensitivity of the analysis algorithm. These variables can therefore be used to fine-tune the expert system to the user requirements, such as whether the expert system is used for early fault detection, or for fault monitoring, as is often the case in the mining and minerals processing industries. The required information to operate the VES analysis algorithm includes variables for peak, baseline and haystack detection. Variables for OWDES include detection and alarm level percent-

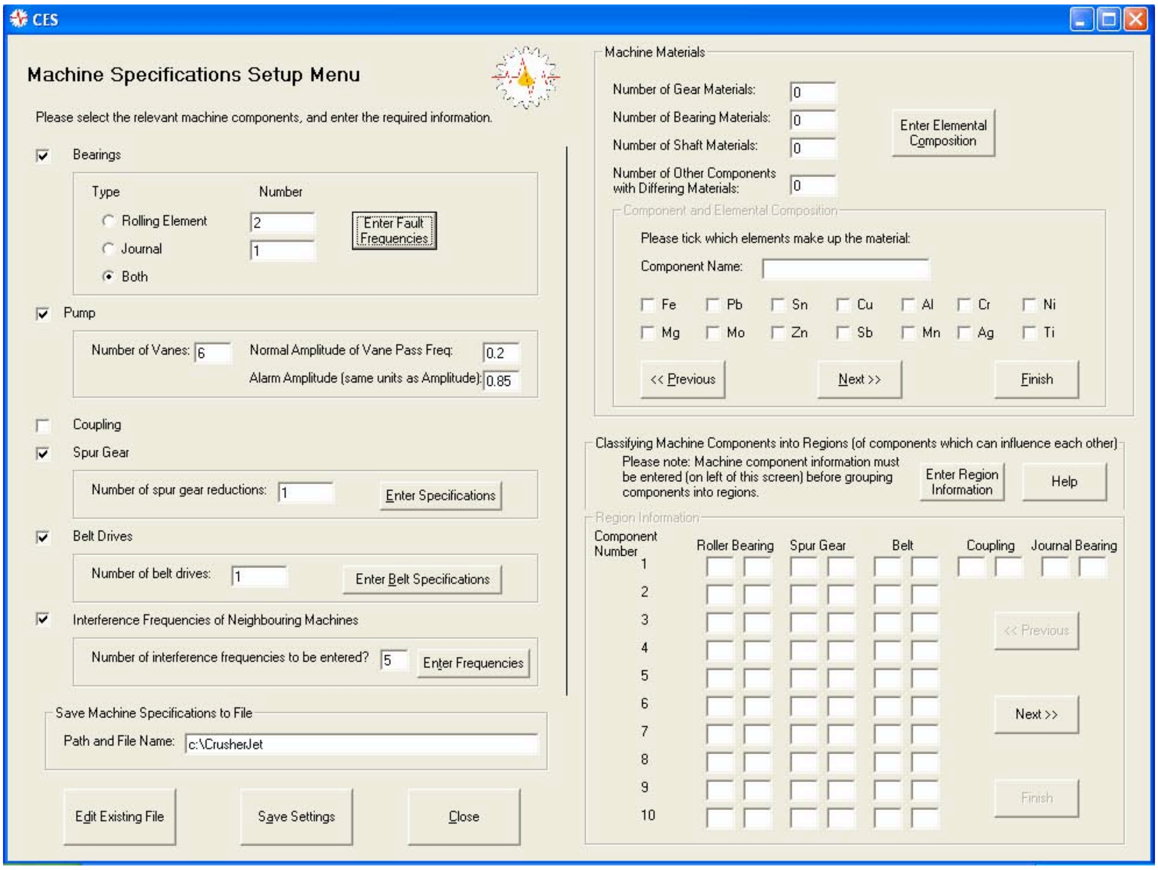


Figure 7.2: *The Machine Specifications setup menu.*

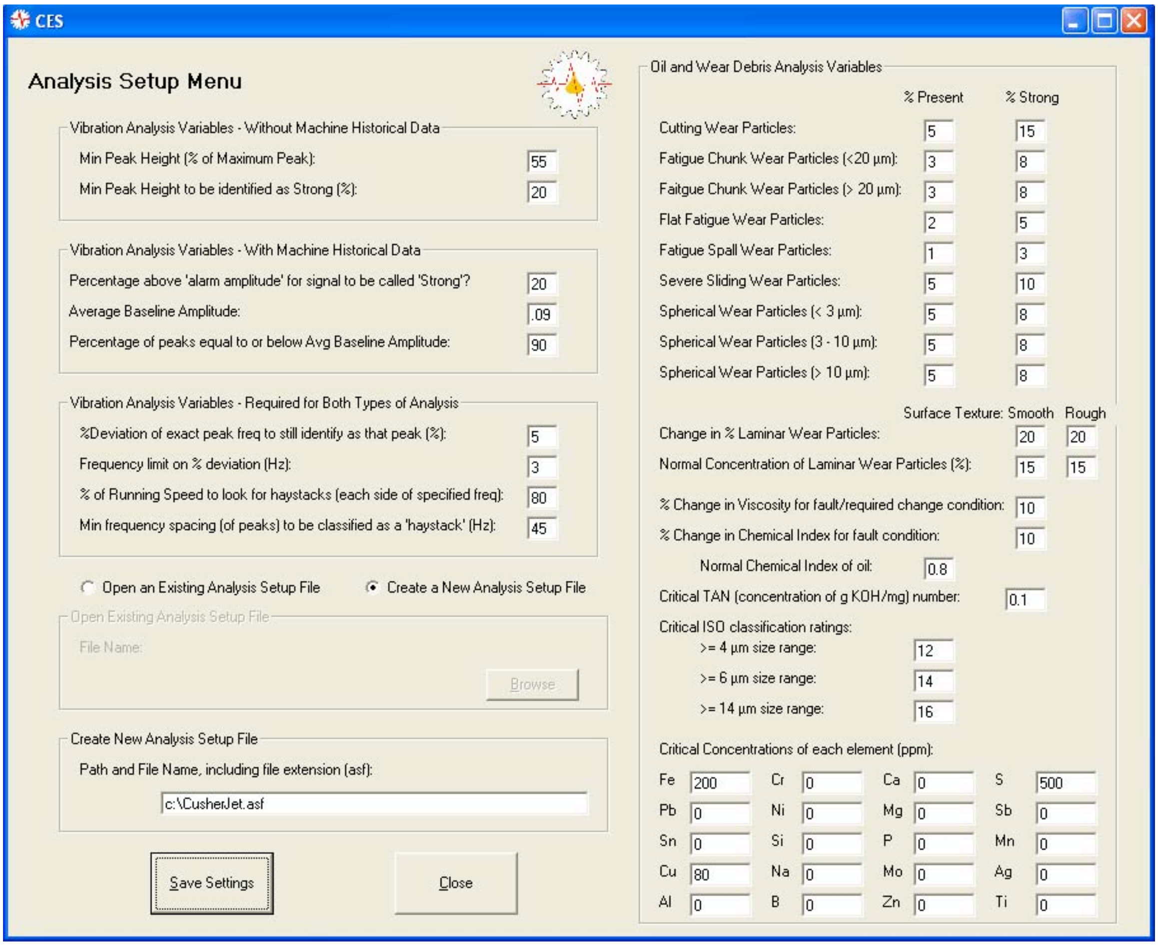


Figure 7.3: *The Analysis Information menu.*

ages of wear particles, new and critical lubricating oil specifications, as well as critical concentrations of typical wear and contaminant elements. The analysis information menu developed to allow the operator to enter the required data is shown in Figure 7.3.

The data to be analysed consists of a number of text files for each primary expert system. The compulsory data required to execute VES analysis is a text file containing two columns comprised of frequency and amplitude. This type of file can generally be exported as raw data from vibration analysers, and is therefore easy to obtain. Optional data that can be analysed include time domain data, and demodulated spectra data. Oil and wear particle analysis can be performed when wear particle data is available, which has been considered as the compulsory data required to execute the OWDES analysis. If additional information is provided including new and used oil viscosity, particle count and elemental analysis results, improved fault detection can be achieved. As every oil analysis laboratory has different reporting standards, a data entry menu of the user interface was developed to allow the information can be entered into a text file as well as edited. The compulsory data includes wear particle type and relative percentages, and wear particle colour with relative percentages.

7.2.2 Analysis Algorithm Development

The development of an analysis algorithm capable of correlating vibration, oil and wear debris analysis output reports was structured into a three stage sub-project. The first part was concerned with the research into the faults that can be detected by each analysis technique, and establish the faults that can be detected using multiple techniques. The second stage included the implementation of the research findings into an algorithm that would import the analysis results of each technique, and compile one comprehensive output report. Stage three was concerned with the development of a root-cause analysis algorithm, capable of analysing the detected faults and categorising the faults into primary and secondary type faults.

The first stage of analysis algorithm development focused on the fault detection of the vibration, oil and wear particle analysis techniques, and the identification of any detection overlap among the techniques. This research revealed that while vibration analysis was able to locate and diagnose specific gear and bearing faults, oil and wear particle analysis was only able to contribute the lubricant condition and wear modes occurring. A summary of all of the detectable faults is shown in Figure 7.4, with faults divided into their representative techniques. Correlation of all possible detectable faults, only gear misalignment could be detected by both vibration and wear particle analysis. Misalignment is evident through the presence of a high amplitude peak at the rotational speed frequency and the occurrence of 2 body wear, in vibration and wear particle analysis respectively. This is discussed further in Section 9.2.1.

The algorithm developed for the combined analysis expert system was designed to correlate the analysis results of each primary expert system into a single report — this constituted stage two of the development process. The algorithm was coded to

Bearing Faults

- Looseness
  - \- Loose in housing
  - \- Turning on shaft
  - \- Generally loose (Severe Rotating Looseness - raised noise floor, haystacks)
- Fatigue
  - o Mild - micro cracking
  - o Medium - macro cracking
  - o Severe - severe macro cracking
- Fault
  - \- Cage fault or cage loading
  - \- Ball/Roller fault
  - \- Race defect
  - \- Possible installation fault
- Lubrication Fault
  - o Inadequate lubrication
  - o Lubrication fault (contamination, begin of inadequate lubrication, over-lubrication)

Gear Faults

- Operating Fault
  - \- Input and/or output gear loose
  - \- Input and/or output gear eccentric
  - \- Input and/or output gear loose (major fault) & eccentric (minor fault)
  - \- Input and/or output gear eccentric (major fault) & loose (minor fault)
  - \- Gear or pinion fault
  - \- Preferential wear
  - o Welding
- Misalignment
  - \- Misalignment
  - o Misalignment
- Bent Shaft
  - \- Input shaft bent
  - \- Output shaft bent
- Fatigue
  - o Gear fatigue

Figure 7.4: *Machine fault detection using vibration, oil and wear debris analysis. The fault indicators were coded by using different bullet points, an 'o' denoting indicators from oil and wear particle analysis, while a '-' designates an indicator from vibration analysis.*

utilise the numerical versions of the primary expert systems output files, which allows the results to be read by the algorithm in binary logic, instead of the text based files compiled for operators. This stage also included the display of results in an on-screen menu, which is discussed in Section 7.2.4. This development was presented in [116].

7.2.3 Root-Cause Analysis Algorithm Development

The root-cause algorithm development was a key component of the correlation of the primary expert system results, by relating the faults detected by vibration analysis, to the clues detected by oil and wear debris analysis. This type of analysis had previously only been done by a small number of researchers, using manual methods [1, 2, 73]. The root-cause analysis algorithm was developed to show the operator how consecutive failures of various components may have contributed to the detected faults of the machine. The development of an algorithm to perform root-cause analysis of the detected faults comprised stage three of the analysis algorithm development process. The design objective of the root-cause analysis was to categorise all faults into primary and secondary faults, depending on whether they are a unique failure, or caused by another fault.

The algorithm development required the prior construction of a knowledge base, and included examining the possible failure mechanism of all possible machine faults, and linking these together when numerous faults were detected. The information required to determine which machine faults may have influenced each other is knowledge of both the type of fault as well as the location of the faulty component in the machine. This means that for a secondary fault to occur, the secondary component must be in some form of physical contact with the component that has the primary fault. For the analysis perspective, the machine needs to be divided into a number of regions, where components in each region can cause secondary wear among those components, but not to components in other regions. Additionally, some components can be part of two regions, as would be the case when two gears are mounted on the same shaft for example. The shaft and supporting bearings would be part of the region for each gear reduction, as failure of the bearings would influence both gears.

Another example is shown in Figure 7.5, where an electric motor is coupled to a 2

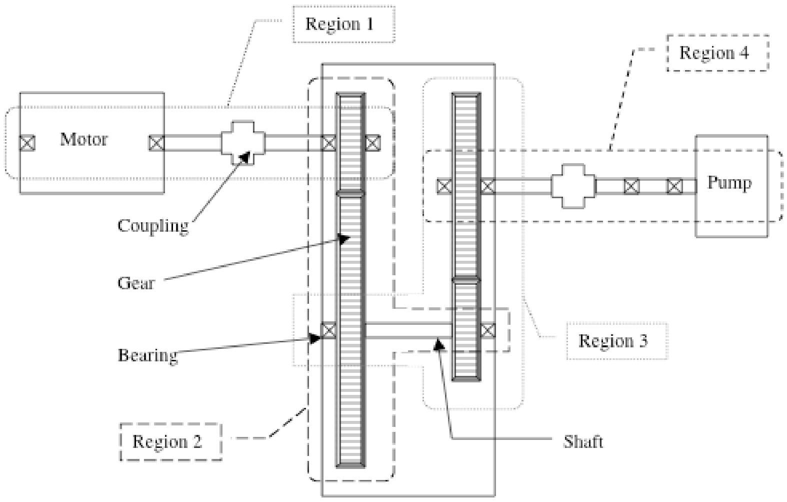


Figure 7.5: *Schematic diagram of an electric motor, gearbox and pump arrangement, showing possible machine region boundaries.*

stage spur gearbox directly driving a pump. Region 1 contains the electric motor bearings and shaft, as well as the gearbox input shaft and bearings. These components can influence each other, if for example the coupling is unbalanced or misaligned. Region 2 contains the input and intermediate shafts, bearings and the gears of reduction stage 1. Region 3 contains the intermediate shaft and output shaft, bearings and gears of reduction stage 2. The intermediate shaft and bearings is thus present in both Region 1 and 2. Region 4 contains the pump, pump input shaft, and gearbox output shaft, and bearings on each of the two shafts.

Once the machine has been divided into the appropriate regions, the detected faults can also be assigned into the particular regions. The faults in each region can then be analysed for possible failure mechanisms. The method assigning the detected faults to those components surrounding the defective component has the benefit of reducing the number of faults detected in each region, while providing a realistic and logical process for root-cause analysis.

It was discovered that in cases where many faults are detected, there is a high probability that some faults will be categorised as both primary and secondary, as they relate to other faults. For example, a bearing looseness fault (primary) may be responsible for gear misalignment (secondary), but the misalignment fault may be primary to a gear fatigue fault that occurred due to the reduced load transmission surface area. When numerous faults are detected, it is difficult to organise faults into primary and secondary classifications, and reconstruct the order of failure mechanisms.

The constructed knowledge base was implemented as the root-cause analysis algorithm. The input data of the root-cause analysis algorithm is the complete list of faults compiled from the primary expert systems. The root-cause algorithm is executed once the initial analysis algorithm has completed, and summarises the results in an on-screen menu, discussed in 7.2.4. The operation of the root-cause analysis algorithm is discussed in Section 7.2.5.

7.2.4 Output Interface Development

The analysis results include a comprehensive list of machine faults, as well as a list of faults categorised into primary and secondary faults by the root-cause analysis algorithm. A separate menu was developed for each list, designed to provide an operator with a quick way to scan for the various faults present, and the ability to investigate the details of each fault if desired. The output menu structure was designed according to the original expert system development objectives, that would allow easy and efficient operation. The menu structure and user interface including data input and analysis results output menu screens are shown in Appendix Section H.1 and H.2.

The general analysis results menu was designed to include the major fault areas, such as bearing, gears or pump related faults, on screen and a sub-menu to list the detailed information about each fault. The menu therefore contains 20 fault identifications, summarised into 8 types of machine components. This format of summarising the detected faults was adopted as it allows the data to be displayed in a one page view, giving an operator a quick overview of the general machine condition. The results menu lists the component and the general fault that has been detected. Faults that were detected by VES generally allow the faulty component to be identified, due to the unique fault frequencies generated by different bearings and gears. This feature allows the occurrence of a fault to be displayed for bearing and gear faults except fatigue, as well as belt and pulley faults.

The sub-menu is accessible through a selection button next to each detected fault, and is used to list all individual detected faults and their confidence factors. The layout of the general results menu is shown in Figure 7.6. When a fault is detected, the highest confidence factor of all faults under the general heading is displayed in the general results menu. For example, if bearings 2, 4 and 7 were detected to be loose, the highest confidence factor would be displayed. The details sub-menu would then display the particular fault associated with each of the bearings, including loose in housing, loose on shaft, or general excessive looseness, as well as their respective confidence factors.

The development of the general results menu also included the design of an alternative menu intended for the case when no faults were detected by the analysis algorithm, as shown in Figure 7.7. The menu consists of an information box notifying the operator that no faults were detected, including a warning that this may be due to the alarm limits of fault detection being set too high. The warning message was included for new learning operators, as well as for new machines where the appropriate alarm detection limits have not been determined accurately.

The menu for displaying the root-cause analysis results was developed to display all faults as primary or secondary faults, as well as list additional recommendations useful for the maintenance department. The simple display menu shown in Figure 7.8 serves the design objectives, by allowing all necessary data to be displayed on one screen.

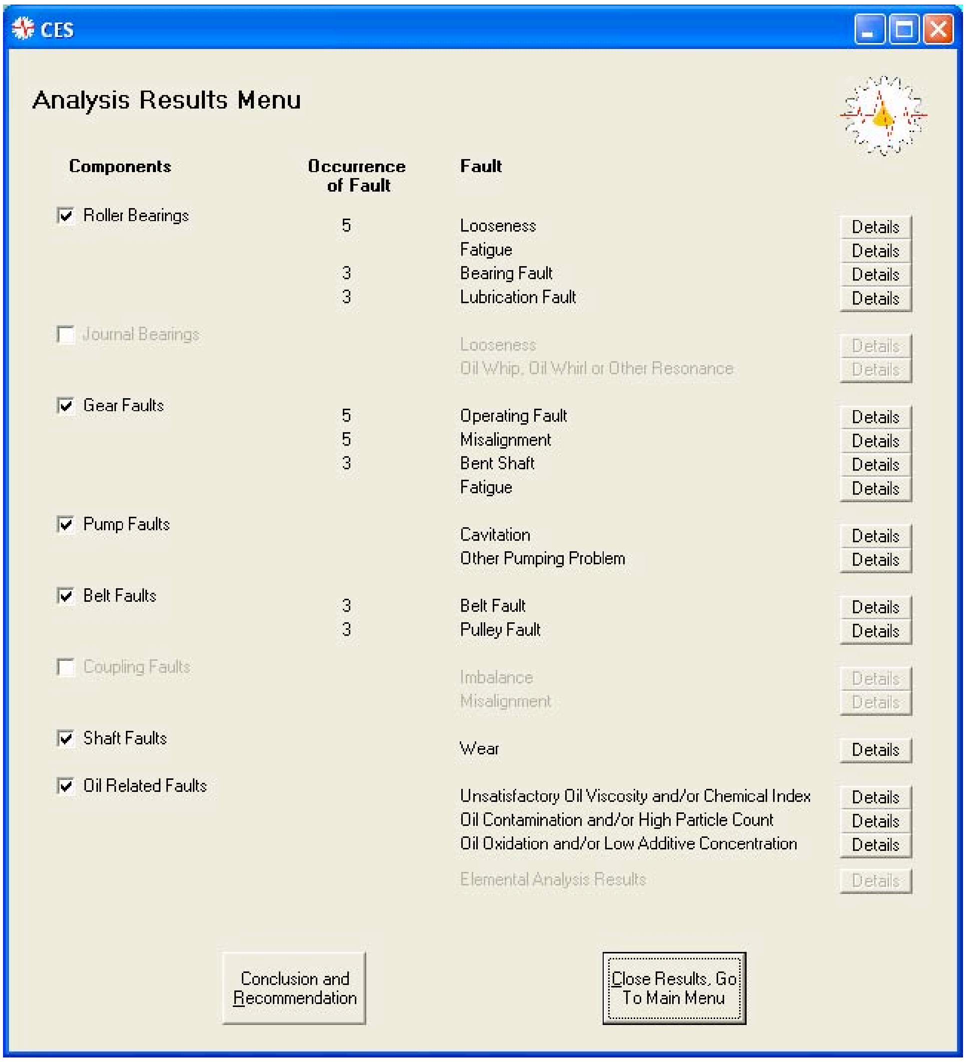


Figure 7.6: *The Analysis Results Menu of the Combined Analysis Expert System.*

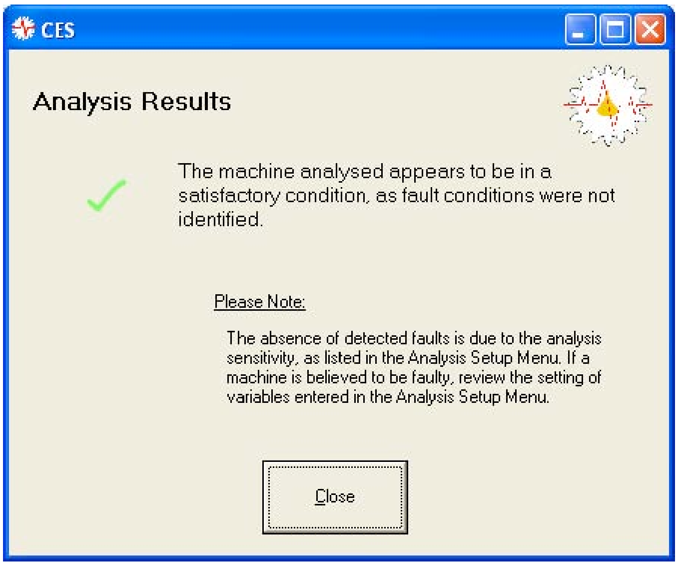


Figure 7.7: *Alternative Analysis Results Menu when no faults are detected.*

7.2.5 Analysis Algorithm Operation

The combined analysis expert system (CES) is the secondary expert system that has been developed to correlate the conclusions of the primary expert systems into one set of reporting outputs. The aims of the correlation were to determine the condition of a machine, and perform a comprehensive fault analysis that provides an insight into how the faults initiated and developed, in an automated software package. This was achieved by calling each primary expert system independently, and then using the individual results to establish the condition of the machine and performing fault root-cause analysis. The use of the primary expert systems for initial data analysis simplified the system structure, and has the added benefit of allowing each primary system to be used in stand-alone mode.

The analysis process consists of the execution of four analysis modules. The first two modules to be executed are the vibration and oil and wear debris analysis expert systems, which carry out fault detection on the raw data. The third module to be executed is the combined analysis expert systems analysis algorithm, which categorises all detected faults into the fault groups presented to the operator. Part of this algorithm is the calculation of the confidence factor of each fault, which allows the expert system

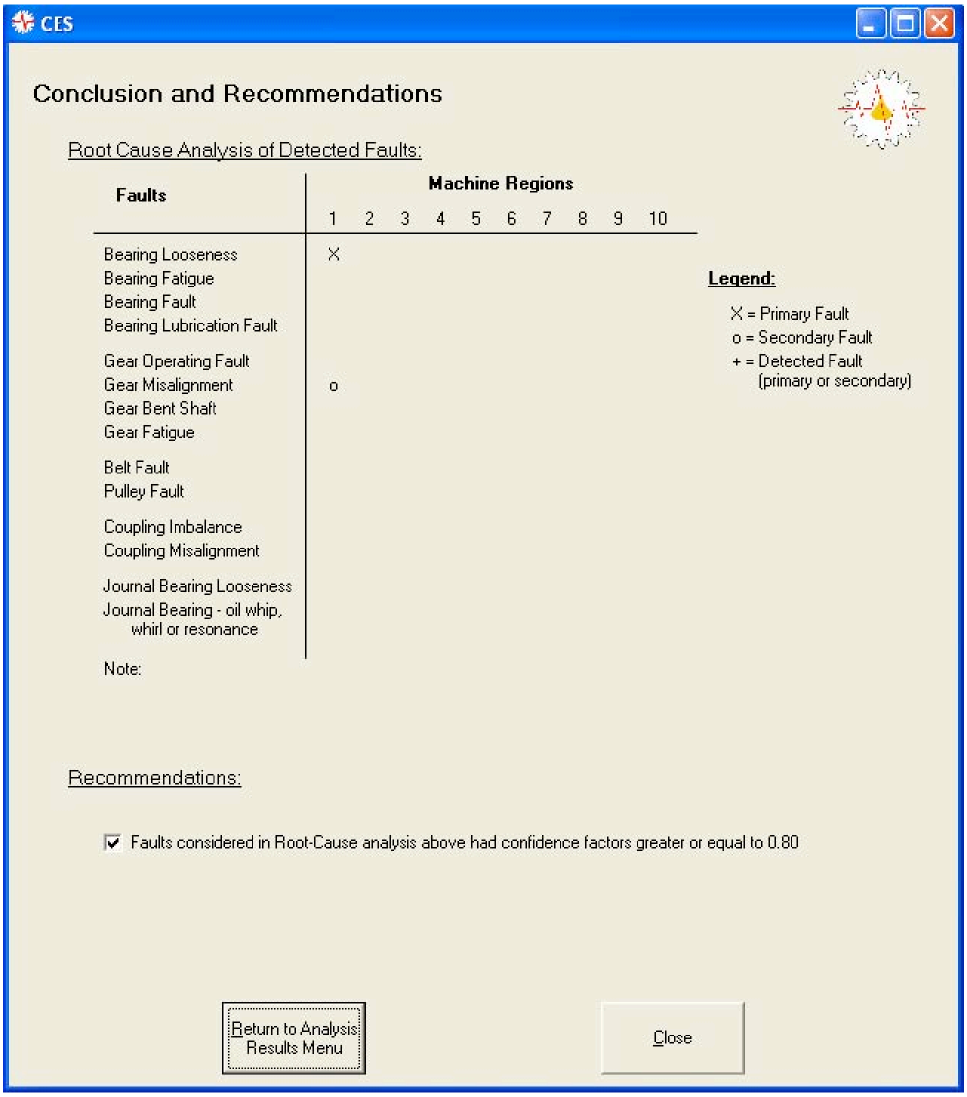


Figure 7.8: *The Root-Cause Analysis results window, showing an example where bearing looseness caused gear misalignment.*

to perform an efficient and objective data analysis. The fourth module to be executed is the root-cause analysis, which analyses the detected faults relative to the position of each component within the machine. Finally, the information obtained from the four analysis stages are displayed on the analysis results screen, as shown in Figure 7.6.

The detection algorithm of each primary expert system includes the calculation of a confidence factor for that fault occurring. These confidence factors are then evaluated for the 20 output faults of the CES, to obtain a confidence factor for these faults. The confidence factor was developed to allow the operator to judge how successfully each fault was detected by its respective algorithm. The confidence factors are between 0 (fault does not occur) and 1 (the probability that the fault occurs is 100 %), and are reported in the results window.

The confidence factors reported in the CES analysis results window are the highest confidence factor of all faults for the particular machine component. The detailed view of each fault lists all of the detected faults and their confidence factors, arranged in order of increasing component number. The output faults of each primary expert system were determined to be the faults which could be detected by that technique with reasonable confidence, where the confidence factor represents the success of fault detection. The faults, as well as their detection algorithm were developed by consulting literature as well as industry representatives who can be considered experts in their field. The expert systems were individually tested using data obtained from a laboratory test rig featuring a single reduction spur gearbox.

Once the analysis results of the primary expert systems have been compiled, these are input to the root-cause analysis algorithm for further processing. The faults are grouped into the defined machine regions, and the faults in each region analysed for possible failure mechanism. All faults are identified as either primary, secondary or unknown chronology faults, depending on how the component faults originated. The results are then displayed in the root-cause output menu, as shown in Figure 7.8.

The expert system developed to correlate the results from individual vibration analysis, and oil and wear debris analysis has achieved the design objectives by providing a comprehensive machine condition report, without relying on operator expertise. This is accomplished by compiling the results of the primary expert systems into one set of outputs using the developed logic algorithm, and a numerical confidence factor in the root-cause analysis algorithm.

7.3 Testing and Discussion

The development of the three expert systems included a thorough testing procedure, which included individual testing of the primary expert systems, followed by complete case study type analysis. Two of the case studies used for testing are discussed, one using data from a laboratory gearbox, and the other analysing data from a gearbox operating as a grain auger gearbox in the agricultural industry.

The first test case analysed with the combined analysis expert system was of a single reduction laboratory gearbox operating under constant overload of approximately 125 % of the rated gear power. This test was chosen as an overloaded condition is not easily detected directly, and early fault detection is crucial in avoiding premature failure. The measured vibration data consisted of tri-axial spectra, time domain and demodulated spectra, taken at the input side of the input shaft, and the output side of the output shaft, as described in Section 4.2.2.

Vibration analysis of the spectra detected bearing faults including a medium to severe output shaft race defect, possible bearing looseness, as well as a bent input shaft, and gear looseness. The oil and wear debris analysis expert system detected gear fatigue and the presence of blue coloured tempered particles. The blue particles were generated by the high gear teeth contact pressures caused by the overloaded operating condition. High wear particle concentration was also detected towards the end of the test, caused by a high wear rate. The detected faults were combined by the CES into the following faults summary:

- 2 Bearing Looseness - possible bearing looseness
- 2 Bearing Faults - output shaft race defect, and cage defects
- Gear Operating Fault - possible loose input and output gears

- Bent Shaft - bent input shaft
- Gear Fatigue

The root-cause analysis algorithm concluded that the bent shaft and gear fatigue were primary faults, while the remaining faults could not be categorised into either primary or secondary faults. The analysis algorithm interprets a bent shaft condition as a primary fault, as drive shafts are not often bent in service, but more commonly by incorrect installation and handling. Similarly, gear surface fatigue is also a primary fault, as it is caused by cyclic loading and not as a result of other machine damage. Visual inspection of the gearbox verified the presence of the detected faults.

The second case study used to verify the operation of the expert systems was a two-stage spur gearbox, operating on a grain auger in the agricultural industry. The gearbox was close coupled to a 0.55 kW four pole constant speed electric motor and a total reduction of 4.81 to 1. The motor and gearbox arrangement is shown in Figure 7.9. The total run time was estimated at 3000 hours during the 10 year operating period. The intermediate and output drive shafts of the gearbox were supported by journal bearings, while the pinion gear was supported by the motor shaft. The vibration data taken were the same type as of the first case study. Oil and wear debris data consisted of wear particle type and concentrations, as well as particle colour. Normal operating vibration data was obtained from a gearbox of the same type, which had operated for approximately 300 hours. This data was used to set up the amplitude levels of a healthy gearbox.

The faults detected by vibration analysis included a loose output gear, gear misalignment and preferential wear of reduction set 1, and possible eccentric gears of reduction set 2, as shown in the vibration analysis expert system output file in Figure 7.10. Possible lubrication problems of the journal bearings were also detected. Oil and wear debris analysis detected possible gear misalignment due to the presence of cutting wear particles, and the onset of gear fatigue as fatigue chunk particles were found. A small percentage of particles were found to have striations on the surface, indicating the presence of occasional scuffing. The oil and wear debris analysis expert

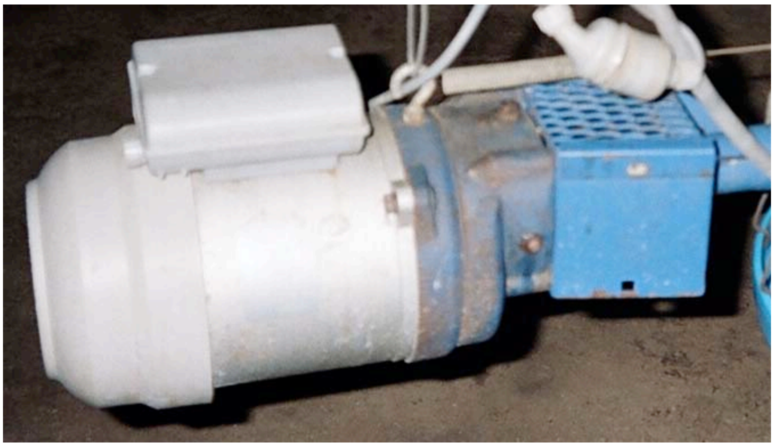


Figure 7.9: *Photo showing grain auger gearbox and close coupled electric motor.*

system output file is shown in Figure 7.11. The root-cause analysis identified the gear fatigue as a primary fault. The misalignment may have been caused by a loose fit between the journal bearings and drive shaft. However, excessive bearing looseness was not detected, only a possible bearing lubrication fault. Visual inspection confirmed that misalignment of reduction set 1 had indeed occurred, and that the gears of reduction 2 were slightly out of round (eccentric). The journal bearings were found to have a scratched surface, while the corresponding drive shaft positions were polished. The loose bearing fault may have been masked as a lubrication problem as the gearbox was filled with high viscosity oil, of 337 cSt at 40°C.

The testing process demonstrated that the combined analysis expert system successfully executed the individual vibration, and oil and wear debris analysis expert systems, and correctly compiled their analysis results. The root-cause algorithm was verified to operate according to the developed knowledge base, by identifying primary machine faults. As these are the faults that occur first, the machine life can be optimised by adjusting the operating conditions or maintenance schedule in order to minimise the factors that cause the primary faults.

Detected Faults:

=============

* Oil whirl, oil whip or other machine resonance present.

    (If change in speed causes change in vibration frequency, then fault is most likely oil whirl).

* The output gear is loose.

    (The gear mesh frequency has a sideband at 6 times the output rotational speed, at lower frequency than the GM frequency).

    (The sideband peak is the 34 harmonic of output shaft speed).

    (Gear set number 1).

* Possible misaligned gears, and or tooth wear & backlash (gear set 1).

    (Radial amplitudes of 2 GM > GM, and or 3 GM > GM)

* Preferential wear occurring at gear set 1

    (The input and output gears have a common factor other than 1, assembly phase frequency (horizontal direction) detected)

* The input gear is eccentric.

    (The gear has 5 high (eccentric) regions).

    (The gear mesh frequency has a sideband at 5 times the input rotational speed, at higher frequency than the GM frequency).

    (The sideband peak is the 30 harmonic of input shaft speed).

    (Gear set number 2).

* The output gear is eccentric.

    (The gear has 7 high (eccentric) regions).

    (The gear mesh frequency has a sideband at 7 times the output rotational speed, at higher frequency than the GM frequency).

    (The sideband peak is the 43 harmonic of output shaft speed).

    (Gear set number 2).

***** End of Vibration Expert System Output File *****

=======================================

Figure 7.10: *Vibration Analysis Expert System output file for the grain auger gearbox analysis. Note: the file header as well as the analysis information printed at the end of each file has been omitted.*

```
Detected Faults:
=============
Contamination Faults:
        None
Lubrication Faults:
        None
Wear Related Faults:
* Possible Misalignment
        Confidence Factor is 0.5
* Sliding Wear Occurring
        Confidence Factor is 1
* Gear Fatigue
        Confidence Factor is 1
Corrosion Faults:
        None
List of Possible Gears Which Experience Fatigue (gears with Gear Materials:)
        None
Non-Machine Wear Originating Elements found in sample:
--------------------------------------------------
        None
Table Listing the Number of Critical Elements Found in Each Component:
----------------------------------------------------------------
* The list is descending, ordered in material type.
* The total number of critical elements found in the sample is: 0.
        None
***** End of Oil & Wear Debris Expert System Output File *****
=========================================
```

Figure 7.11: *Oil & Wear Debris Analysis Expert System output file for the grain auger gearbox analysis. Note: the file header as well as the analysis information printed at the end of each file has been omitted. As elemental analysis data was not available, the results lists are blank and labeled as 'None'.*

7.4 Summary

The expert system development discussed in this chapter demonstrated the benefits of a combined use of the vibration, oil and wear debris analysis techniques, by using a root-cause algorithm to link fault indicators with detected faults. It was found that root-cause analysis increases the fault detection ability by providing a more complete report on the machines health status, when compared to the individual use of each analysis technique. The expert system correctly diagnosed the faults of the testing data, without relying on operator experience for interpretation, thereby demonstrating that it had correlated vibration, oil and wear debris analysis successfully.

The combined automated analysis of vibration, oil and wear debris analysis data to provide a comprehensive machine condition report based on quantitative data analysis algorithms has been achieved for the first time. The expert system analysis algorithms utilised quantitative analysis techniques including numerical wear particle identification, and detection confidence factors based on fuzzy logic, to perform objective data analysis and fault diagnosis. The results obtained during the testing phase of the expert system indicate that machine condition monitoring can be performed by maintenance technicians using artificial intelligence for data interpretation and fault diagnosis.

Chapter 8

Remaining Lifetime Estimation

8.1 Introduction

Machine health monitoring has become a common component of pro-active maintenance programs by providing early fault detection and an insight into the general operating condition of the machine. Once a machine fault has been detected, the rate of degradation and the operating time to failure are two factors of interest to the maintenance department. Remaining lifetime estimation is a powerful tool for supplementing machine condition monitoring data, aiding maintenance departments in scheduling machine repair as well as deciding for optimum timing of equipment replacements.

The developments outlined in this chapter deal with the estimation of lifetime by focusing on material wear. This contrasts the common approach of treating machine lifetime in a statistical manner such as by describing the bathtub shape failure curve using mathematical parameters [78, 79]. However, in order to predict machine lifetime using the statistical approaches [80], statistical analysis of the failure data must be carried out. This data may not be available if machine failure is not a common occurrence, as is the case with well designed and maintained machinery.

An alternative strategy for machine remaining lifetime estimation has been developed, based on the volume of material that can be worn away from a particular component before it is rendered unserviceable. This analysis of components is used in the remanufacturing or overhaul of machinery, where all component critical dimensions are inspected and compared to wear out limits provided by the manufacturer. It is therefore possible to judge the components condition with respect to new and wear out limits of the wearing surfaces. Although the analysis of components is common practice in the machine servicing industry, it presents an innovative approach for remaining lifetime estimation.

The aim of this research was to develop a strategy for remaining lifetime estimation, which allows condition monitoring information to be used to update the estimate throughout the operating life of the machine. The potential benefit of such a technique is that an estimate can be established assuming normal operating conditions, and updated if the machine experiences abnormal operating conditions such as lubricant contamination or overload. Another objective of the research was to automate the strategy by integration with an expert system for condition monitoring, which provides the required machine condition information to estimate the remaining lifetime.

The developed strategy has been discussed in this chapter together with the requirements of this new technique. The technique has also been applied to the wear of a spur gearbox, with the real data being presented and discussed. Although the experimental data confirms the operation of the strategy, the prime objective was to present the strategy as a case study and not purely for verification of the technique.

8.2 Knowledge Base Development

The knowledge base was developed to incorporate common accepted and tested wear equations in an automated package for machine remaining lifetime estimation. Wear processes have been found to be extremely complex with many additional variables apart from load, speed and component hardness, which may have a significant effect on the calculated accuracy. Some of these factors include varying machine condition, differences in lubricants and component metallurgy, type and concentration of contaminants, and duty cycle of operation.

In order to develop a strategy for remaining lifetime estimation, a knowledge base for four common wear modes found in gearbox type machines was compiled. The wear modes are comprised of abrasive, adhesive, cutting and sliding wear, which are discussed in detail in the following sub sections. Although surface fatigue is also commonly encountered in gearboxes, this type of wear is dependent on cyclic loading and general overload, which can be detected easily by measuring the input power. By the time wear can be detected using oil and wear particle analysis, surface damage has already resulted. Additionally, surface fatigue propagates undetectable to vibration, oil and wear particle analysis until significant permanent surface damage has occurred, thereby preventing the remaining lifetime to be calculated without considering additional information such as gearbox power input and rated power to estimate the fatigue life.

8.2.1 Abrasive Wear

Abrasive wear occurs when a hard material abrades a softer material. The softer material is referred to the machine component undergoing wear, while the harder material is composed of either a rough hard surface or a soft surface containing a hard contaminant. This definition of abrasive wear therefore covers the two-body abrasive wear process. The three-body wear process is significantly more complex as it contains an abrasive particle in between and in contact with two softer surfaces. This results in increased variables, as the angularity and softer surface hardness may not be uniform, and as the abrasive particle may slide or roll between the surfaces. In view of reducing the complexity of the model to allow the remaining lifetime to be estimated, the use of two body wear approximation is beneficial.

The abrasive wear rate has been found to be directly proportional to load and sliding distance, and inversely proportional to the abraded material hardness. Although this relationship remains true for all practical abrasive wear situations encountered, the impact of hardness and abrasive size on the resulting wear rate can change in certain scenarios. One example is when the hardness of the abrading material approaches the hardness of the abrasive, as could be the case when sand (silicon dioxide) of Brinell hardness approximately 750 kg/mm^2 contaminant wears against steel (Brinell hardness of 200 to 1000 kg/mm^2). The effects of the hardness ratio can be included in the wear equation by using an appropriate wear coefficient, according to the graph shown in Figure 8.1. The wear equation that has been developed to successfully calculate wear volume is [117]:

$$\text{Wear Volume} = \frac{\mathrm{K_{ABR}} \times \text{Load} \times \text{Distance}}{\text{Hardness}} \tag{8.1}$$

where

- wear volume is the removed volume of the softer material in mm^3
- $\mathrm{K_{ABR}}$ is the abrasive wear coefficient as shown in Figure 8.1 and Table 8.1,
- Load is the normal load in kg,
- Distance is the sliding distance in mm,
- Hardness is the Brinell hardness in $\mathrm{kg/mm^2}$.

The abrasive wear constant is dependent on the physical weighted average of the cutting angle of the abrasive particles with the abraded surface. The relationship is:

$$\mathrm{K_{ABR}} = \frac{\mathrm{Tan}\theta}{\theta} \tag{8.2}$$

where

- $\mathrm{K_{ABR}}$ is the abrasive wear coefficient,
- $\mathrm{Tan}(\theta)$ represents the weighted average of the cutting angle of the abrasive particles with the abraded surface.

The wear equation (8.1) has been found to apply both to three-body as well as two-body wear modes, although the abrasive wear coefficient used differs. While $\mathrm{K_{ABR}}$ is in the vicinity of 6×10^{-2} to 6×10^{-3} for two-body wear, typical values for three-body wear are about half this at 3×10^{-2} to 3×10^{-3}. Rabinowicz [117] comments that as the abrading geometry would be similar for the two-body and three-body cases, the abrasive grains in three-body wear would spend about 90 % of the time rolling and 10 % sliding (and abrading). This theory is supported by the experimental values measured for coefficient of friction, which is significantly lower for three-body wear [117].

The wear equation above assumes that a constant wear rate can occur over the duration of the sliding distance. However, a different wear equation can also be used

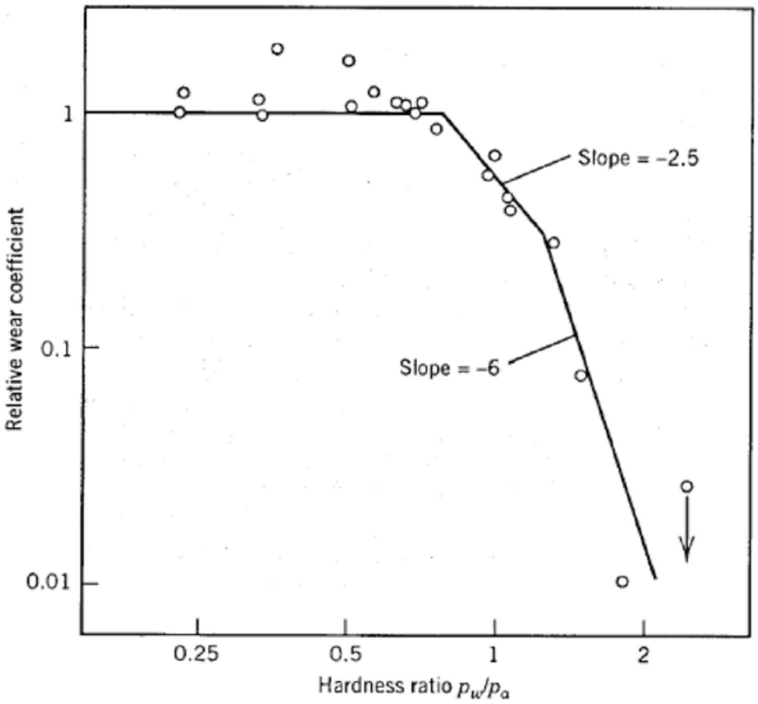


Figure 8.1: *Variation of relative wear coefficient vs hardness ratio [117].*

which is based on the blunting effect and clogging of an abrasive during sliding. The wear rate has been found to be abrasive size dependent up to a critical size, after which the wear rate is independent on the abrasive particle size [83, 118]. The phenomenon has been explained by the clogging up of the fine abrasive particle by larger wear debris particles, and results in the wear rate decreasing over the sliding distance. The equation developed for this phenomenon is shown below, and represented graphically in Figure 8.2.

$$\mathrm{V} = \mathrm{V}_{\infty}(1 - \mathrm{e}^{-\beta \mathrm{L}}) \tag{8.3}$$

where

- V is the wear volume,
- V_{∞} is the wear volume at infinite sliding distance,
- L is the sliding distance,
- β is a constant.

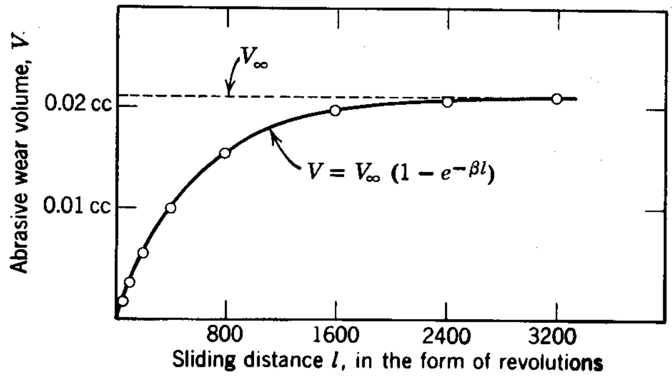


Figure 8.2: *Abraded wear volume as a function of sliding distance [117].*

Table 8.1: *Abrasive wear coefficients for metals [117].*

Lubrication	File	Abrasive Paper, New	Loose Abrasive Grains	Coarse Polishing
Unlubricated	5×10^{-2}	1×10^{-2}	1×10^{-3}	1×10^{-4}
Lubricated	1×10^{-1}	2×10^{-2}	2×10^{-3}	2×10^{-4}

The wear equation chosen for inclusion in the knowledge base is equation (8.1), based on load and hardness. This equation was chosen over equation (8.3) as the abrasive concentration can change with each machine oil change, and new abrasive introduced. As V would need to be determined, a new curve as shown in Figure 8.2 would need to be determined for each load and abrasive concentration. However, as multiple oil changes are typically performed during the life of gearboxes, each oil change period would operate in the low sliding distance part of Figure 8.2 where the wear volume is proportional to sliding distance. It was therefore considered more efficient to approximate wear according to a constant wear rate equation.

In order to use equation (8.1) for real gears and bearings as opposed to wear machines such as pin-on-disc apparatus, the sliding speed and sliding distance of the components must be determined. As gears and rolling element bearings are designed for rolling rather than sliding, the sliding speed component of the total rotational speed must be determined and used in the wear equation when calculating remaining operating time. As this information is dependent on the type and design of the component, the knowledge base was designed to accept the sliding speed as a percentage of the total operating speed. This information is therefore assumed to be available from either component manufacturers, or measured by independent tests.

8.2.2 Adhesive Wear

Adhesive wear is the process when two materials either of different or similar hardness slide against one another. In the case of two materials of differing hardness, more fragments and also of larger size are generally observed of the softer material. However, the harder material usually also undergos wear although wear particles are fewer and smaller. One possible explanation to the harder material wearing is the existence of low strength regions within the harder material.

The wear equation developed to calculate the wear associated with adhesive wear is similar to that used for abrasive wear, although with different wear coefficient. This is due to adhesive wear also being found to be proportional to load and sliding distance, while inversely proportional to the hardness of the worn material. Although numerous equations have been developed over time such as based on statistical wear particle size distribution, the equation that is similar to the abrasive wear equation has been based on the energy concerned with removal of particles from the rubbing surfaces [117]. The wear equation is shown below:

$$\text{Wear Volume} = \frac{\text{K}_{\text{ADHESIVE}} \times \text{Load} \times \text{Distance}}{\text{Hardness}} \tag{8.4}$$

where

- wear volume is the removed volume of the softer material in mm^3
- $\text{K}_{\text{ADHESIVE}}$ is the adhesive wear coefficient as shown in Table 8.2,
- Load is the normal load in kg,
- Distance is the sliding distance in mm,
- Hardness is the Brinell hardness in kg/mm^2 or the wearing (softer) material.

Table 8.2: *Adhesive wear coefficients for metals [117].*

Lubrication	Metal on Metal Identical	Metal on Metal Compatible	Partially Compatible/ Partially Incompatible	Incompatible
Unlubricated	1500×10^{-6}	500×10^{-6}	100×10^{-6}	15×10^{-6}
Poor	300×10^{-6}	100×10^{-6}	20×10^{-6}	3×10^{-6}
Good	30×10^{-6}	10×10^{-6}	2×10^{-6}	0.3×10^{-6}
Excellent	1×10^{-6}	0.3×10^{-6}	0.1×10^{-6}	0.03×10^{-6}

The accurate calculation of the wear volume is dependent on the accuracy of the required entities, including the adhesive wear coefficient. While typical coefficient values for many different material combinations have been reported in literature, differences in lubrication conditions between the approximated and actual case can result in significant differences in wear coefficient [117]. This is evident in Table 8.2, showing the documented adhesive wear coefficients for metals. As the differences in wear coefficients are large for the different lubrication conditions, deviations from the four documented categories can greatly influence the accuracy of the calculated wear volume.

Lubricant additives can also affect the value of the adhesive wear coefficient, as the coefficient is dependent on the rate of oxide film formation of the wearing material, classified as the severity of wear [117]. If a metal oxide film can form as fast as it is worn away, the wear is classified as mild, while situations when the oxide film cannot reform rapidly is classified as severe wear. Additives such as extreme pressure additives can therefore result in the wear regime to shift from severe to mild, as the oxide film can reform rapidly thereby influencing the adhesive wear coefficient.

High accuracy wear estimation using tabulated wear coefficients as shown in Table 8.2 is generally considered not achievable due to typical high statistical scatter of wear, and experimental error. However, a possible strategy to improve the calculated wear volume is to determine the value of the actual wear coefficient by experimentation. While this can be done for critical machinery, it is not feasible for general condition monitoring of machinery unless this information is made available from manufacturers for the recommended lubricant. As the lubrication regime is also dependent on the load, the wear coefficient values from manufacturers would also need to include load limits to ensure that the machine operates in the desired lubrication regime. The knowledge base has been designed to accept a wear coefficient value from the operator which is then used for calculations. It is therefore the responsibility of the operator to supply a suitable value, either from the manufacturer, experimentally derived or tabulated.

8.2.3 Cutting Wear

The cutting wear process is different to the other three types of wear, as it is a machining process rather than related to surface scratches or adhesion between one surface and another. Although machining processes have received significant research attention which has resulted in numerous equations to be established [89, 117], cutting wear of gears is somewhat more complex than the commonly referred to cutting tool lathe model. The cutting tool model allows parameters such as absorbed power, chip size and metal removal rate to be determined easily once cutting angle, feed rate, material diameter and rotation rate are known. However, this simple model cannot be applied to gears easily as the gears themselves are the cutting tool, and the tool does not have a feed rate or particular cutting angle.

Although the simple lathe tool model cannot be applied easily, a number of simplifying assumptions can be made in order to create a new model to estimate the cutting wear from one of the most common cutting wear mechanisms — gear misalignment. Firstly, the total possible volume of wear can be calculated once the angle of misalignment is known, as well as the gear widths, shaft lengths and dimensions of where the gears are mounted. The total wear volume (V) is therefore the amount of material worn due to the particular misalignment angle, which is assumed to be constant for the calculation. For small angles of misalignment, the gear contact surface will generally become approximately equal to the contact area prior to the misalignment, which would not alter the surface fatigue life significantly.

Another complexity of gear wear compared to the lathe tool model is that gear

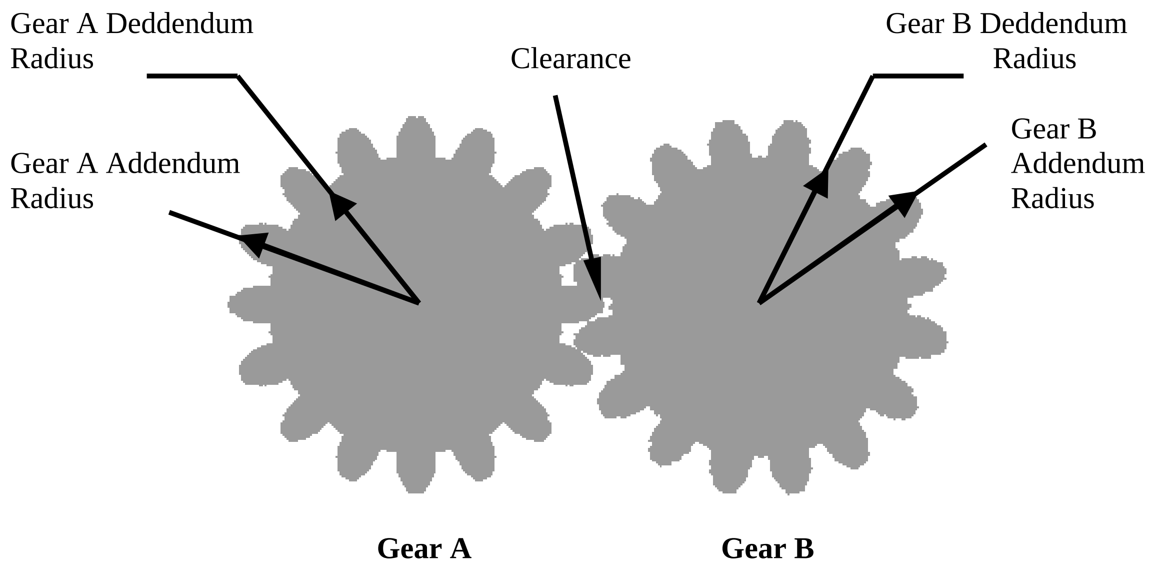


Figure 8.3: *Meshing of Gear Teeth within Addendum and Deddendum Radii of Each Gear.*

teeth are quite complex three-dimensional objects which are worn diagonally. The assumption made in order to simplify the shape complexity is to treat the gear teeth as rectangular. This means that the developed algorithm calculates a greater material removal at the teeth tips than actually was worn, as the teeth are really narrower at the top than at the base. A conservative estimate is therefore obtained, especially when the misalignment angles and shaft lengths are small.

The next step in the knowledge base development was to approximate the wear when diagonally slicing the tip of the gear teeth. In order for this to be performed, the assumption was made that the meshing area is made up of solid gear teeth, half of which belong to gear A and the other half of which belong to gear B, as shown in Figure 8.3. This allows the wear volume to be calculated by using a 2D model of the gear and assuming that it is machined into the shape of a cone, as shown in Figure 8.4. The calculations are summarised in Appendix Section G.

When considering gear geometry design it is necessary that the tip of gear teeth are shorter than the inter gear spacing in order to avoid interference between the gear teeth tips. This causes a situation where the space covered by overlapping gear teeth (between addendum and deddendum radii) includes an air space at the tip of each

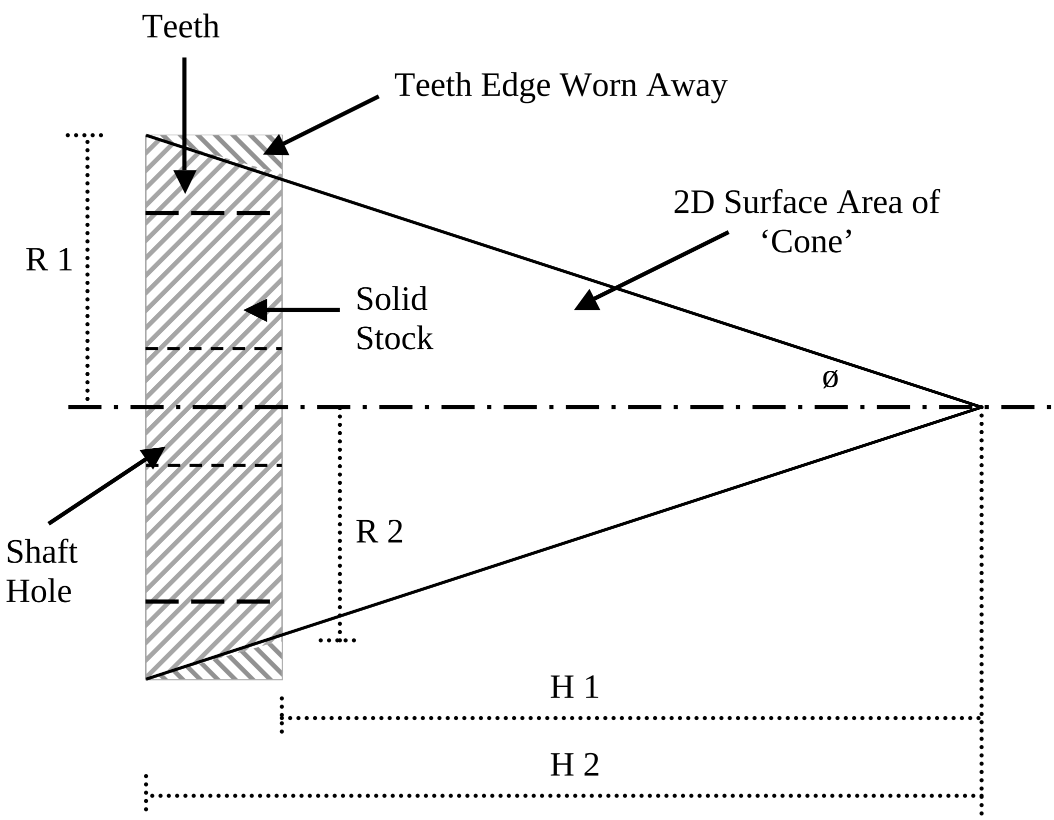


Figure 8.4: *Calculation of gear volume wear using conical machining model.*

tooth. This air space has been incorporated into the wear volume removal equation by accepting a percentage of the total space that is covered by gear teeth. For example, if in the space mapped out by the addendum and deddendum radii of each gear, 95 % of the space is covered by gear teeth, then the Gear Interference Factor (GIF) is equal to 0.95. This means that 5 % of the space is actually air gaps arising from the shortened gear teeth as well as the space required for each tooth to move while meshing.

8.2.4 Sliding Wear

In the condition monitoring field, sliding wear is typically characterised by wear particles featuring surface scratches, coinciding with high sliding speeds. Sliding wear particles are not generally found in spur and helical gearbox applications, allowing the term sliding wear to be used for abnormal operating conditions such as bent shaft operation where the teeth scratch over one another either apart from or in combination with the normal rolling motion. However, in the field of fundamental wear research, the use of sliding wear as defining a unique wear mode is not universally accepted. Since sliding is required for all wear modes except cutting and fatigue, it is argued that sliding wear is part of adhesive or abrasive wear [117]. Some researchers argue that since one material receives scratches it is an abrasive wear mode, while others argue that sliding wear is part of the adhesive wear mode as the wear particles are formed by adhesion, by the transfer of particles from one surface to the other. This theory is based on the condition that abrasive wear requires one surface to be harder and rougher than the other [117].

As the wear equations for both abrasive and adhesive wear are similar except for the appropriate wear constant, it would be expected that either wear mode calculation can be used to approximate the wear volume provided that the appropriate wear constant is used. The general adhesive wear equation has been adopted into the knowledge base for the purpose of remaining lifetime estimation.

8.3 Remaining Lifetime Estimation Strategy

The developed strategy was designed to estimate the remaining lifetime of a machine, with the ability for this estimate to be updated during the life of the machine by using condition monitoring data. In order to predict the remaining lifetime in hours, the volume of material that can be worn away from the components must be determined, which together with the wear rate allows the time to be calculated. The wear rate is dependent on the operating conditions, such as contamination and overload, which can be obtained from the machine condition data collected during routine health monitoring of the machinery. As each machine component wears, the approximate material removed can be calculated from the wear rate over each oil change period. Hence, the remaining material to be worn away is calculated which allows the remaining life to be determined. This is the summary of the lifetime estimation strategy, which is discussed in detail below.

The information and calculations required in order to estimate the remaining lifetime of a machine is displayed graphically in Figure 8.5. From this figure, it is evident that 4 items of information are required, consisting of the design life of each component, the new and wear out limits, condition monitoring information and the current component dimension. The design life of the component as well as the new dimensions and wear out limits of each component can be obtained from the manufacturer, where in the case of gears, the design life is generally concerned with surface fatigue. Most manufacturers publish wear limits for components that govern whether a part can be re-used in a rebuild or whether it should be replaced. Condition monitoring information is required to give an insight into the conditions experienced by the machine, including concentration and types of contaminants, load, and the operating hours since the last oil change. The current dimension of each component is a data field that will be updated for each estimate during the life of the machine.

The remaining lifetime estimation strategy involves 4 calculations to be performed before the lifetime can be determined using a fifth calculation. These have been labelled from 1 to 5 in Figure 8.5, to aid with their description. Calculation 1 is concerned with

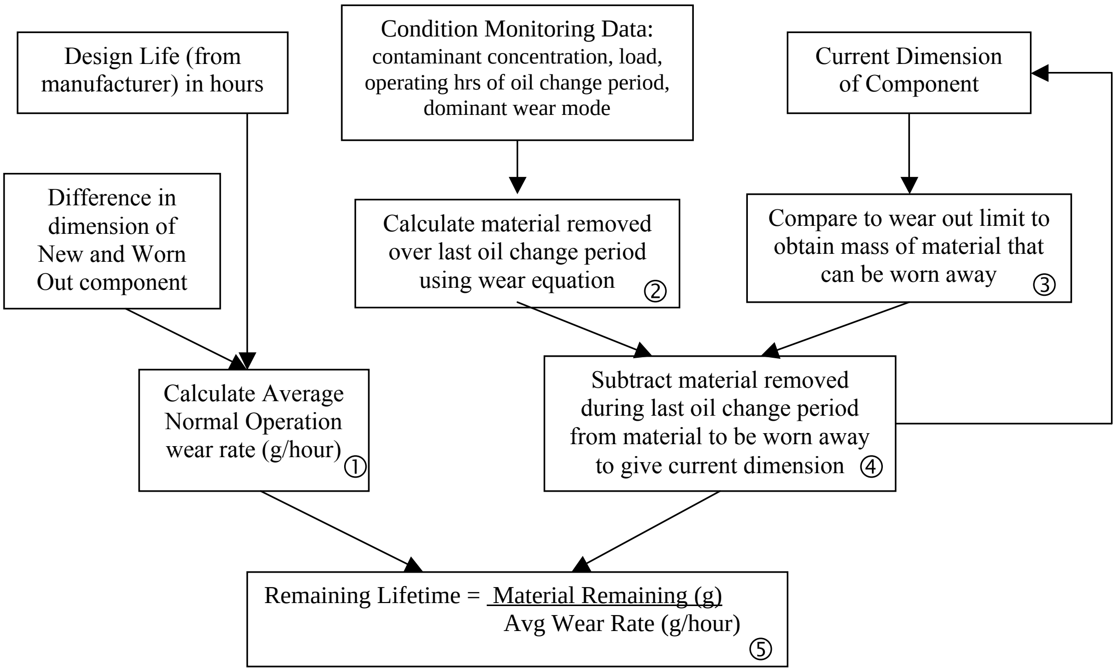


Figure 8.5: *Calculations required to determine machine remaining lifetime.*

determining the average wear rate when the machine is run at normal operation. It is therefore the material loss in grams given by the new and wear out limits of the component, divided by the design lifetime of the component in hours.

The common wear equations of calculation 2 (and discussed in Section 8.2) are used for estimating the volume material loss over the monitoring period, given the core governing factors including load, sliding speed and material hardness, for adhesive and abrasive wear situations.

The third calculation is concerned with determining the amount of material that can still be worn away, given the current component dimension and the wear out limit. Calculation 4 then involves updating the current dimension of the component by subtracting the amount of material worn away during the last oil change period. This method is used to track the approximate mass of material of the component that remains to be worn away before the component exceeds the corresponding wear out limit. The material worn away during each oil change period can therefore be added together using the principal of cumulative damage, to allow the approximate mass of each component to be tracked.

The final step in determining the remaining lifetime of the machine is summarised in calculation 5, which involves dividing the mass of material to be worn away calculated in 4 by the average wear rate expected for the machine, the result of calculation 1. If a certain abnormal wear condition is assumed for the machine, such as a high contaminant concentration which is typical for the operating environment of the machine, then the wear rate of calculation 1 can be substituted with the wear rate of calculation 2. In this case, the second option results in a more accurate life estimation, and if the abnormal operating condition is absent, the estimate is conservative.

8.4 Application of Estimation Strategy

The performance of the strategy for estimating the remaining lifetime of machinery was evaluated by obtaining gear condition data from a laboratory spur gearbox operating under abrasive wear conditions. This test was performed to facilitate preliminary verification of the strategy, in this case, for abrasive wear. The test scenario was chosen due to the common occurrence of contamination in industrial gearboxes, resulting in premature failure from abrasive wear.

The conditions of the test were such that the gearbox was operated at 80 % rated load for the duration of the test. The gearbox was operated initially for 100 hours to allow for the transition from wear-in to normal operation to occur. The lubricating oil was changed at approximately 45 hour intervals, allowing the gears to be weighed and fresh oil and contaminant added, for a test duration of 141 hours as shown in Table 8.3. The contaminant used for this test was silicon dioxide at approximately 5000 ppm (w/v) concentration, with a random particle size range of 8 to 50 microns. Silicon dioxide is a common contaminant of dust, and is a hard abrasive compared to the gear materials of 147 and 154 Brinell Hardness for the small and large gears respectively. A high concentration of contaminant allowed the gears to wear at a high rate compared to that of normal operation, while also preventing the sheer-mixed layer from forming which would result in an additional variable in the wear equation. The

Table 8.3: *Abrasive wear test results.*

Test Interval	Operating Time (hrs)	Gear Mass (g)	Pinion Mass (g)	Contaminant Concentration (ppm, w/v)	Change in Gear Mass (g)	Change in Pinion Mass (g)
Start	0	113.3467	48.7918			
1	49.5	113.0156	48.4967	2988	0.3313	0.2951
2	93.2	112.5161	48.0330	5058	0.4995	0.4637
3	141.2	112.0204	47.5673	4683	0.4957	0.4657

hardness of the wearing gear teeth surfaces can therefore be assumed to be similar to that of the bulk gear material.

The remaining lifetime estimation strategy as outlined in Section 2.5.2 utilises the well established wear equations in order to calculate the material removal volume for abrasive and adhesive wear. According to these equations, the wear volume is directly proportional to sliding distance and therefore operating time. Also, due to the low concentrations of contaminant, the wear volume is linearly dependent on the concentration [119], as the contact area between the two wearing surfaces is not saturated with contaminant particles.

The raw experimental gear mass loss data of Table 8.3 can therefore be used to calculate the specific gear and pinion mass loss (SGML and SPML respectively) in grams, referenced per hour of operation and per ppm of contaminant concentration. This information is shown in Table 8.4. The average specific mass loss of each gear was calculated to be 2.24×10^{-6} and 2.06×10^{-6} g/hr$\times$ppm for the gear and pinion respectively.

The hardness of the gears was measured using a ball indenter, and were found to have a Brinell hardness of 147 and 154 for the pinion and gear respectively. The gears were also measured using a vernier calliper, to allow the non-wearing weight of each gear to be determined. The solid non-wearing mass (the mass of the gear excluding the

Table 8.4: *Experimental specific gear mass loss results.*

Test Interval	Specific Gear Mass Loss (g/hr×ppm)	Specific Pinion Mass Loss (g/hr×ppm)	Difference of SGML to Average SGML (%)	Difference of SPML to Average SPML (%)
1	2.2402×10^{-6}	1.9954×10^{-6}	0.20	-2.93
2	2.2617×10^{-6}	2.0996×10^{-6}	1.16	2.14
3	2.2053×10^{-6}	2.0718×10^{-6}	-1.36	0.79

teeth) of the pinion and gear was found to be 42.83 g and 105.38 g, respectively, using a density of 7850 kg/m^3. The lubricant used throughout the test including during the wear-in phase was Shell Tivela S320, which is a non-extreme pressure ISO VG 320 oil (at 40°C). Although the bearings are generally splash lubricated from a shared oil reservoir with the gears, the seals of the bearings was not removed for this contamination test, resulting in the bearings being grease lubricated.

The gears experienced significant wear during this abrasive wear test as is evident in the teeth profiles shown in Figure 8.6. As the gear teeth were offset by approximately 0.5 mm, the original gear profile is visible on one side (b). The unsymmetrical tooth profile due to wear is clearly visible in photo (a). The wearing surface of both gears was worn to a dull smooth appearance, as was expected from the test conditions.

The test demonstrated that the abrasive wear equation can be used successfully to determine the material loss due to abrasive wear with good accuracy. However, when applying this strategy to machines to estimate the remaining lifetime, the accuracy will depend on the uncertainty contained in the wear coefficient and sliding speed. These entities were not analysed in this test, as the material loss was known while the unknown was made up of the wear coefficient and sliding speed. Further testing has been planned to investigate the accuracy that can be expected when determining the remaining lifetime using the presented strategy.

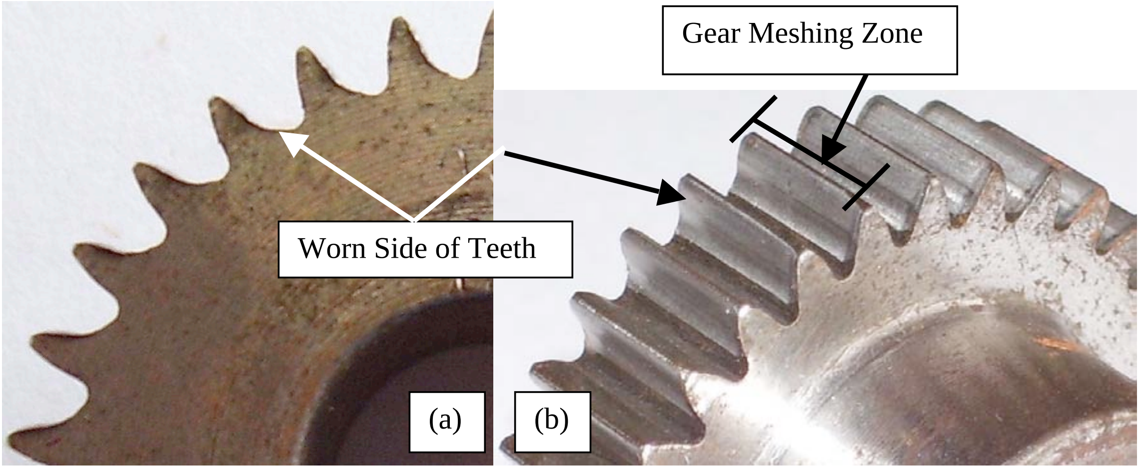


Figure 8.6: *Gear tooth profiles — post test (a) end view, (b) original profile visible due to offset in gear mesh.*

8.5 Software Implementation

The knowledge base was implemented in the completed expert system code, and positioned in the main menu of the combined analysis expert system. The remaining lifetime menu has been designed as a single input-output screen as shown in Figure 8.7.

The remaining lifetime estimation algorithm has been included in the expert system package to utilise the potential benefits of this feature, as well as for research purposes to further improve the current algorithm. As the code is still considered in the development phase, it has not been fully integrated into the expert system in terms of data porting from the expert system results to the remaining lifetime algorithm. It is therefore necessary to manually enter the required information for each component or sub-component analysis. The required information is composed of the amount of material than can be worn away, as well as the entities of the relevant wear equation. This information could be stored in a text file and analysis performed automatically, as the analysis of vibration, oil and wear particle data. The current code also has no provision for tracking the remaining lifetime data for each component, as shown in Table 8.3 for example. The output of the code could however be written to a text file in a spread sheet compatible format to allow more efficient data management. It is anticipated that these improvements would be performed when compiling the code into a prototype for commercialisation.

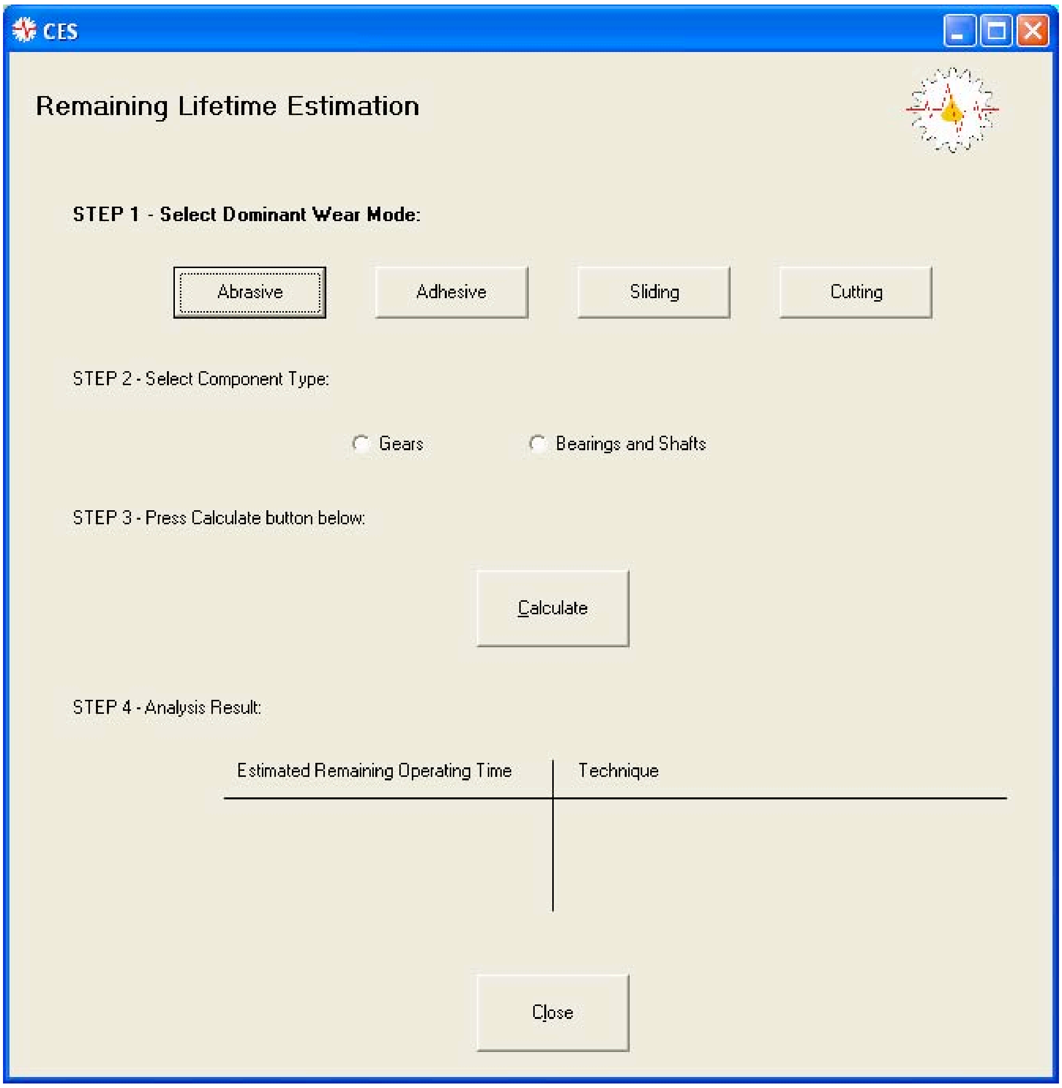


Figure 8.7: *Remaining Lifetime Estimation menu.*

8.6 Summary

The strategy for estimating the remaining lifetime of a machine presented in this chapter allows the condition of each component to be tracked, as well as updated according to the actual operating conditions experienced. This is an alternative approach to statistical methods that rely on past failure data to predict the possible failure lifetime of the machine. The benefits of the presented strategy include the ability to assess the condition of each component within the machine using the principal of cumulative damage, to determine those components that require replacing and those that can be re-used before an overhaul. This aids maintenance departments in optimising and management of spare part inventories.

The wear test performed using a spur gear laboratory test rig demonstrated that the strategy can be used successfully to predict the remaining lifetime of a gearbox. The test results confirmed that the assumptions of constant wear rate assumed by the wear equation was valid over the oil change period, as well as a constant sliding speed, abrasive wear coefficient and a linear relationship of wear rate and contaminant concentration.

This strategy represents an innovative approach for remaining lifetime estimation, that complements machine condition monitoring by using oil analysis to assess the operating condition of the machine. Compared to statistical lifetime estimation methods, this strategy allows easy implementation, as most of the required input information should already be available. This development therefore represents a great potential for industry, by providing a systematic approach to remaining lifetime estimation using information that in most cases is readily available.

Chapter 9

Discussion

9.1 Project Organisation

The primary objective of the research project was to correlate the fault detection and diagnosis ability of the vibration, oil and wear debris analysis techniques. The possibility of correlation has been reported in literature, where case studies of certain machine failures were analysed using vibration, oil and wear particle analysis. While correlation in the test cases was demonstrated, other findings noted contradicting conclusions resulting from the condition monitoring techniques. Due to the complexity and conflicting nature of existing research, the information cannot be applied to condition monitoring in industry and therefore has limited usefulness in practical application. An investigation into the complementing ability of the three techniques was therefore crucial to verify that the techniques can indeed be correlated. Once the proposition of correlation was verified, an extensive study was conducted to investigate the fault detection and overlap of the techniques for the specific failure modes of equipment found in the mining, mineral processing and manufacturing industries.

It was decided that the objective of correlating the three condition monitoring techniques should result in a comprehensive list of machine faults, as well as an analysis that utilised additional unused pieces of information from each technique to provide useful hints regarding machine health. This comprehensive analysis possible by collating results from different techniques has been found in numerous case studies [1, 2, 71], where authors have commented on the complementing fashion of vibration, oil and wear particle analysis. Detailed study of the fault detection ability of each technique lead to the conclusion that each technique could diagnose some faults in detail, while the detection of others was vague or uncertain. Examples of these uncertain detected faults are excessive looseness detected by vibration analysis, wear modes detected using wear particle analysis, and particle counts of oil analysis. These abnormal operating conditions can be diagnosed, but do not lead directly to a faulty component. However, when the detected abnormal operating conditions detected by each technique are combined, these conditions may be able to be linked to other faults detected with greater certainty. It is therefore possible to assign the cause of all abnormal operating conditions to detected or possible faults, thereby generating a comprehensive machine health report.

Once the primary expert systems (VES and OWDES) were completed, the respective output reports could be correlated into one set of machine faults. This was performed using the developed correlation of results algorithm. The development of this algorithm included an investigation of the possible results conflicts that could occur.

The root-cause analysis algorithm was developed to allow faults to be categorised as primary or secondary faults, where a primary fault is a cause of one or more secondary faults. This categorisation of faults is useful to maintenance technicians, as the prevention of primary faults will also negate the initiation of the inherent secondary faults. The early detection of primary faults and timely replacement of affected components is therefore critical in reducing the costs associated with the secondary faults occurring. The root-cause analysis algorithm was developed by studying the possible failure scenarios and interactions between bearings, gears, belts, couplings and centrifugal pumps. This information was structured into flow charts (shown in Appendix Section E) that were implemented as the analysis algorithm. This algorithm development procedure was selected over neural network type AI development as the primary and secondary causes of failure can be identified through machine failure knowledge. While neural networks are useful in identifying the relationship between inputs and outputs, this relationship is already known. The algorithm development therefore consisted of identifying all possible failure mechanisms and including these in the knowledge base.

The developed analysis algorithms were each implemented in an expert system by coding into If-Then-Else loops and the inclusion of a user interface to allow stand-alone operation on any PC using the Microsoft Windows type operating systems. Due to the project objectives stating that the finished system should be capable of being used in a commercial environment, the Visual Basic (VB) programming language was selected, as it allows easy development of interface menus and screens, as well as the inclusion of help menus throughout. Additionally, the VB menus coincide with the general MS Windows operation and look, which aids in usability.

Upon completion of each analysis algorithm, laboratory and industry data was used to verify the correct operation of the developed expert system. The fault diagnosis analysis algorithms testing procedure is discussed in Sections 5.3 and 6.3, while the testing of the correlation of results and root-cause analysis algorithms are discussed in Section 7.3. The project organization outlined here allowed the realisation of the project objectives, and for the first time the correlation of vibration, oil and wear particle analysis techniques using an AI system capable of being used in a maintenance laboratory.

9.2 Project Challenges and Solutions

The progression of the research project faced numerous significant challenges which were critical in order to meeting the project objectives. The first challenge originated from the varying success of correlation reported in literature, which questioned the validity of the project objective of correlating the vibration, oil and wear particle analysis techniques. The initial investigation into the correlation was therefore begun by analysing case study type failures of experimental gearbox test rigs to verify that the techniques indeed complement each other for fault diagnosis. Although this investigation verified that the techniques can complement each other in fault detection, a strategy for dealing with conflicting analysis results as reported in literature [2] had to be developed. In order to develop an AI system for integration of the MCM techniques in an objective manner, it was decided to study the fault detection and diagnosis ability of each individual technique in an extensive machine failure analysis.

The data used to carry out the in depth correlation analysis was derived from case studies sourced from literature, as well as real life condition monitoring data. However, the acquisition and processing of data from industrial machinery presented another difficulty. As condition monitoring and maintenance information can reveal machinery inventory, operating strategies and management practices, this information is generally classified as confidential. Due to fears of this information being used by external financial reviewers or competition, large public companies are very hesitant to provide this data to external institutions. Furthermore, the participating industrial partner not only had to be willing to share information with JCU, but also operate vibration, oil and wear particle analysis programs for their equipment. While numerous large mining and mineral processing companies were identified to operate a suitable condition monitoring program, only one was willing to participate in this research project. The acquired data was however sufficient to test the developed expert systems, while expertise in the machine health diagnosis were also made available.

The difficulty of obtaining data from industrial machinery was also evident in obtaining data of sufficient quality in terms of the abnormal operating condition causing failure (primary fault), and operating conditions. Variability in machine duty cycle were found to originate from differing load cycles due to operator shift change and seasonal throughput. The data quality was also affected by inherent communication difficulties between plant maintenance departments and MCM laboratories, resulting in laboratories not being properly informed of machinery repairs or exchanges. While these issues were resolved by careful data trend analysis and additional operator information, it was concluded that data obtained from experimental test rigs would be more reliable for correlation investigation, as failure modes can be initiated independently.

9.2.1 Correlation of Machine Condition Monitoring Techniques

The correlation investigation was performed in order to verify the complementing features of fault detection by the monitoring techniques as reported by studies in literature.

This investigation was conducted as discussed in Section 3.2, and was followed by an extensive investigation of the fault detection abilities of vibration, oil and wear particle analysis. This proved to be a key component of the research project, forming the foundation for the correlation of results knowledge base.

The extensive investigation into the correlation of the three analysis techniques was conducted by analysing the fault detection abilities of each individual technique. The investigation included the compilation of a list of all possible fault indicators provided by each analysis technique, using case studies from literature, as well as laboratory and industry machine condition monitoring data. The generated faults table is shown in Figure 7.4. It was revealed that fault indicators can be organised into two categories: firstly direct fault detection, and secondly, general indicators for a particular fault type. The first classification includes detection typical for vibration analysis, where unique frequencies can be diagnosed to a failure of a certain component. General indicators however, consist of the detection of a fault condition, but which cannot be linked to any particular component without additional information. This kind of fault detection includes haystacks and raised baseline of vibration spectra, and typically all of the detected faults of oil and wear particle analysis. Although elemental analysis can help in predicting which component is undergoing failure, this requires knowledge about the machine construction and will be accurate only when machine components have unique constituent elements.

As shown in Figure 7.4, the direct fault detection ability overlap between each technique is very limited. The only fault that can be directly detected by vibration and oil and wear particle analysis is gear misalignment, and a gear operating fault (when wear particle analysis detected welding). The predominant fault indicators of oil and wear particle analysis are wear modes, contamination and lubricant related faults including viscosity and dielectric specifications. It was also concluded that oil and wear particle analysis are unable to detect installation faults such as misalignment and bearing damage caused by improper handling, until abnormal wear is produced as a result. However, lubricant faults such as foreign particle contamination or incorrect viscosity can be detected by oil analysis, but not with vibration analysis until the condition results in component damage. It was therefore evident that successful and reliable early fault detection could only be performed when vibration, oil and wear particle analysis results are correlated into one concise machine health report.

The automated analysis of machine condition data using an integrated approach requires the prior development of a knowledge base containing the appropriate analysis and reasoning logic. The difficulty in the development of this knowledge base was concerned with the possible conflicts in analysis results between the vibration analysis and oil and wear particle analysis knowledge base outputs. Literature research and consultation with experts of the machine condition monitoring field revealed that these conflicts do not occur frequently, and are generally concerned with deciding whether a fault is present or not present in a machine, whether a fault is severe or in initiation, and identifying the primary/major fault if more than one fault has been detected. Further research and consultation with industry representatives concluded that these conflicts could be resolved as follows:

- If a fault is detected by only one technique, then the detected fault is passed to the correlated faults output list.
- When the severity of a fault is conflicting, the more severe result is passed to the correlated faults output list.
- When more than one fault is detected, a root-cause analysis can be used to separate primary and secondary faults.

Due to the differing fault detection ability of vibration and wear particle analysis, it is possible that one technique can detect the developing fault while the other technique does not. This scenario has been reported by Maxwell and Johnson [1], and it has therefore been concluded that if a fault is detected by one technique, it will be passed into the correlated list of machine faults. A similar approach was taken when the severity information of a fault is conflicting. Here a decision is made according to increased safety, and the result passed to the correlated fault list is the more severe one. This was chosen because a severe result from the expert system allows operators to perform additional tests to confirm the fault severity status. Furthermore, as unexpected failure is generally more expensive than premature component exchange, a cautious approach to fault severity is justified. The identification of primary and secondary faults, when numerous faults are detected in an analysis, can only be performed using a dedicated root-cause analysis knowledge base and algorithm, containing possible machine failure mechanisms.

The completion of the correlation investigation was followed by an analysis of machine failure mechanisms in an attempt to develop a root-cause analysis knowledge base. It was found that in order to perform root-cause analysis, structural information about the machine must be known, including the positions of all of the machine components. This information is used to relate primary failures of one component to secondary failures of another, due to close proximity. The primary failure of a bearing supporting a gear drive shaft can result in gear misalignment of that gear, as the two components are in close proximity, for example. In this case, the gear can be considered to be dependent on the correct operation of the bearing, such that a primary failure in it will result in a secondary failure of the gear.

The study of possible failure mechanisms of gearboxes lead to the development of a root-cause analysis knowledge base, that can be used in conjunction with the correlation knowledge base. The results from the study revealed that machine structural information can be used effectively to combine the general fault indicators with the directly detected faults. When the general fault indicators can be used for fault detection in this way, the effective overlap between the VES and OWDES is greater than when considering only the directly detected faults. For example, although it is not possible to infer which component is wearing out if severe sliding wear was detected, knowledge about the machine design reduces the possible choices. This is the type of overlap between vibration and oil analysis techniques that has been confirmed by case studies such as [1, 73]. In each case, the analyst had knowledge about the machine construction and visual inspection of the worn components before discussing the fault detection indicators that each technique had provided.

The extensive investigation into correlation and root-cause analysis allowed the integration of vibration, oil and wear particle analysis using a systematic approach for the first time, by the development of the knowledge bases and corresponding analysis algorithms. The methodology for dealing with possible conflicting conclusions from the three condition monitoring techniques discussed above, provides an effective strategy for repeatable and reliable automated fault detection. Including information about machine construction proved to be the crucial element necessary for relating the general fault indicators to directly detected faults, which was found to increase fault detection and diagnostic ability considerably.

9.2.2 Artificial Intelligence System Development

The AI system has been included in the project to allow automated processing and interpretation of the large volume of data required in a combined vibration, oil and wear particle analysis condition monitoring program. In order for the system to perform this task, it requires the integration of knowledge bases into the chosen AI type system, an expert system structure as discussed in Section 3.3.1.

The development of an AI system for complete correlated machine condition analysis was commenced with individual expert systems for vibration analysis, and oil and wear particle analysis. This allows all faults, directly detected and general fault indicators, to be identified and stored in an organised manner. While expert systems for these operations have been developed, the available systems have significant limitations which hinders the conclusions to be correlated. The existing systems do not use sufficient condition monitoring data to allow faults to be detected with sufficient accuracy, and machine faults are generally reported using only directly detectable faults while general fault indicators are not mentioned. The interface also limits the available systems, as the analysis is typically carried out using an on-line questionnaire process, with results finally only displayed on-screen. These limitations prompted the need for expert systems to be specially developed that feature good fault detection for a broad range of machinery, the reporting of all faults and fault indicators, and an interface that allows results to be stored in a text format.

The developed expert systems for individual technique analysis were then integrated into one system by the development of a correlating expert system, incorporating the knowledge base for correlation and root-cause analysis. The integration of results by the individual expert systems was made possible by a three step process. Firstly, all faults detected by all techniques were recorded in the comprehensive machine health report, which included directly detected faults. Secondly, all faults only detected by one technique were also added to the health report, using the reasoning discussed in Section 9.2.1. The third step is the linking up of general fault indicators and performing the root-cause analysis, where the general fault indicators can be assigned to the detected faults. This execution process was developed during the correlation and root-cause analysis knowledge base development, then implemented into an expert system.

The development of the integration expert system revealed that while faulty components could easily be identified by the algorithm, conflicting conclusions of the analysis techniques could still occur regarding the type of defect of the faulty component. This difficulty was solved by calculating a confidence factor for each detected fault and defect type, and using the conclusion with the highest confidence factor to determine the likely fault. This strategy was tested and found to efficiently resolve possible conflicts in analysis conclusions, while also providing the operator with a gauge for the confidence with which the fault was diagnosed.

9.2.3 Development Capabilities and Application

The developed AI system is able to meet the research project objectives in both analysis ability as well as software usability. The outcomes of the research project include an analytical model for the correlation between vibration, oil and wear particle analysis, which unlike previous discrete case-study type attempts for a particular machine component, is capable of diagnosing typical faults in a wide range of machinery in an automated manner. The analysis algorithms provide fault detection and diagnosis for the majority of machines found in the mining, mineral processing and manufacturing industries, including spur gear reductions, journal and roller bearings, pumps, timing and V belts, as well as couplings.

The system testing with laboratory and industry data demonstrated that the integrated analysis approach allows machine condition to be determined more accurately than by using the analysis techniques independently. This coincides with conclusions made by the available literature, and presents new opportunities for industrial operations to improve the efficiency of their maintenance programs by implementing the developed AI system. As the system was designed for use in a commercial environment, it represents a capable prototype that could be developed further into a marketable product. While the analysis algorithms and user interface are fully functional, improvements could be made in terms of more efficient software code, as well as refined graphical layout of the menus.

The developed AI system can be used to monitor most equipment used in industry, although the analysis algorithms are not suitable for monitoring turbines, reciprocating engines and compressors, and electric motors. The same analysis techniques can be used to monitor this equipment however. While these machines are also commonly used in industry, they were not included in the analysis algorithms as the research project focused on the fault detection of gearboxes and the external equipment that could impose a gearbox failure, such as belts and couplings. As misalignment, imbalance and bearing faults can be detected by the AI system, turbines, and electric motors can be partially monitored, although electrical faults of motors will not be detected. Reciprocating engines and compressors have several factors making condition monitoring difficult, including complex vibration signals, and possible high soot levels in lubricating oils (especially diesel engines). These complications make condition monitoring using the integrated system difficult, as quality data is required for both vibration, oil and wear particle analysis. Furthermore, the current system can still diagnose many faults in these machines, and demonstrates the benefits of an integrated machine condition monitoring system.

9.2.4 Remaining Lifetime Estimation

The ability to determine the remaining lifetime of a machine is a critical component of an efficient machine condition monitoring program. The strategy outlined in Chapter 8 has been developed with a view to monitor the life of gearboxes, as demonstrated by the experimental data in Section 8.4. However, the strategy could also be applied to other machine components, provided that the input information is available as discussed in Section 8.3.

While the developed remaining lifetime estimation strategy can be used for most machine components, two assumptions govern the ability of this approach to predict the machine remaining lifetime. The first assumption is that every component has only one critical surface which experiences material removal or wear. The second assumption is that the dimension of the component does not depend on external factors such as interference fits, but only on wear. The strategy can therefore be applied to components such as gears, but not for roller or journal bearings where the internal dimensions of roller to race clearances depend on the interference fits of the housing and shaft, unless these are known.

The common wear equations have been used to allow the material removal to be estimated, although these may give varying accuracy depending on whether the wear coefficients can be obtained for the specific gearbox. The wear equations have been found to contain high statistical scatter, highlighting the need to determine the corresponding wear coefficients with sufficient accuracy. The wear coefficients may be available from the machine manufacturer. However, they could also be derived by in-house experiments on the particular gearbox by measuring the material loss of the components to be monitored over several oil change periods. If none of this is feasible, wear coefficients could either be adopted from case studies using similar equipment, or from laboratory tests using the same materials and equivalent load in wear test apparatus.

The design life is the life determined by the manufacturer taking into account the typical operating conditions such as operating speed and load, as well as a suitable maintenance strategy. Fundamental gearbox design theory would base the design life on the surface fatigue life of the gear surfaces, and assuming the absence of contamination, or other component faults. The design life typically does not focus on the material removal at the wear-in, normal and wear-out stages. As the wear-in stage is a normal process that occurs with any new gear system, the machine life is not reduced more rapidly during wear-in than normal wear, even though the material removal may be greater during wear-in.

The wear-out limits for machine components are generally available from the manufacturers, which are typically used to grade a component as to the suitability for continued use in a machine overhaul or rebuild operation. These dimensions can be used in this strategy to classify the end of the operating life of the component. However, as it would be expected that the machine should still be operating when the component reached the wear out limit, the determined remaining lifetime will be a conservative estimate in most cases.

The remaining lifetime experiment as discussed in Section 8.4 relied on the assumption that the hardness of the wearing surface was consistent with that of the bulk gear. Although this was a valid assumption for the particular test as the gears were not hardened, it would not apply to surface hardened gears. For this case, the strategy would need to account for the change in hardness encountered when the material thickness of the hardened layer was removed. This modification would have to be accounted for in calculation 2 (of Figure 8.5), where the lower hardness value would need to be used once the layer was worn off. Similarly, work hardening of the wearing surfaces could cause the actual hardness to vary from the bulk hardness. However for abrasive wear, work hardening is generally not observed due to the rapid material removal.

The spur gear test performed as outlined in Section 8.4 was used to demonstrate that the remaining lifetime strategy can be applied to real machines. This test was concerned with measuring the material loss over three oil change intervals, with the contaminant concentration, operating time being known, and constant load. Using the abrasive wear equation, the resulting entity determined was composed of load, sliding speed and abrasive wear constant. The wear equation used to calculate material loss due to abrasive wear assumes that the wear rate is constant over each oil change period, accounting for contaminant concentration, load and operating time. The results shown in Table 8.4 demonstrate that when the test results were corrected for concentration and operating time, with load being constant, the specific material loss was effectively constant with a variability of less than 3 %. This result indicates that the load, sliding speed and abrasive wear coefficient were indeed constant over the test duration. The practical application of this development is that while load is generally not constant for industrial machines, once the sliding speed and abrasive wear constant have been determined for the gearbox, the strategy can be implemented and the remaining lifetime determined with good accuracy.

9.3 Uniqueness of Developments

The analysis algorithms developed for this project were designed to allow the project to be implemented according to the objectives stated in Chapter 3. The correlation of vibration, oil and wear particle analysis has not previously been performed in an organised process, but only in individual case-study type failure investigations. While, discrete expert systems for vibration, and oil and wear particle analysis have been developed for commercial use, these systems are unable to combine information in a correlated analysis.

The investigation into the possibility of correlating the vibration, oil and wear particle analysis techniques was undertaken by performing a series of systematic laboratory tests aimed at comparing the techniques for particular gearbox failure modes. While literature reported the existence of correlation for rolling element bearing failures using a case-study approach, the potential difficulties of integrating these analysis techniques are also reported. The tests conducted as part of this project allowed a knowledge base to be compiled for the fault detection and fault monitoring ability of each technique for both gears and bearings.

The expert systems developed during this project allowed the analysis of the testing data using true correlation of vibration, oil and wear particle analysis techniques by an artificially intelligent system for the first time. This achievement would not have been possible without the initial development of expert systems for individual vibration, and oil and wear particle analysis data, with a common output reporting format that could later be processed by a correlation of results algorithm. Although the concept of utilising expert systems to interpret individual vibration, and oil and wear particle data is not new, the analysis algorithms of these two developed expert systems contain features that enhance fault detection ability compared to those that have already been developed. The VES algorithm has been developed to interpret tri-axial frequency domain, demodulated frequency domain and time domain data, where previous developments relied only on frequency domain data [99]. Similarly, the OWDES algorithm was designed to utilise comprehensive wear particle information provided using either conventionally by consulting a wear particle atlas, or by state of the art laser scanning confocal microscopic images and particle identification expert system [27]. The individual fault diagnosis algorithms are therefore new developments, due to their additional features and improved fault detection capabilities.

The correlation of results and root-cause algorithms are entirely unique developments, as this type of analysis has not previously been performed using AI techniques. Although the concept of correlating vibration analysis with oil and wear particle analysis has been proposed by studies including Troyer and Williamson [2] and Maxwell and Johnson [1], a detailed analysis of exactly how these techniques could be correlated has not been undertaken. The machine condition conclusions that can be obtained using the AI system algorithms therefore extend the capabilities currently available for fault detection and diagnosis, allowing a machine health report to be compiled with unprecedented comprehensiveness.

The success of the AI system in detection and diagnosis of a wide range of equipment was aided by the use of multiple advanced techniques into one system, including quantitative image analysis, fuzzy logic and the use of AI. Qualitative image analysis for wear particle identification and shape description allow acquisition and interpretation of a 3D particle image. This provides improved accuracy over conventional 2D images, as particle features such as surface roughness can be evaluated. Fuzzy logic was incorporated in the confidence factor calculations, to enable the value to be based on the magnitude of several fault indicators. The expert system type AI system was used as a basis for implementing the developed knowledge bases and user interface. The completed AI system has resulted in a novel approach for integrated condition monitoring using vibration, oil and wear particle analysis, featuring numerous innovative developments and data processing techniques.

Research and development on estimating the remaining lifetime of a machine has received limited attention due to the complexity of wear occurring in industrial machines, as well as the difficulty of modelling wear. Although the knowledge base was compiled from commonly accepted wear equations, these were derived from wear machines generally operating in pure sliding wear. These equations were adapted for real machines such as spur or helical gears and rolling element bearings, which predominately operate by rolling.

Due to the typical high statistical scatter in wear situations, remaining lifetime is often predicted using statistical models, which may not be useful for individual machine life prediction. However, these do not provide the ability for updating as condition monitoring data becomes available. The use of wear equations in combination with a correlated condition monitoring approach is a new development, which has the potential for improved prediction accuracy due to the wear taking into account the actual operating conditions of the machine. The predicted lifetime is therefore less dependent on previous machine failure data, which may change due to variation in plant throughput and modifications.

9.4 Benefits of Developments for Industry

The development outcomes of this project contain numerous potential benefits for the maintenance and condition monitoring industry, which will therefore also be an asset to the mining, mineral processing and manufacturing industries. The core objective of the project was to improve the efficiency of conventional machine condition monitoring (MCM) practices by correlating the outcomes of vibration, oil and wear particle analysis. The successful implementation of this project objective allows pro-active maintenance programs to be operated at a new level of effectiveness, while also providing a new basis for further research in the MCM field.

The correlation of analysis results using vibration, oil and wear particle analysis allows improved detection and diagnosis of faults compared to when each technique is used on its own. This finding, as discussed in Section 9.2.3, also corresponds to conclusions of case studies such as conducted by Maxwell and Johnson [1]. The implications of this result extend beyond the improved MCM program to provide secondary benefits to the mining, mineral processing and manufacturing industries. These benefits include improved machine reliability, reduced maintenance costs associated with unexpected failures and secondary damage caused by primary faults, as well as more efficient use of spare parts depots and maintenance personnel. The adoption of AI technology allows the machine to be analysed with only minimal operator input. This reduction in operator time per machine health analysis significantly decreases the effective analysis cost, thereby making MCM available to a broader range of equipment that could not cost effectively be included in the program using conventional methods. Due to the large overall costs associated with plant maintenance in these industries, substantial savings could be realised by implementation of the developed expert systems.

The estimation of remaining lifetime can be of significant benefit to industry as it aids maintenance departments in deciding the number and type of spare parts to keep in stock, equipment service schedules, and repair/replacement strategies. As condition monitoring and proactive maintenance principles are adopted by equipment operators, decisions concerning the efficient operation of machinery are often based on historical failure experience than on the actual machine condition and life expectancy. The integration of a remaining lifetime algorithm in an automated condition monitoring package would therefore be of certain benefit to industry by allowing operators to estimate machine lifetime without extensive knowledge of the subject.

The project developments present advancement on the conventional techniques currently used for MCM in industry, while also providing research with an investigation and correlation strategy for integrating vibration, oil and wear particle analysis into one AI system. The project developments possess the potential to improve the operating efficiency of machinery plant, thereby contributing to increased export earnings for the Australian economy.

9.5 Summary

The project was conducted in a way that the fault detection and diagnosis ability of each technique could be investigated, and later correlated using a specially designed algorithm. This investigation led to the discoveries that the overlap in fault detection between the two techniques is very minimal, and that additional information about the machine condition can be obtained compared to when the techniques are applied individually. The additional information is distilled from the hints of faults that each technique detects, but is unable to assign the abnormal operating condition to any particular component. This analysis was implemented in a root-cause analysis algorithm to allow the complete data analysis and interpretation to be performed by an artificially intelligent system featuring a discrete user-interface, as planned for in the project objectives.

The development of the expert systems for vibration, oil and wear particle analysis represented a critical first step in the quest to correlate these three machine condition monitoring (MCM) techniques. Although expert systems for this purpose have been prepared, the expert systems developed as part of this project are able to process a broader range of input data while presenting the output data in a format that can be processed by the correlation of results algorithm. The development of the correlation of results and root-cause analysis algorithms allows correlated MCM to be performed by an AI system in a repeatable manner for the first time, with numerous benefits to both industry and research.

The developments of this project enable maintenance programs for fixed plant to be operated with a new level of efficiency, allowing the benefits of pro-active maintenance to be better realised. These benefits include increased plant reliability, lower maintenance costs and thus improved financial viability of mining, mineral processing and manufacturing plants. The advances this project presents to the research community are the comprehensive investigation and implementation of correlation knowledge base developed for vibration, oil and wear particle analysis techniques. The findings of this research project present numerous advantages to industry and the economy if implemented instead of the conventional MCM programs commonly used for fixed plant health monitoring.

Chapter 10

Conclusion and Future Work

10.1 Conclusion

This PhD research project focused on improving the accuracy of machine health analyses as well as making this technology available to a broader user base who are not experts in the condition monitoring field. The project aims designated to advance in this area were:

- to develop an artificially intelligent system that analyses and interprets machine condition data
- to develop an algorithm that is capable of assessing machine health using vibration, oil and wear particle analysis techniques in an integrated manner
- to develop an interface for the AI system that:
    1. allows machine condition monitoring to be performed by non-expert staff, and
    2. serves as a usable prototype for possible commercialisation of the developed algorithms
- research the feasibility of and develop an algorithm for determining the remaining lifetime of a gearbox system

These aims were implemented by structuring the project in sub-projects, each targeting part of the objectives above. The completed AI system was tested using a laboratory test-rig and industry sourced data to demonstrate that all of the aims were satisfied. The AI system was developed using the expert system type of machine reasoning, incorporating a number of knowledge bases developed in order to allow machine condition monitoring data to be analysed and interpreted. Knowledge bases were developed for vibration analysis, oil and wear particle analysis, correlated condition monitoring analysis, root-cause failure analysis, and remaining lifetime estimation. The knowledge bases were embedded in an expert system type AI structure as analysis algorithms, while a custom designed user interface ensures that the completed software package can be used by people who are not experts at machine condition monitoring. The user interface also allows the algorithms to be trailed in industry for commercialisation purposes.

The investigation into the feasibility of correlating machine health conclusions obtained from vibration, oil and wear particle analysis revealed that an integrated analysis of the data using the three techniques can indeed be of benefit. Two new benefits were revealed, based on the differing fault detection abilities of each technique. Firstly, an integrated analysis is capable of early fault detection for all possible detectable machine faults, and secondly, faults can be categorised as primary or secondary faults depending on their chronological occurrence. This allows root-cause analysis to be performed, and reveals such useful maintenance information as dominant failure mechanisms and dominant failure causes. This information can be used to order the relevant spare parts in advance, as well as improve the machine operating conditions responsible for causing the majority of failures in order to improve machine operating life.

The research undertaken during this project has resulted in a number of new developments which extend the current knowledge in the machine condition monitoring field, as well as being of benefit to the mining, mineral processing and manufacturing industries. The major developments achieved during this project include:

- The fault detectors for gearbox related faults were analysed for the vibration, oil and wear particle analysis techniques. This study allowed the effectiveness of each technique to be evaluated for the detection and diagnosis of faults possible in geared power transmissions.

- The development of an artificially intelligent software program for analysis and interpretation of machine condition monitoring using either individual or correlated vibration, oil and wear particle analysis techniques.

- The development of an algorithm for root-cause analysis, to allow classification of faults into primary and secondary faults.

- Research into the possible techniques for determining the remaining lifetime of a gearbox, and the development of an algorithm for automated analysis.

The outcomes from this research project have both contributed to knowledge in the condition monitoring field as well as benefiting industry. The study performed into the fault indicators for the three analysis techniques and development of root-cause analysis algorithm is of benefit for the research community by increasing the knowledge of condition monitoring techniques. The completed expert system is a novel development that can provide significant benefits to industry by improving fault detection and diagnosis accuracy.

10.2 Future Work

Although the software package developed during the course of this project is of prototype standard, several modifications and improvements could be performed prior to commercialisation. These include minor improvements to the user interface, and the integration of remaining lifetime into the complete package. The interface modification recommended before commercialisation is concerned with the results layout of the root-cause analysis algorithm. The current table format could be coded into a more graphical flow chart or fault tree layout to improve the user friendliness and general appearance of the menu screen.

The developed combined analysis expert system algorithm is capable of health monitoring of machines commonly used in the mining, mineral processing and manufacturing industries including gearboxes, bearings, fans, pumps, belt drives and couplings. However, the list of supported machines could be increased to cater for the power generation industries, as well as the prime movers of the mentioned industries. This expansion would require turbines, compressors, diesel engines, alternators and electric motors to be added to the analysis algorithm.

The integration of the remaining lifetime section into the remainder of the expert system could be further improved by allowing the remaining lifetime to share the machine specification information available to the fault detection expert system algorithms. This modification would result in less operator interaction required for each analysis, which is of importance if the program is to be used commercially. Similarly, the output of the results could be presented in a text file, or automated spreadsheet file to allow automated tracking of machine component lifetimes, which currently needs to be done manually using the outputs of the program.

The remaining lifetime algorithm would also benefit from further research and testing to both verify the ability of the algorithm in a range of scenarios, as well as provide guidance for operators for choosing an appropriate wear coefficient. As the accuracy of the lifetime estimate depends on the wear coefficient, research into the development of techniques to determine the correct wear coefficient without tedious tests or machine dismantling would be of great benefit to industry and operators of the remaining lifetime feature.

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Appendix A

Bearing & Gear Fault Frequencies

A.1 Rolling Element Bearing Fault Frequency Equations

The fault frequencies generated by rolling element bearings are:

Ball Spin Frequency $= S[\frac{P}{2B}][1 - (\frac{B}{P})^2(cos\phi)^2]$

Ball Pass Frequency Outer $= S[\frac{N}{2}][1 - \frac{B}{P}cos\phi]$

Ball Pass Frequency Inner $= S[\frac{N}{2}][1 + \frac{B}{P}cos\phi]$

Fundamental Train Frequency $= S[\frac{1}{2}][1 - \frac{B}{P}cos\phi]$

where

- S is the shaft rotation speed in Hz,
- N is the number of rolling elements,
- B is the rolling element diameter,
- P is the pitch diameter,
- ϕ is the load angle of the bearing.

These formulae are theoretical, and deviations can occur if slippage or significant thrust loads are encountered [51].

A.2 Spur Gear Fault Frequency Equations

The frequencies emitted by spur gears consist of the gear mesh frequency (GMF) and the hunting tooth frequency (HTF). Harmonics of the GMF may also be observed depending on the condition of the meshing gears. The gear mesh frequency is due to the number of teeth passing each other per second, which is described by the following formula:

$\mathrm{GMF} = T \times S$

where

- GMF is the gear mesh frequency in Hz,
- T is the number of teeth,
- S is the rotational speed of the gear.

This equation also holds for worm gears, where T equals the number of flights on the worm gear, and S the speed of rotation of the worm gear [47].

The GMF can be generated if the number of teeth on each meshing gear has a common factor other than 1, and one gear is eccentric. Every Nth tooth on the good gear can be worn by the eccentric gear, where N is the common factor [47]. This repeated wearing of gear teeth causes the Nth cycle of gear mesh frequency to be higher in amplitude than the other cycles. This phenomenon is called preferential wear. A Fourier analysis of the vibration spectrum will yield the inverse fractional gear mesh frequency, being equal to 1/N. If the gears have a common factor not equal to a prime number, the fractional gear mesh frequency could occur at the reciprocal of the common factor or prime factors of the common factor.

The hunting tooth frequency occurs when the same teeth of two gears come into mesh. The HTF is generally not observed on spectral analysis as the frequency is very low. The formula for the HTF is:

HTF= $\frac{S}{U}$

where

- HTF is the hunting tooth frequency in Hz,
- S is the rotational speed of the gear,
- U is the uncommon factor of the gear mesh.

Appendix B

Laboratory Test-Rig — Test Conditions Summary

B.1 Spur Gearbox Tests

Table B.1: *Normal Operation Test.*

Test Condition	Quantity
Duration of Test (hrs)	120
Number of Oil Samples	11
Number of Vibration Data Samples	11
Lubricant	Shell Tivela S 320
% Rated Load	80
Operating Oil Temperature (∘C)	48-55
Gearbox Components Replaced Prior to Test	Gears, bearings (63001), shafts

Table B.2: *Constant Overload Test.*

Test Condition	Quantity
Duration of Wear-in period (hrs)	133
Duration of Test (hrs)	109
Number of Oil Samples	6
Number of Vibration Data Samples	6
Lubricant	Shell Tivela S 320
% Rated Load During Wear-in	80
% Rated Load During Test	125
Operating Oil Temperature ($\circ$C)	47-50
Gearbox Components Replaced Prior to Test	Gears, bearings (63001)

Table B.3: *Cyclic Overload Test.*

Test Condition	Quantity
Duration of Test (hrs)	80
Number of Oil Samples	8
Number of Vibration Data Samples	8
Lubricant	Shell Tivela S 320
Operating Oil Temperature ($\circ$C)	52-67
% Rated Load	120-160
Gearbox Components Replaced Prior to Test	Gears, bearings (63001)

Table B.4: *Contamination Test.*

Test Condition	Quantity
Duration of Test (hrs)	162
Number of Oil Samples	10
Number of Vibration Data Samples	10
Lubricant	Shell Tivela S 320
% Rated Load	80
Operating Oil Temperature ($\circ$C)	34-41
Gearbox Components Replaced Prior to Test	Gears, bearings (63001), shaft seals

Table B.5: *Bent Shaft Test.*

Test Condition	Quantity
Duration of Test (hrs)	293
Number of Oil Samples	17
Number of Vibration Data Samples	17
Lubricant	Shell Tivela S 320
% Rated Load	80
Operating Oil Temperature ($\circ$C)	40-46
Gearbox Components Replaced Prior to Test	Input shaft (bent), gears, shaft seals

B.2 Worm Gearbox Tests

Table B.6: *Normal Operation Test.*

Test Condition	Quantity
Duration of Test (hrs)	664
Number of Oil Samples	4
Number of Vibration Data Samples	4
Lubricant	Shell Tivela S 320
% Rated Load	80

Table B.7: *Normal Operation Test.*

Test Condition	Quantity
Duration of Test (hrs)	166
Number of Oil Samples	4
Number of Vibration Data Samples	4
Lubricant	Shell Tivela S 320
% Rated Load	80
Contaminant Concentration (ppm)	15,000

Table B.8: *Normal Operation Test.*

Test Condition	Quantity
Duration of Test (hrs)	470
Number of Oil Samples	4
Number of Vibration Data Samples	4
Lubricant	Shell Tecoma 68
% Rated Load	80
MH300.29 Iron Particle Concentration (ppm)	15,000

Appendix C

Vibration Analysis Algorithm Flow Charts

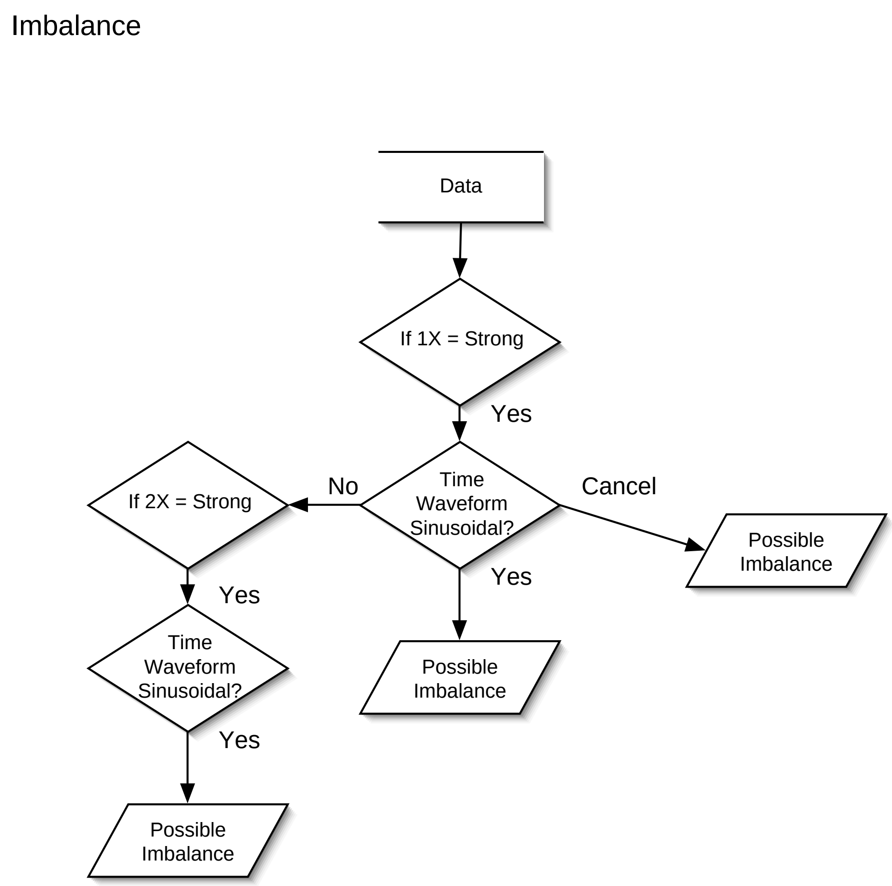

Figure C.1: *General Shaft Imbalance.*

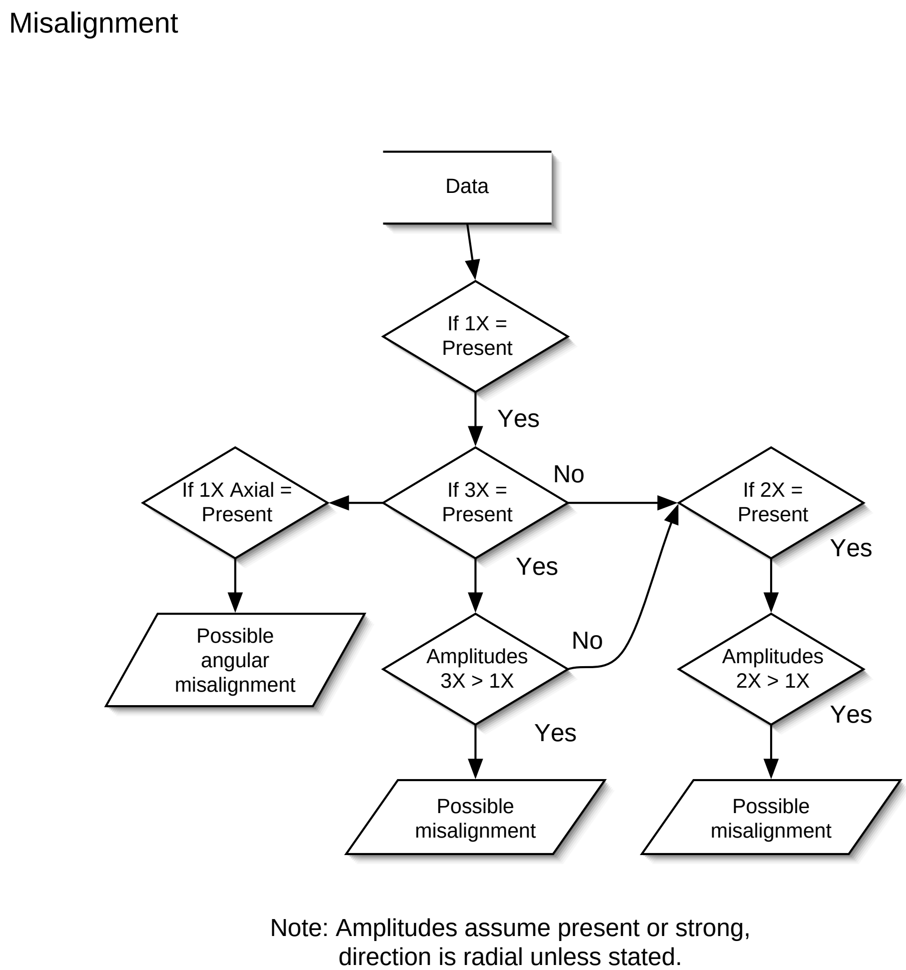

Figure C.2: *General Shaft Misalignment.*

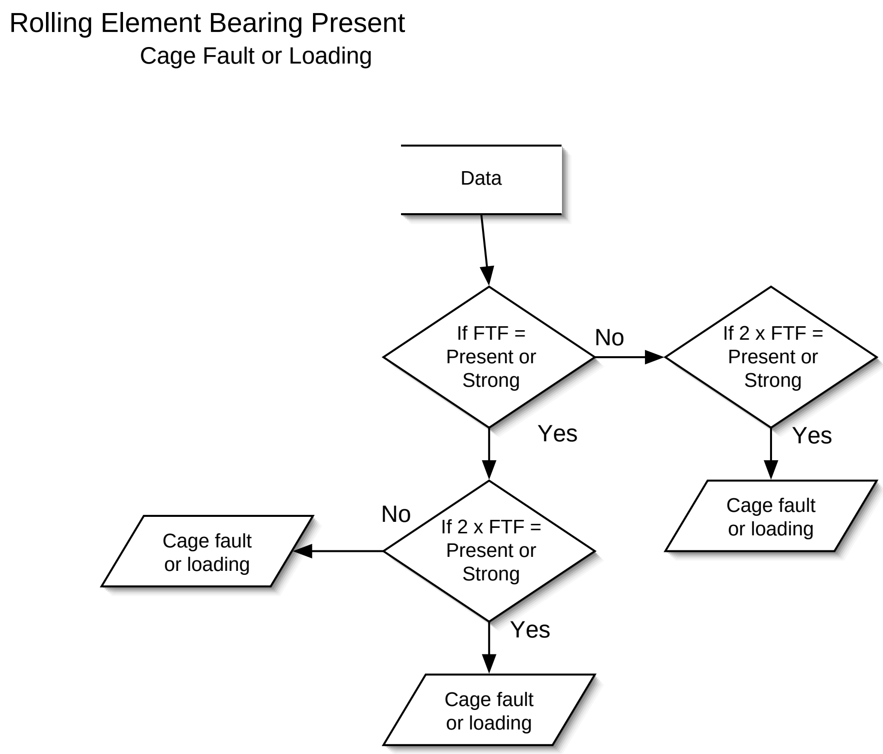

Figure C.3: *Rolling Element Bearing — Cage Fault or Loading.*

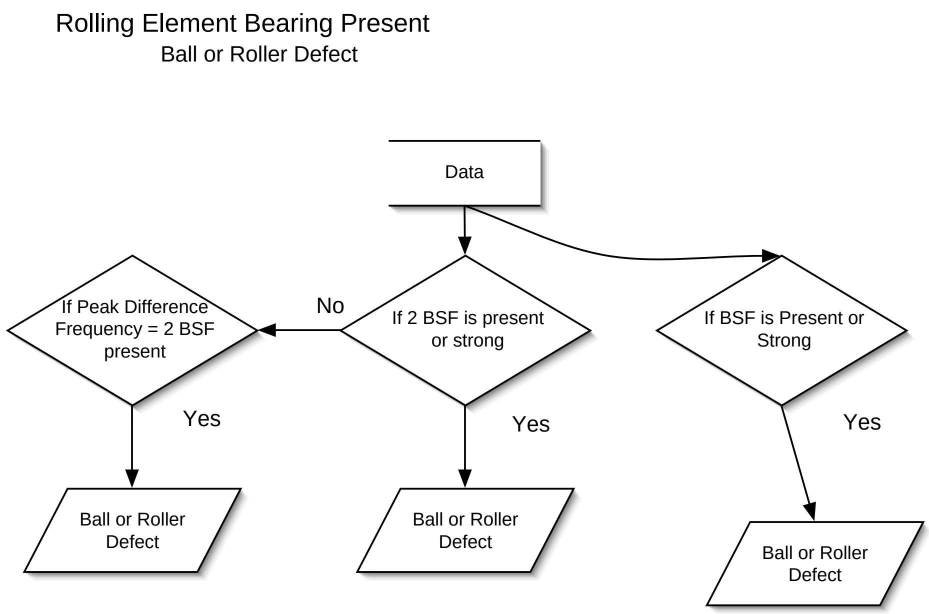

Figure C.4: *Rolling Element Bearing — Ball or Roller Defect.*

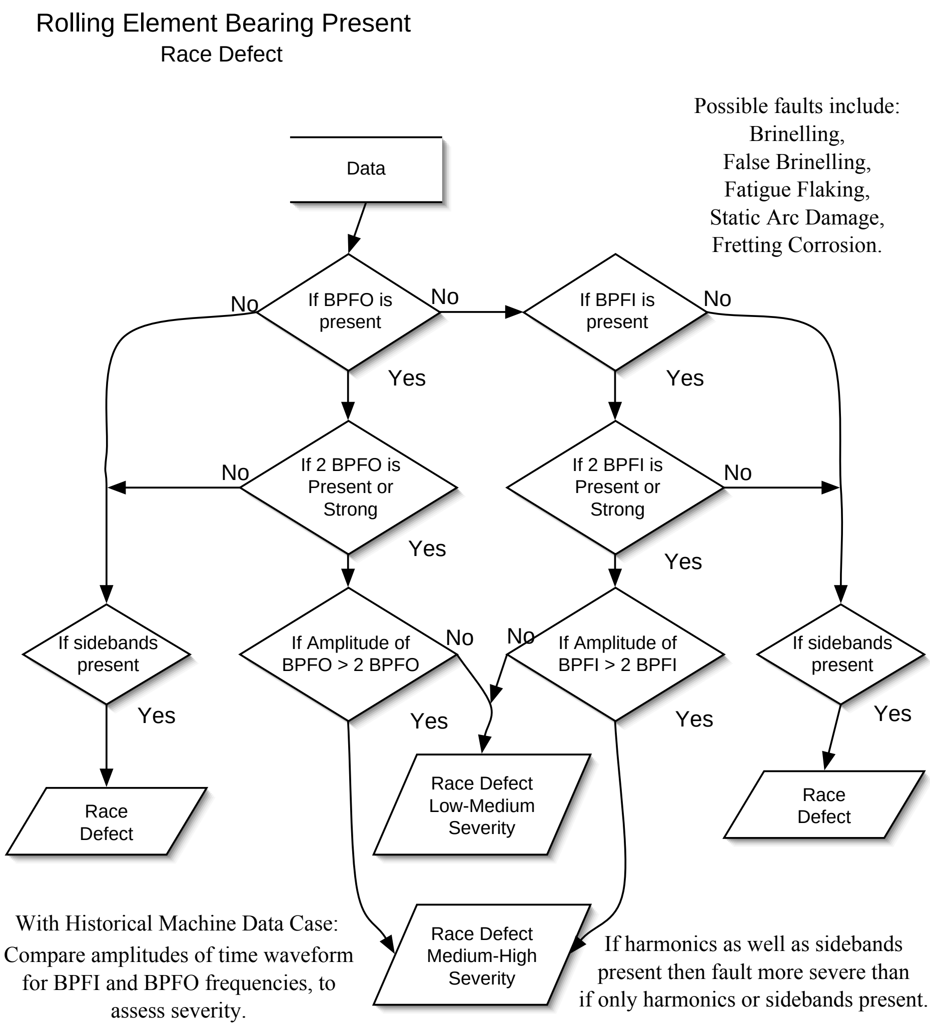

Figure C.5: *Rolling Element Bearing — Race Defect.*

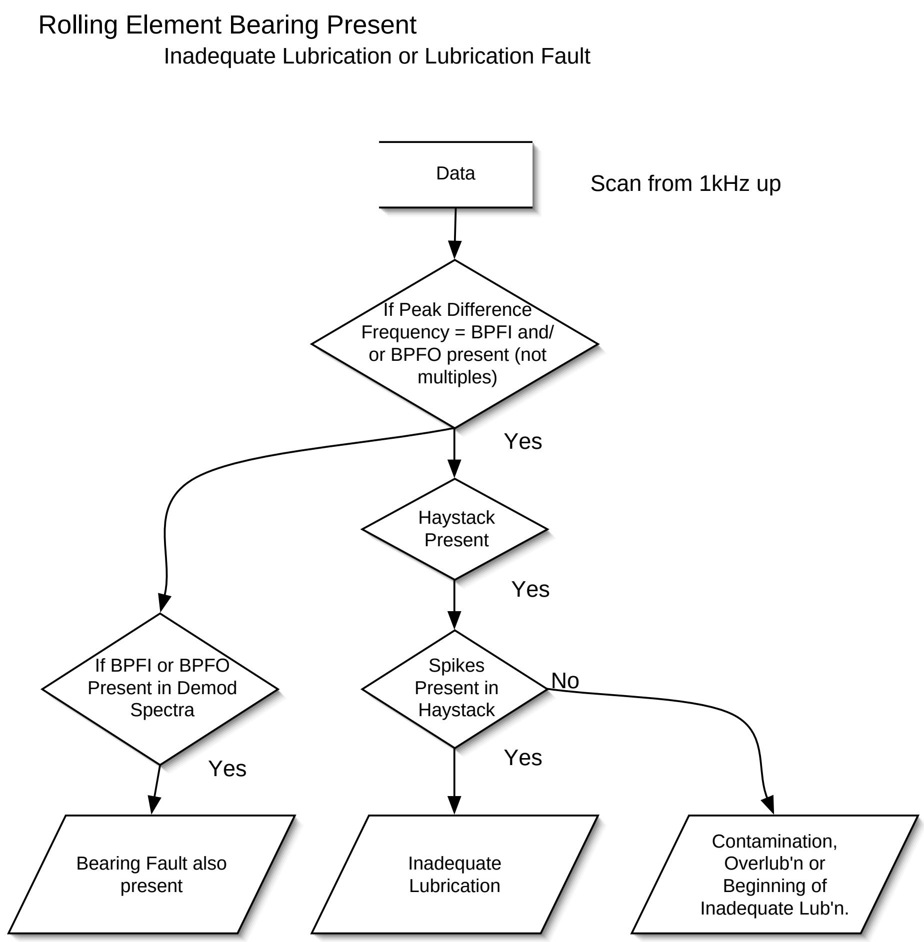

Figure C.6: *Rolling Element Bearing — Inadequate Lubrication.*

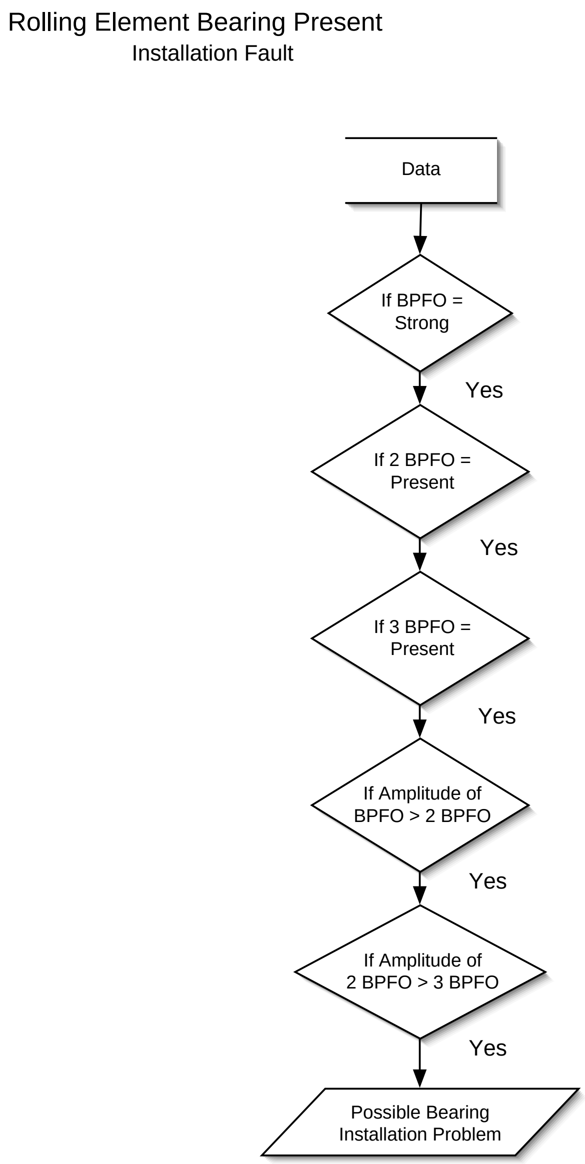

Figure C.7: *Rolling Element Bearing — Installation Fault.*

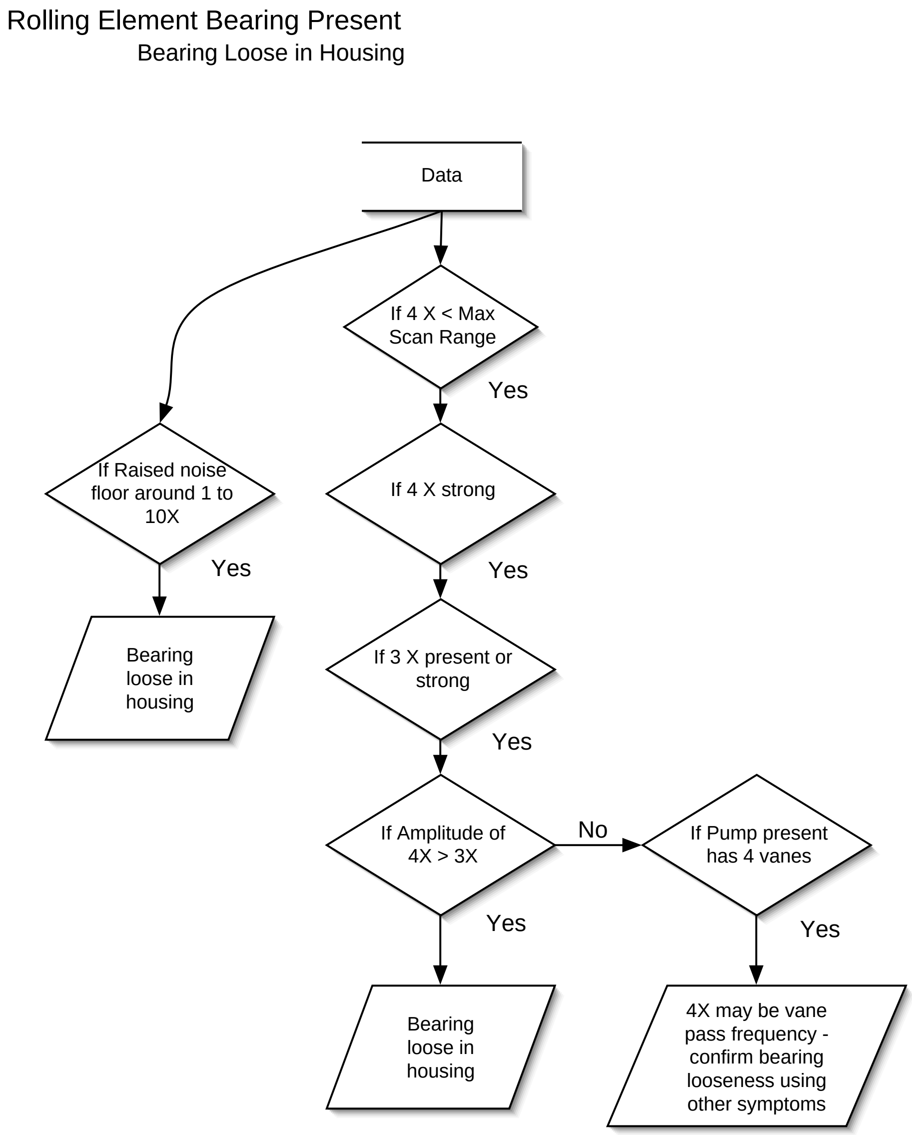

Figure C.8: *Rolling Element Bearing — Loose in Housing.*

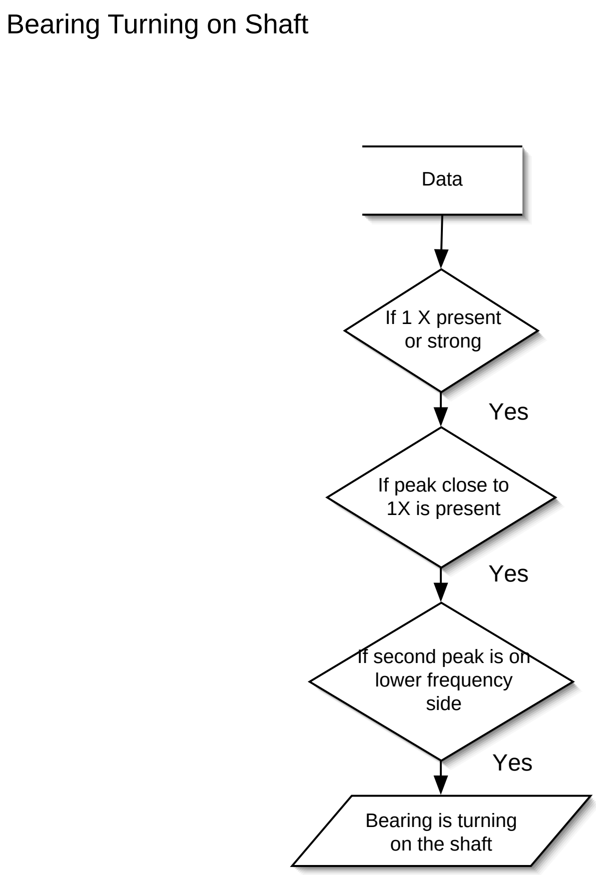

Figure C.9: *Rolling Element Bearing — Turning on Shaft.*

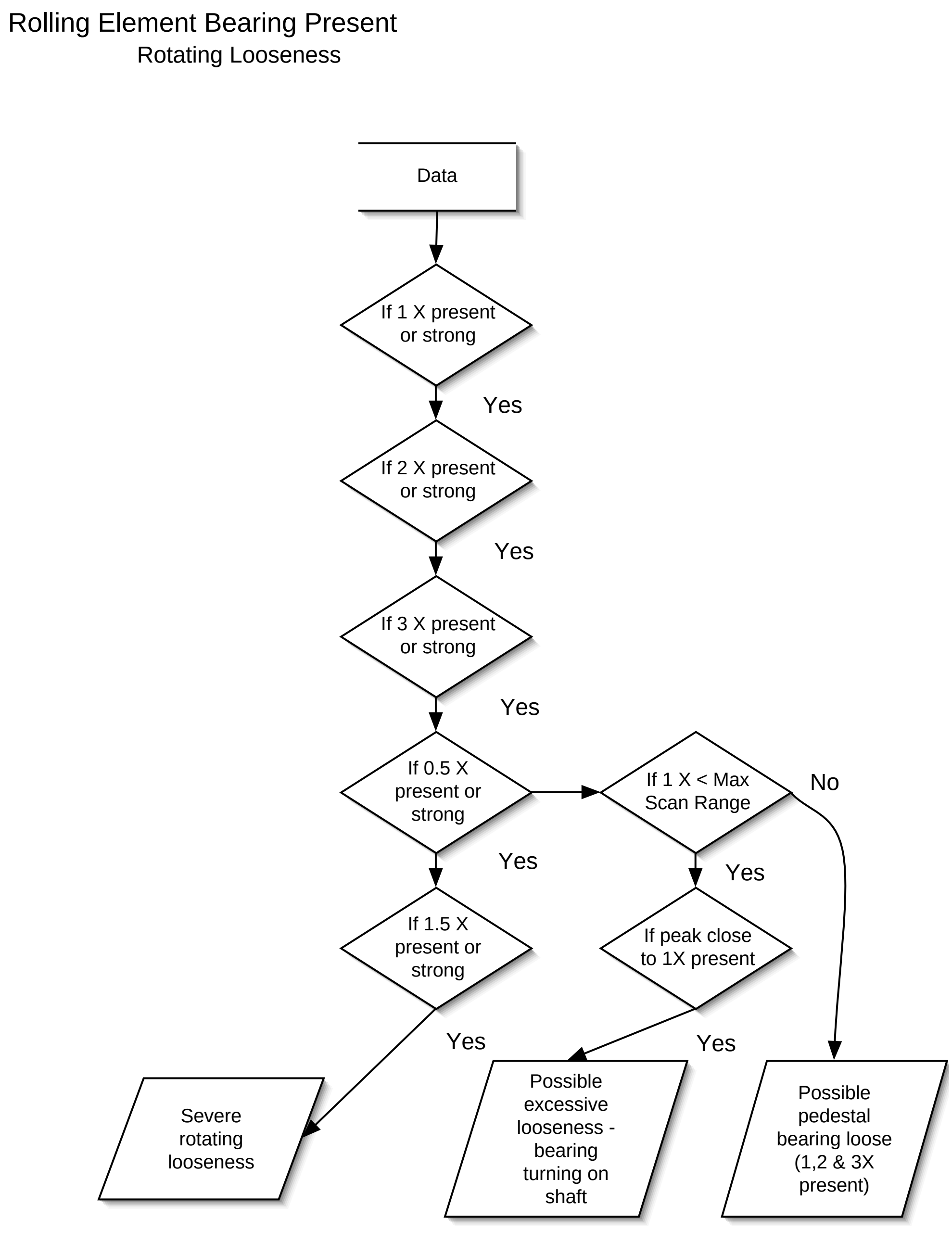

Figure C.10: *Rolling Element Bearing — Rotating Looseness.*

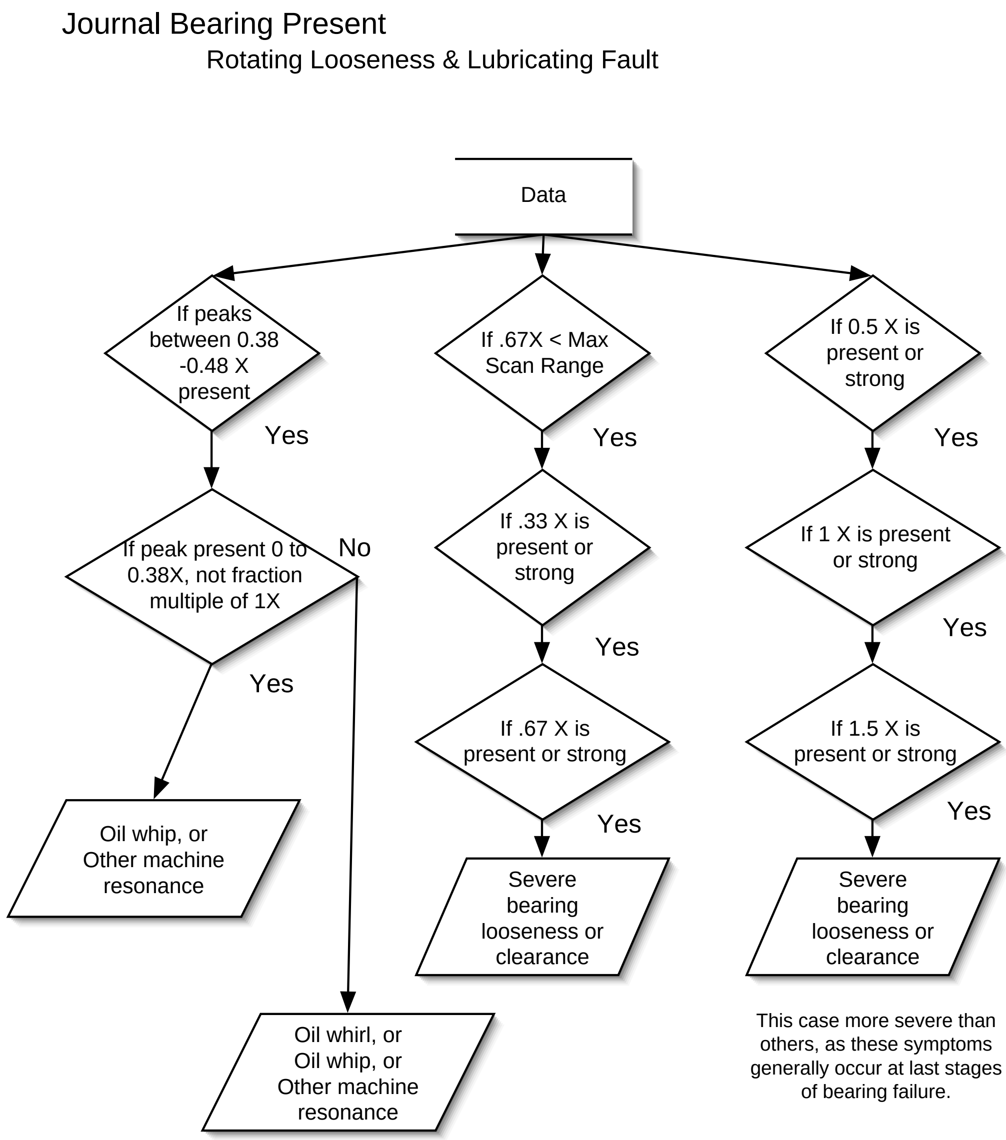

Figure C.11: *Journal Bearing — Rotating Looseness and Lubricating Fault.*

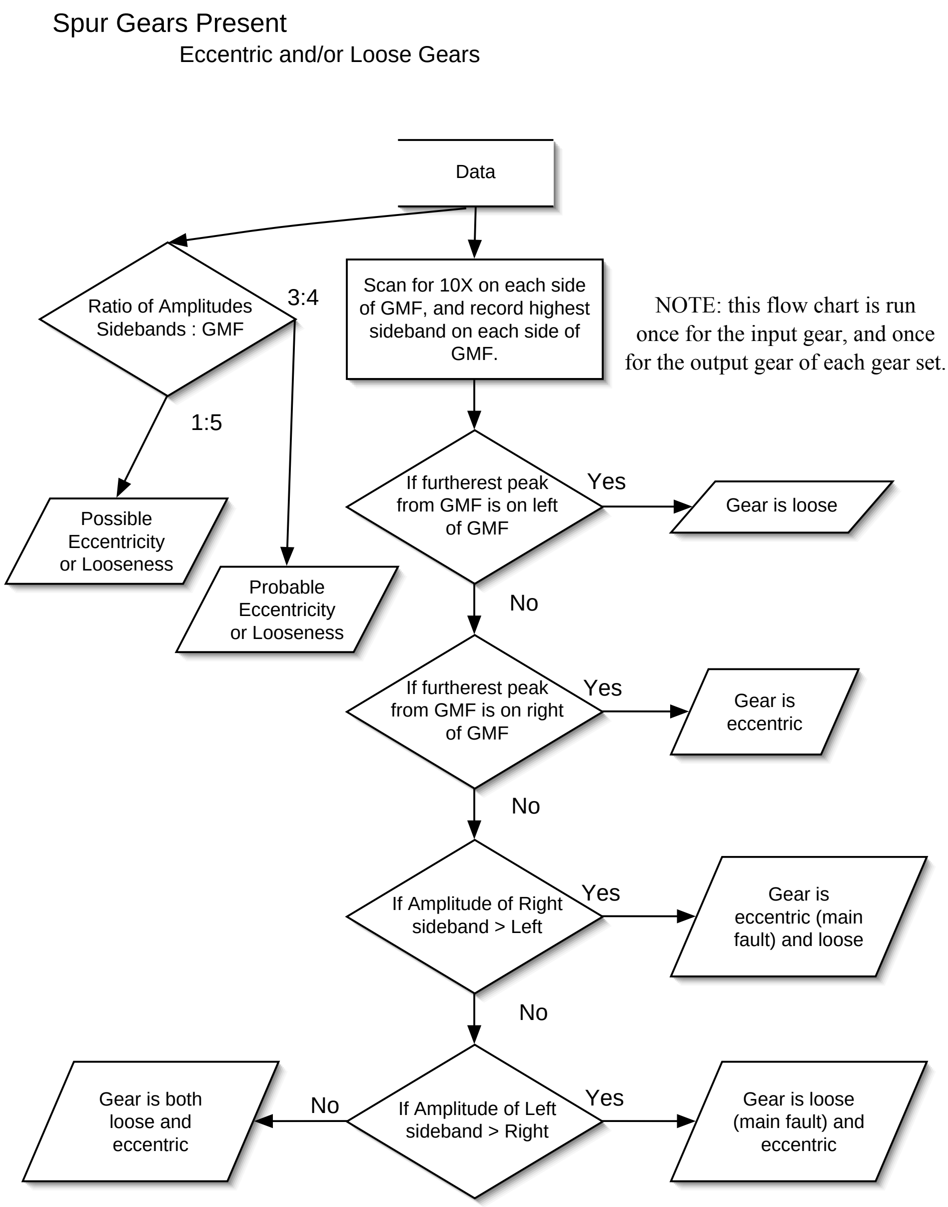

Figure C.12: *Spur Gears — Eccentricity & Looseness.*

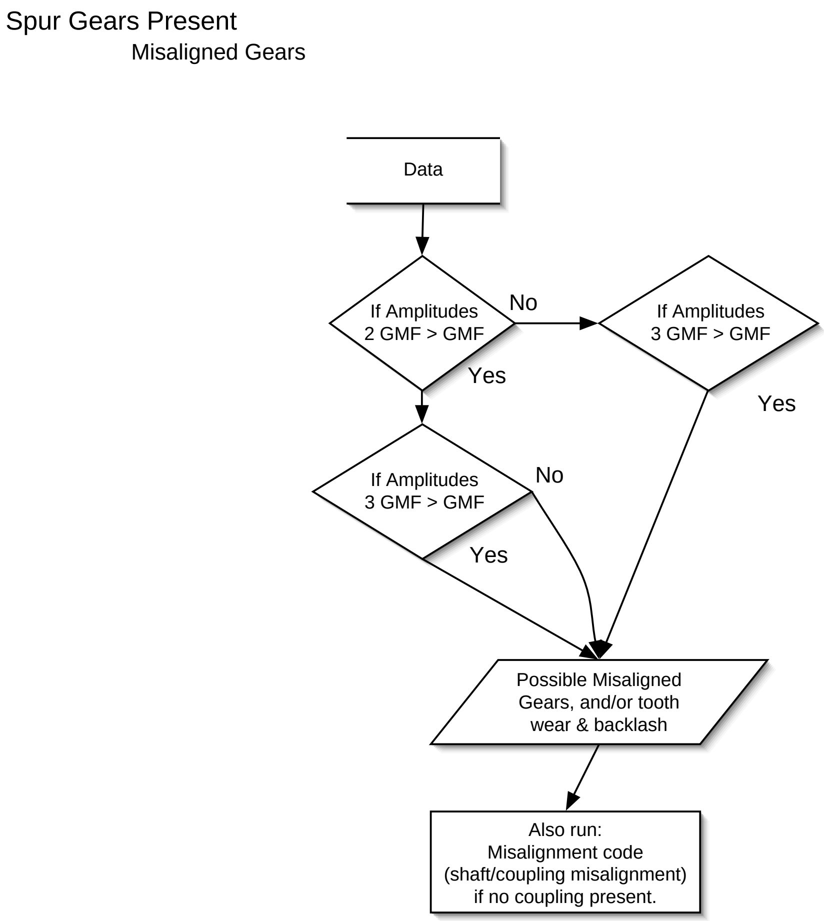

Figure C.13: *Spur Gears — Misalignment.*

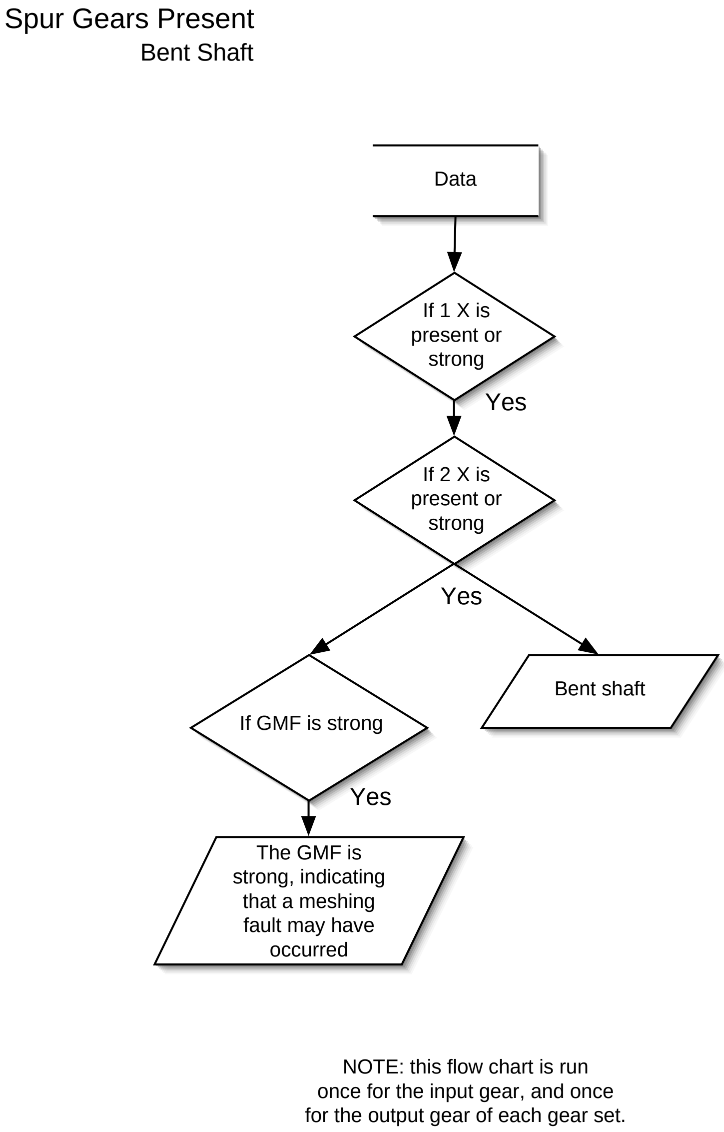

Figure C.14: *Spur Gears — Bent Shaft.*

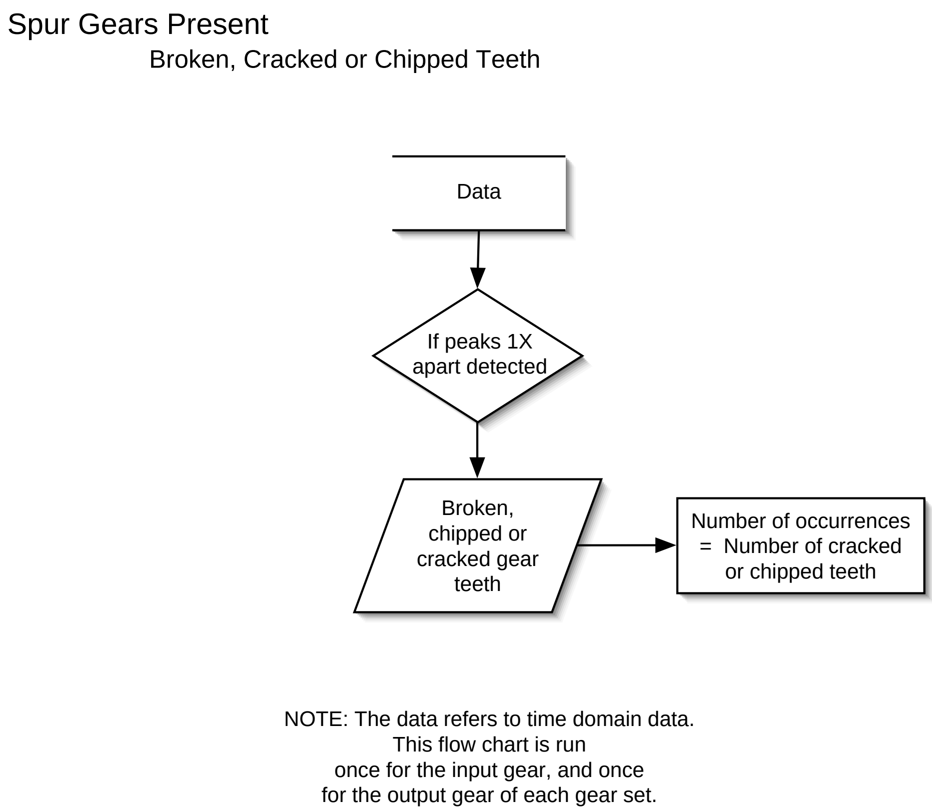

Figure C.15: *Spur Gears — Broken, Cracked or Chipped Teeth.*

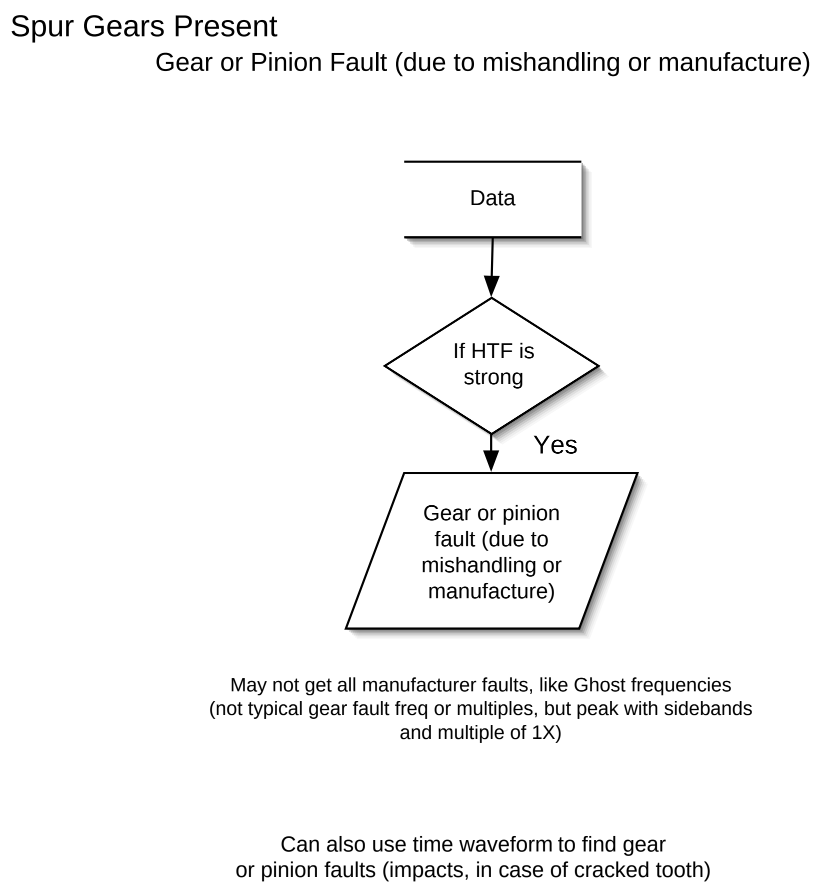

Figure C.16: *Spur Gears — Gear or Pinion Fault.*

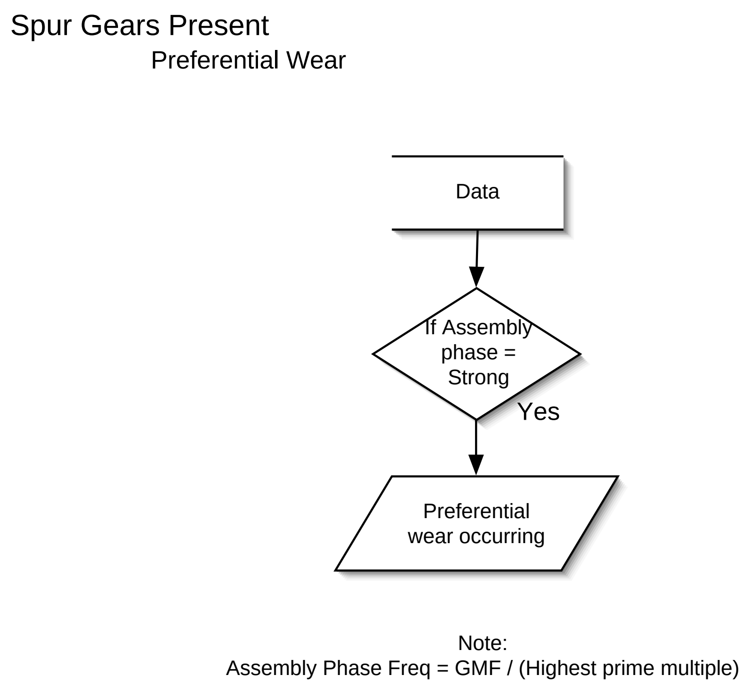

Figure C.17: *Spur Gears — Preferential Wear.*

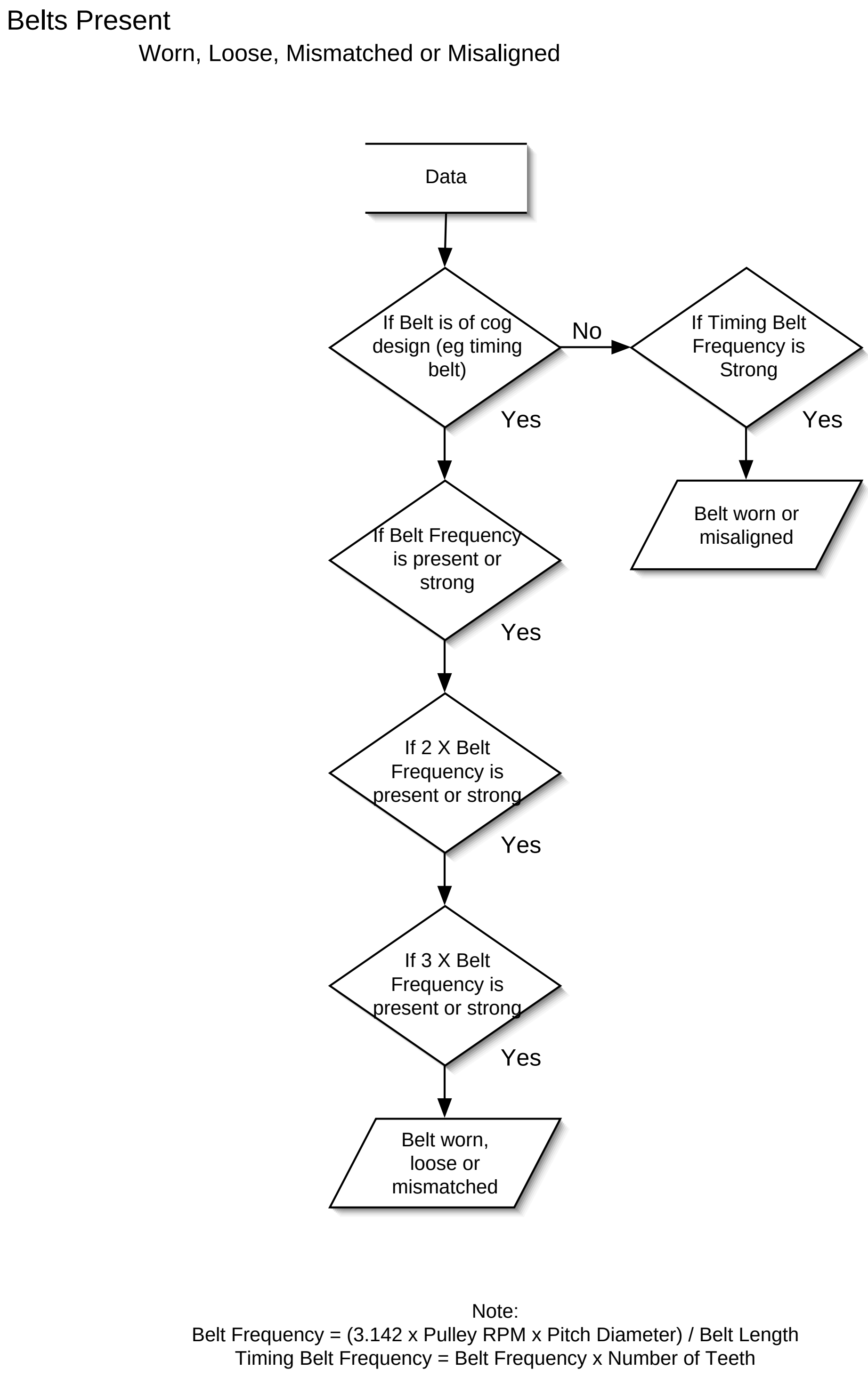

Figure C.18: *Belts — Worn, Loose, Mismatched or Misaligned.*

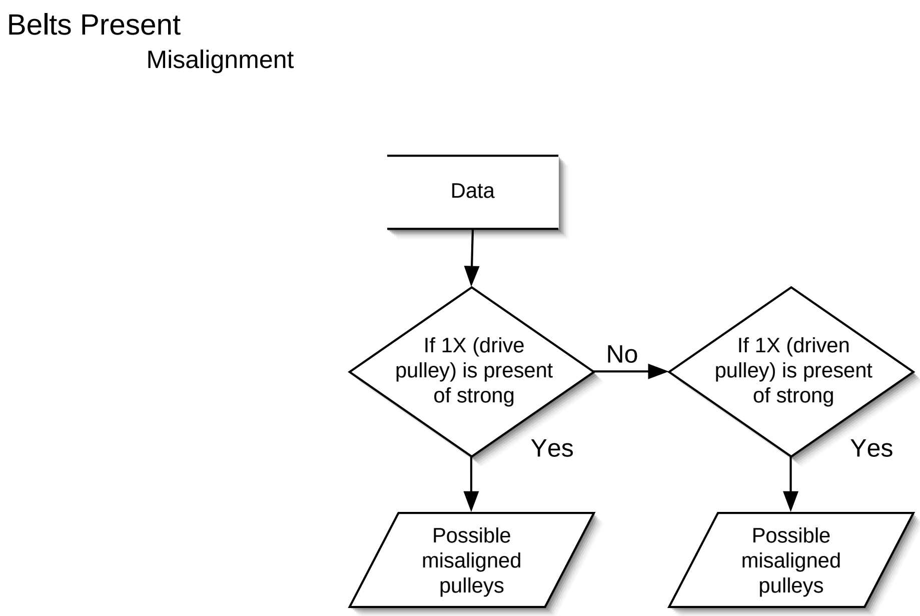

Figure C.19: *Belts — Misalignment.*

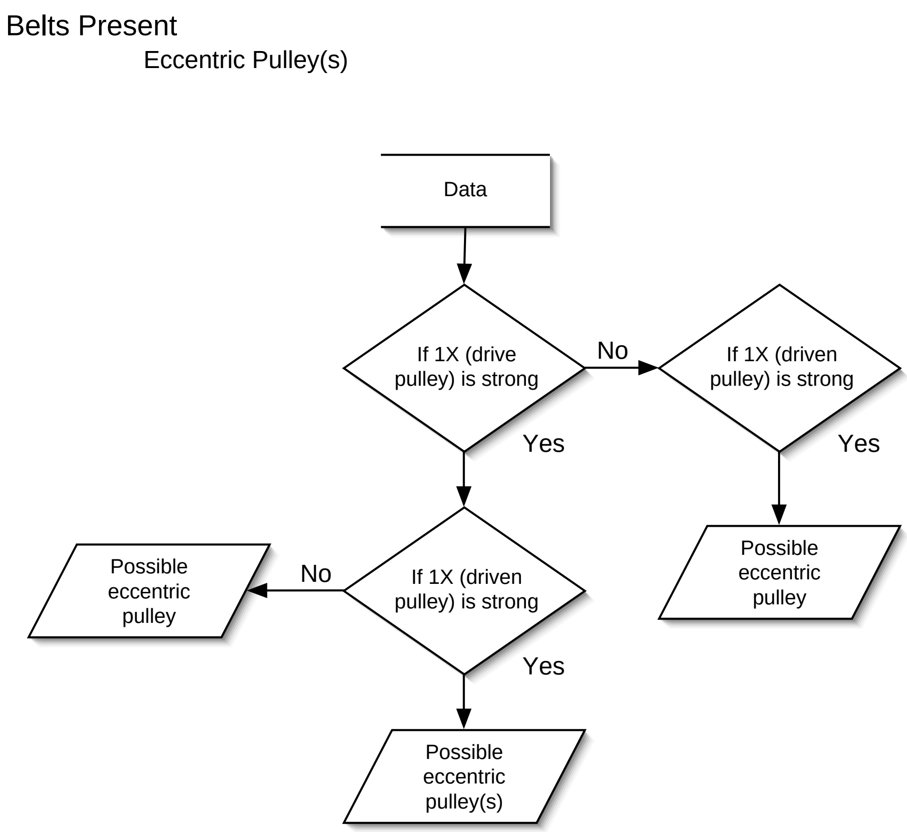

Figure C.20: *Belts — Eccentric Pulley(s).*

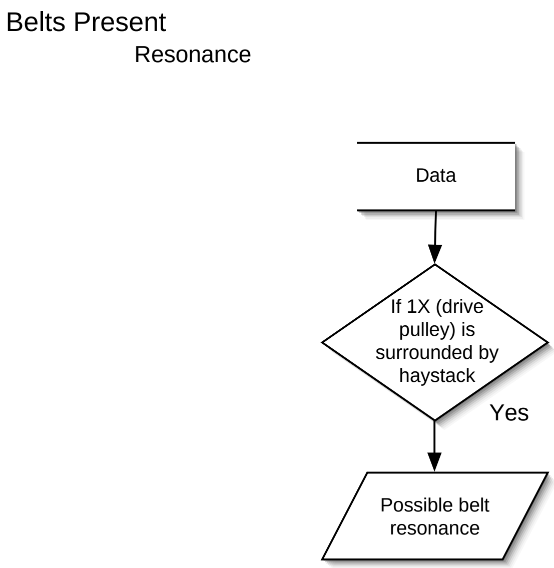

Figure C.21: *Belts — Resonance.*

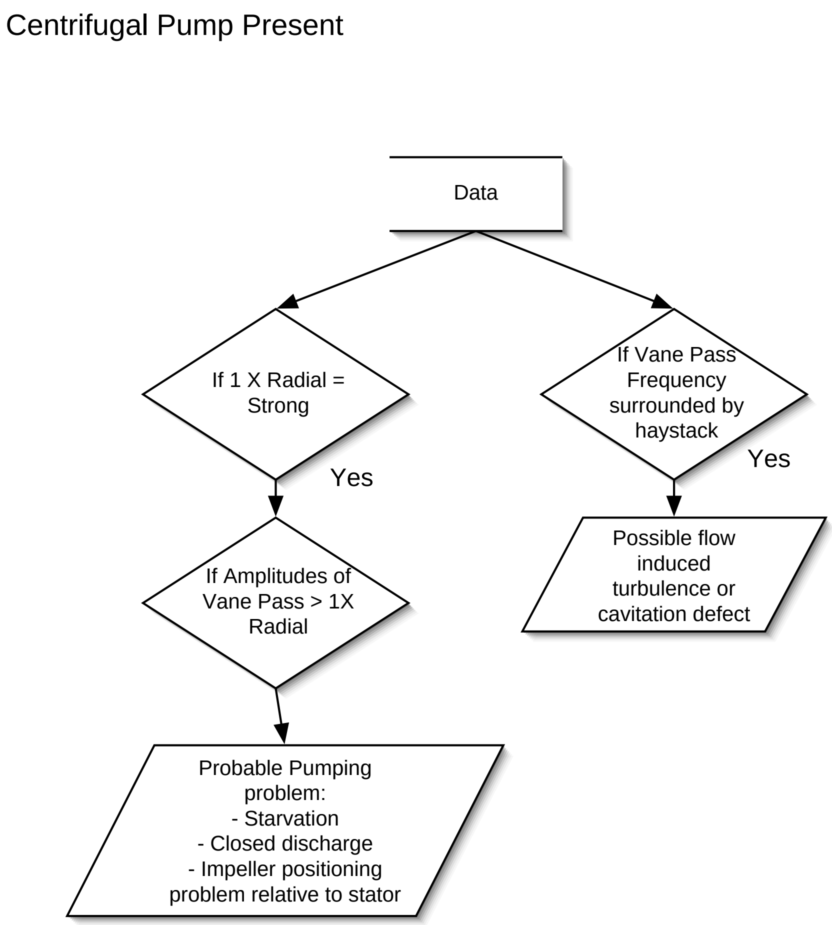

Figure C.22: *Centrifugal Pump Faults.*

Appendix D

Oil & Wear Debris Analysis Algorithm Flow Charts

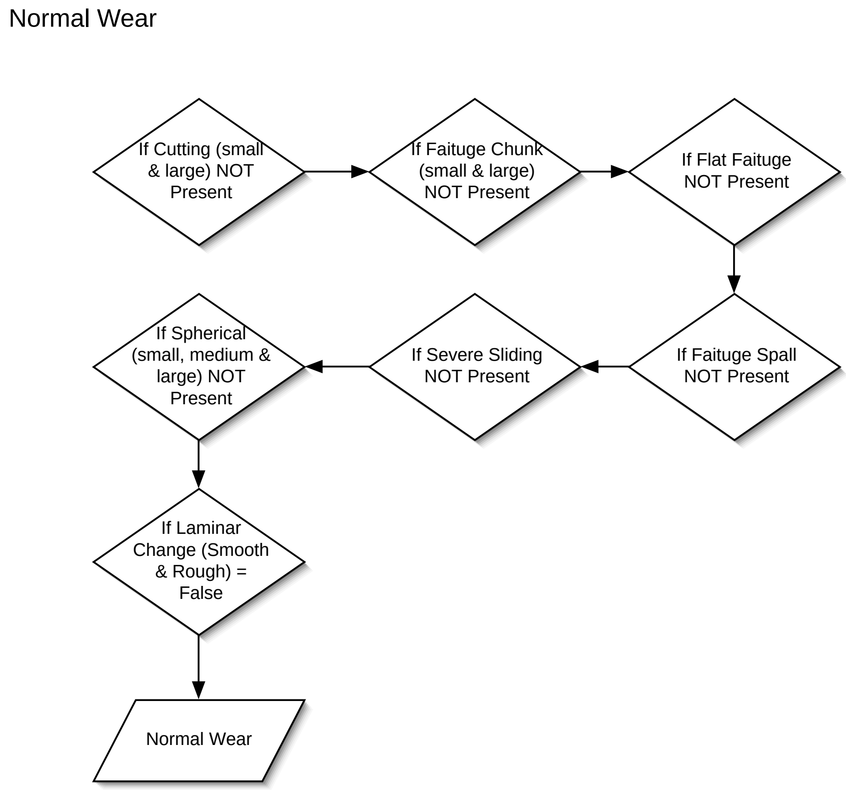

Figure D.1: *Normal Wear.*

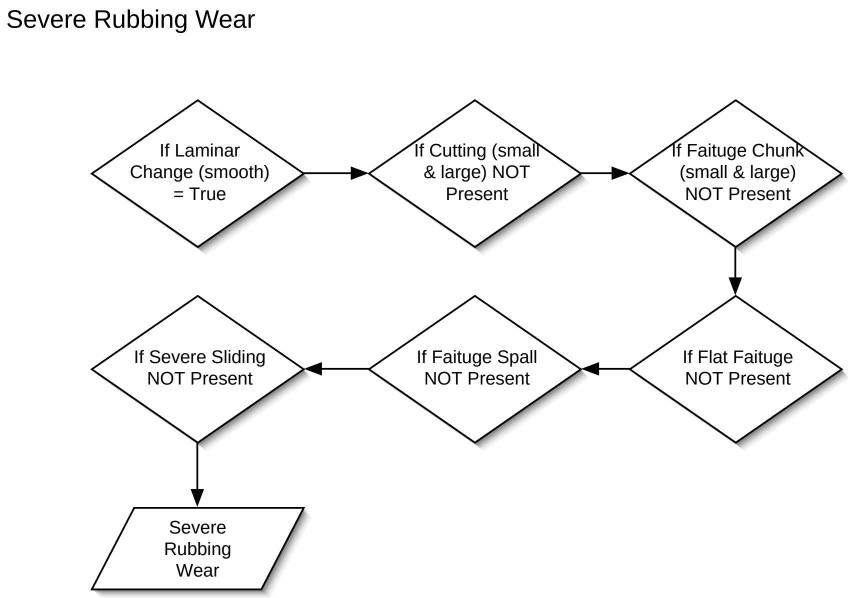

Figure D.2: *Severe Rubbing Wear.*

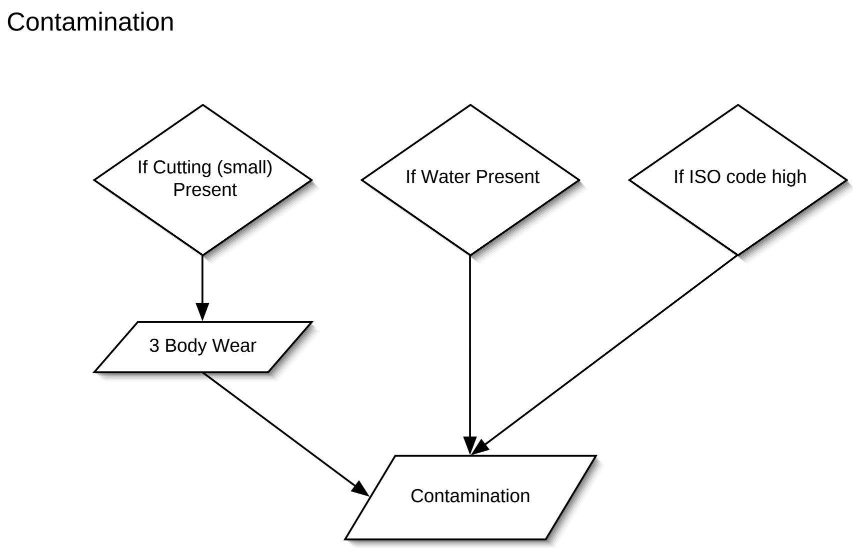

Figure D.3: *Contamination (3 body wear).*

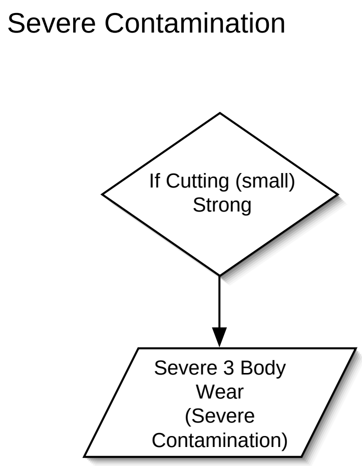

Figure D.4: *Severe Contamination.*

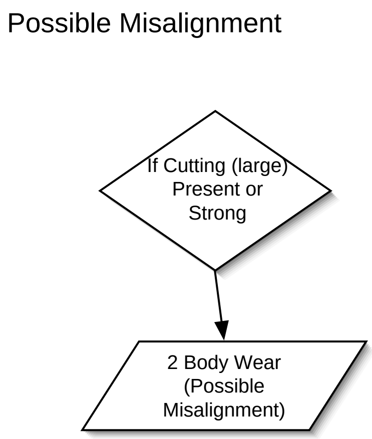

Figure D.5: *Possible Misalignment (2 body wear).*

Welding

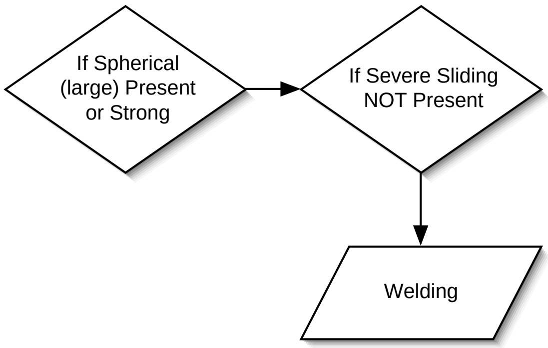

Figure D.6: *Welding.*

Sliding Wear

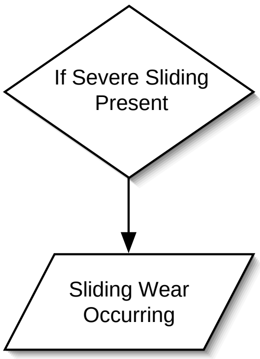

Figure D.7: *Sliding Wear.*

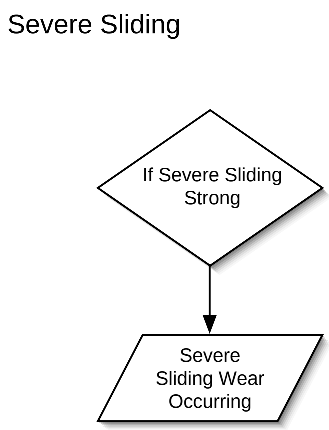

Figure D.8: *Severe Sliding Wear.*

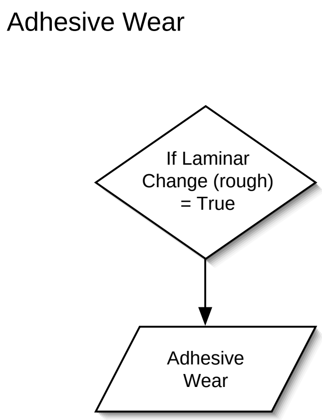

Figure D.9: *Adhesive Wear.*

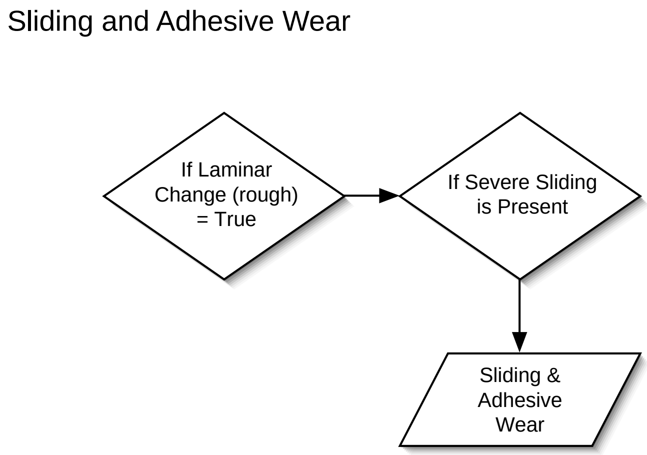

Figure D.10: *Sliding and Adhesive Wear.*

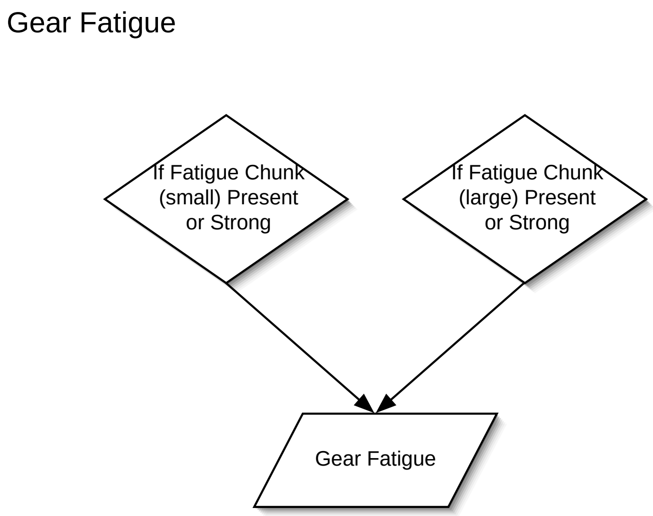

Figure D.11: *Gear Fatigue.*

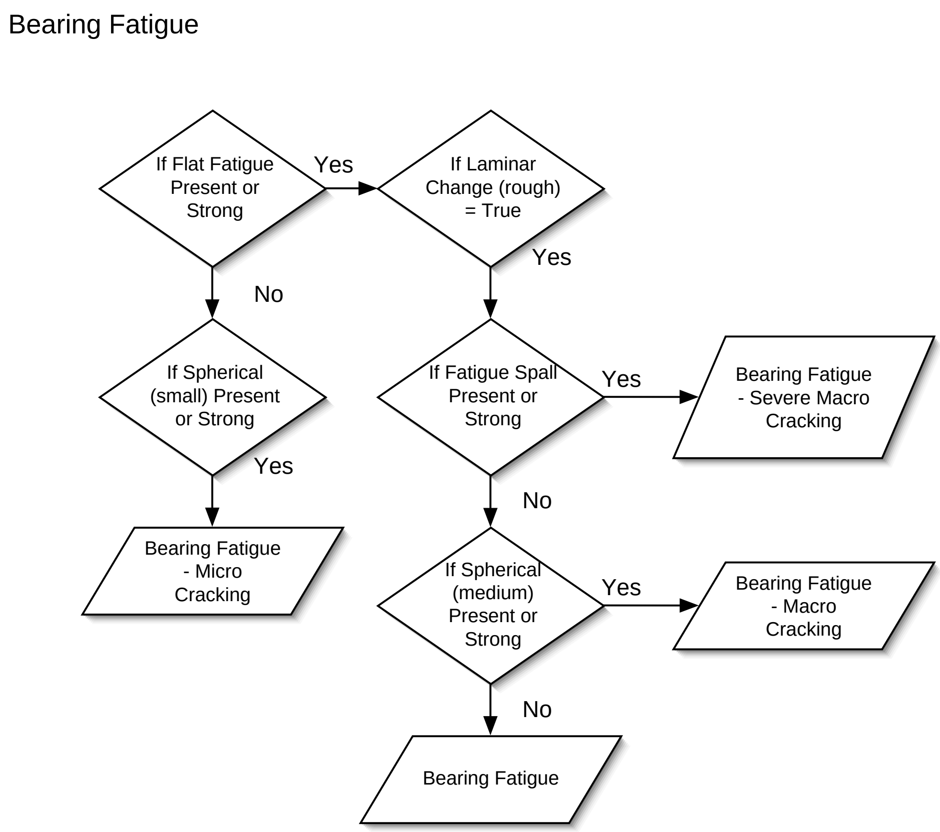

Figure D.12: *Bearing Fatigue.*

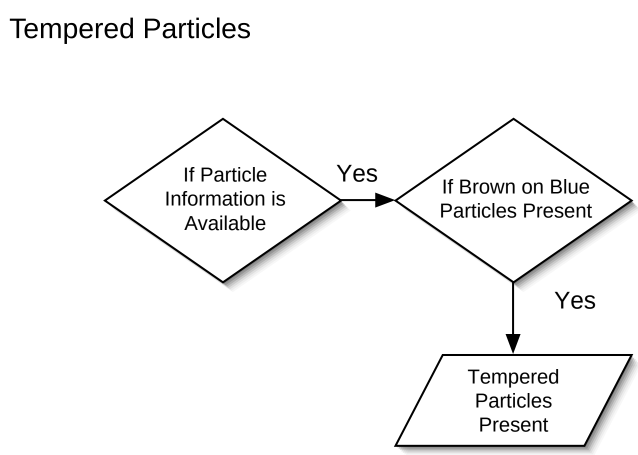

Figure D.13: *Tempered Particles.*

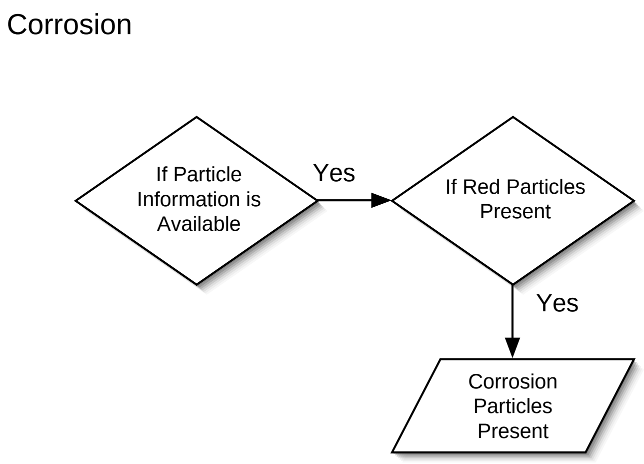

Figure D.14: *Corroded Particles.*

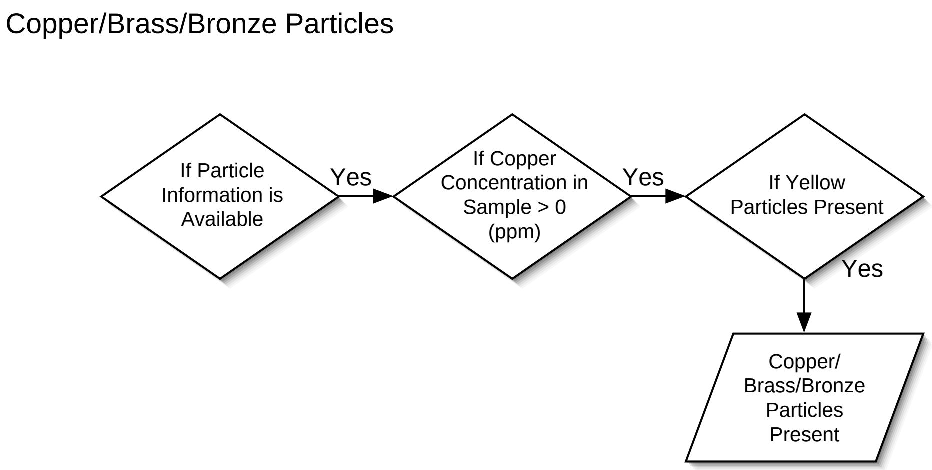

Figure D.15: *Copper/Brass/Bronze Particles.*

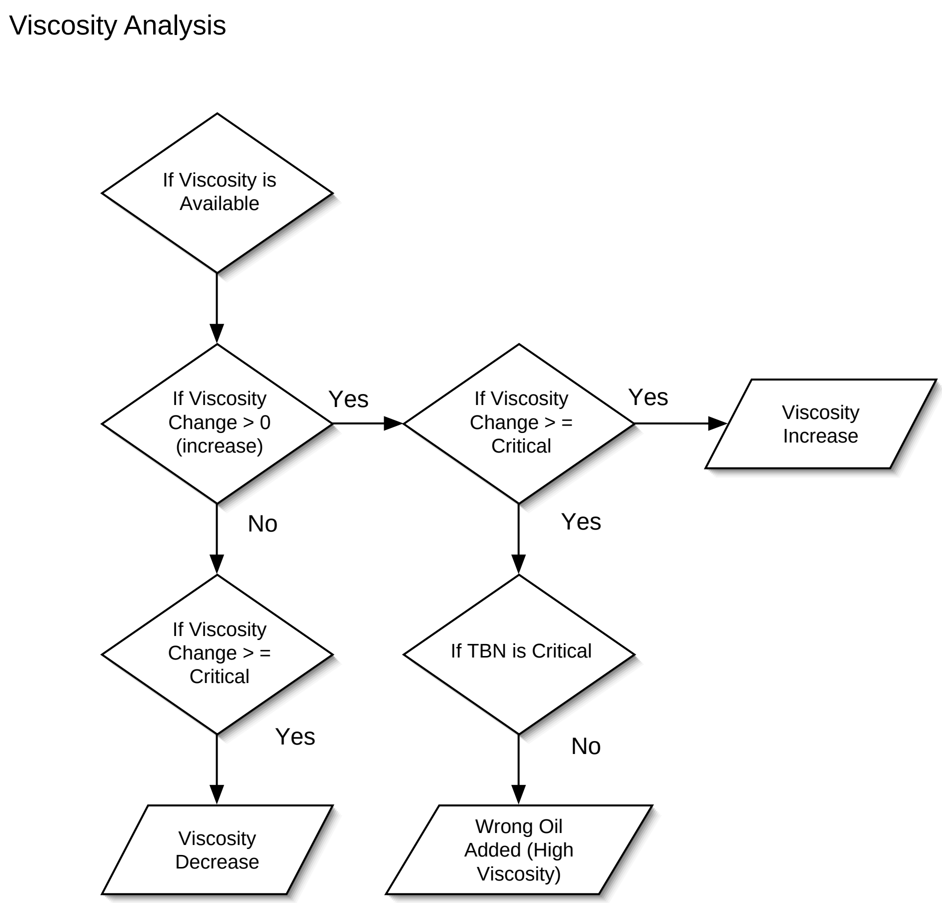

Figure D.16: *Viscosity Analysis.*

Possible causes for detected viscosity faults:

- Viscosity Increase: contamination, water in oil, oil oxidation and addition of wrong viscosity oil
- Viscosity Decrease: solvent/fuel dilution, addition of low viscosity oil

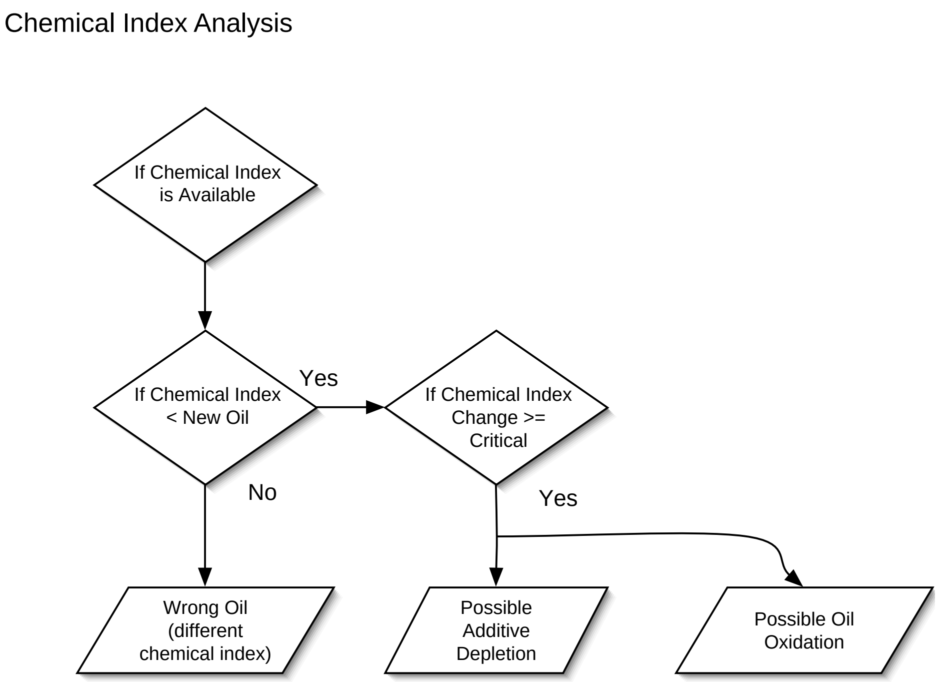

Figure D.17: *Chemical Index Analysis.*

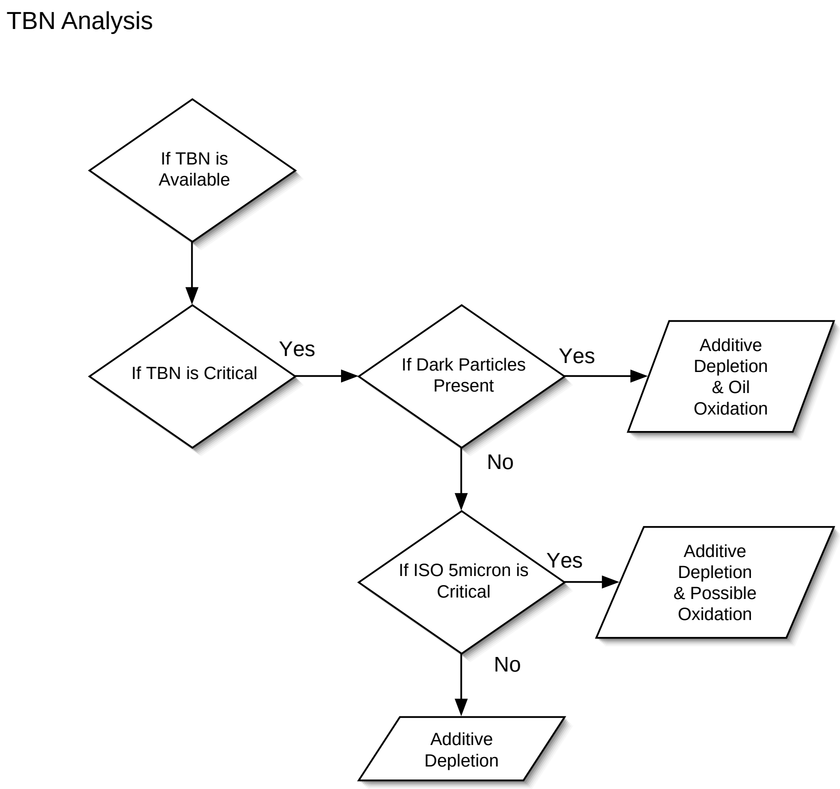

Figure D.18: *Total Base Number Analysis.*

Appendix E

Root-Cause Analysis Algorithm Flow Charts

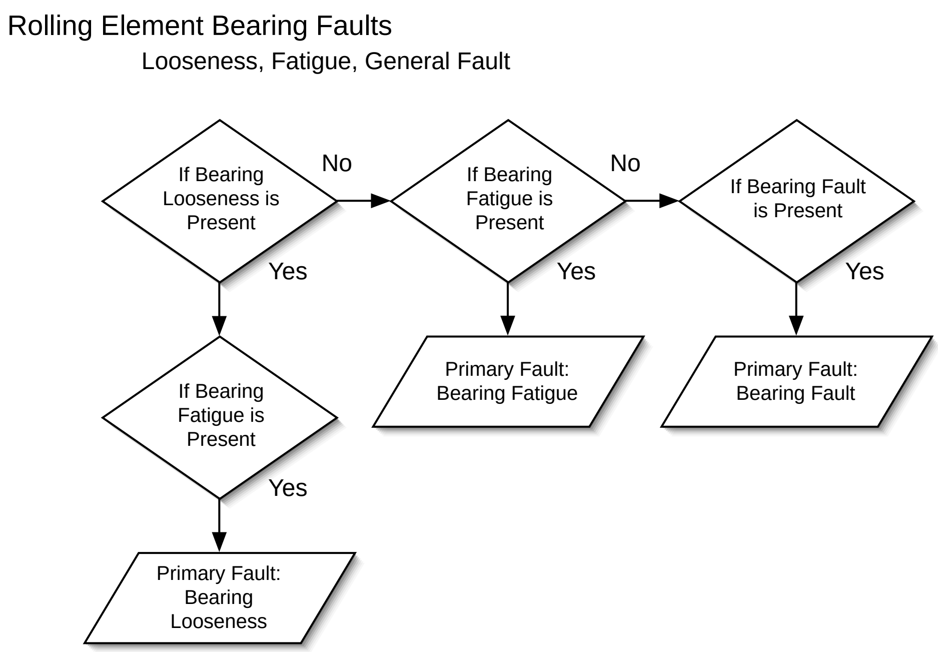

Figure E.1: *Rolling Element Bearing — Looseness, Fatigue and General Faults.*

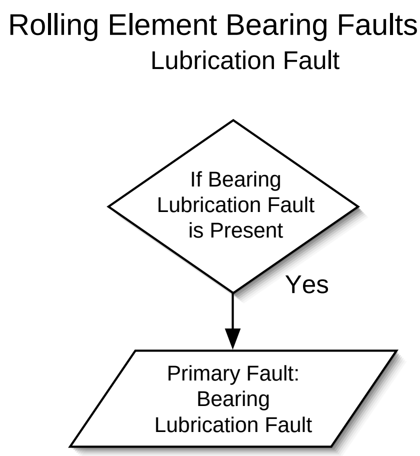

Figure E.2: *Rolling Element Bearing — Lubrication Fault.*

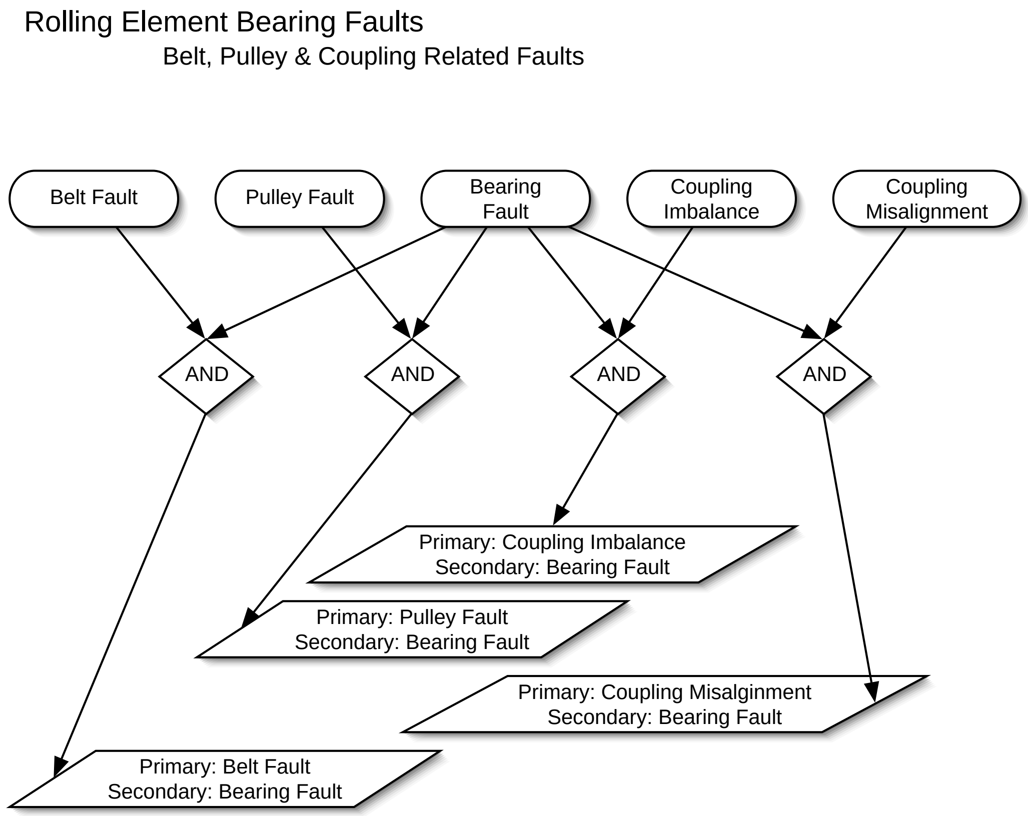

Figure E.3: *Rolling Element Bearing — Belt, Pulley or Coupling Related Fault.*

Note: When multiple faults are detected in combination with 'bearing fault', the secondary fault is the bearing fault, while all other faults are indistinguishable primary or secondary faults.

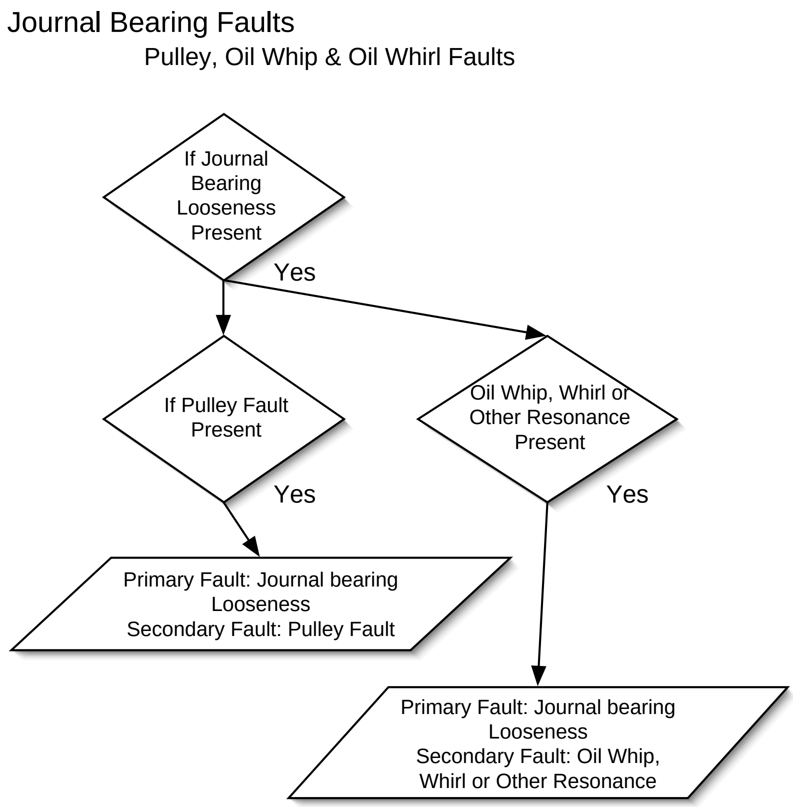

Figure E.4: *Journal Bearing — Pulley or Lubrication Fault.*

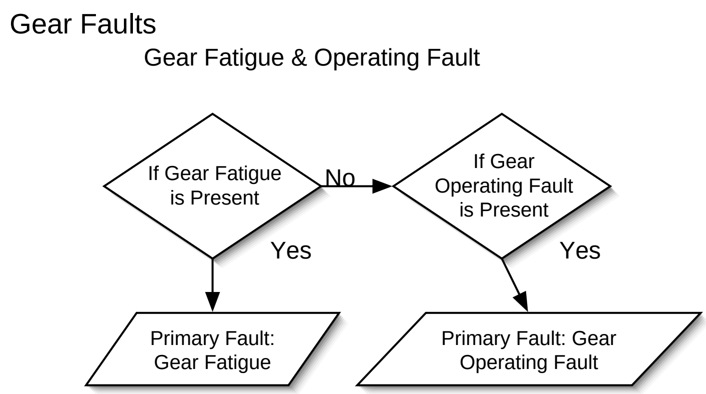

Figure E.5: *Spur Gears — Fatigue & Operating Fault.*

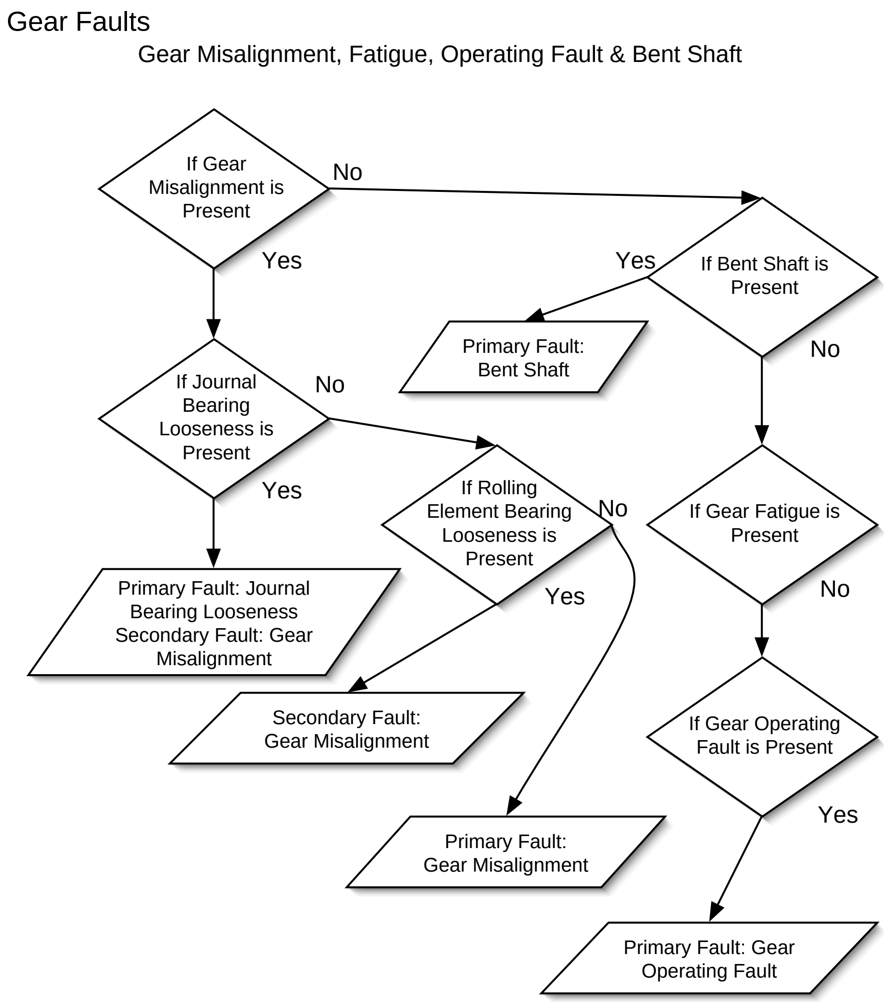

Figure E.6: *Spur Gears — Fatigue, Misalignment & Operating Fault.*

Note: Rolling element bearing looseness can be a primary fault for gear misalignment, but may not be a primary fault itself. It could be caused by a bearing fault or fatigue.

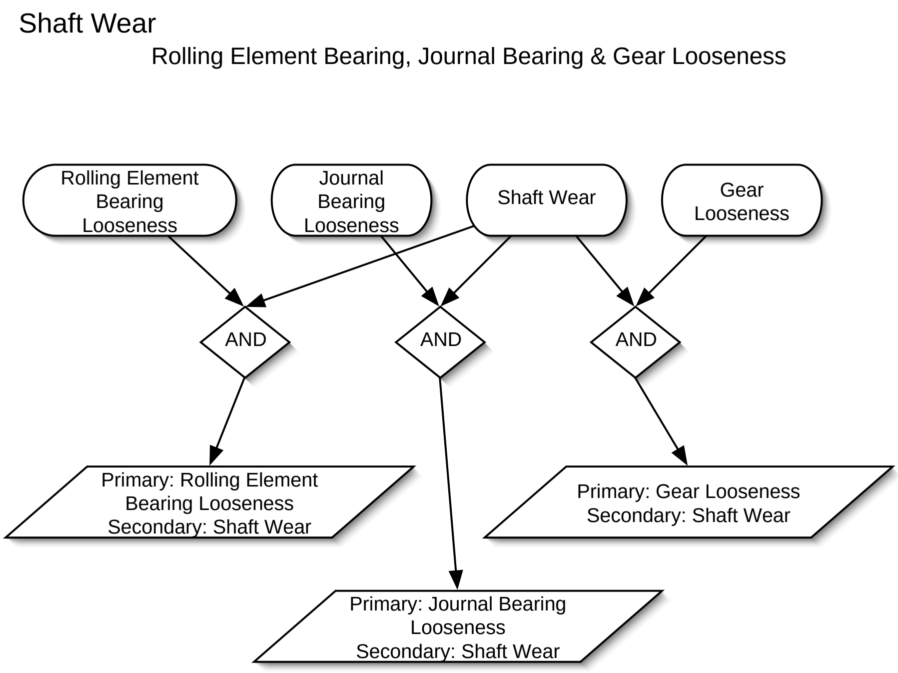

Figure E.7: *Possible Causes for Shaft Wear.*

Note:

- Rolling element bearing looseness and gear looseness include the 'loose on shaft' scenario.
- When multiple faults are detected in combination with 'shaft wear', the secondary fault is the shaft wear, while all other faults are indistinguishable primary or secondary faults.

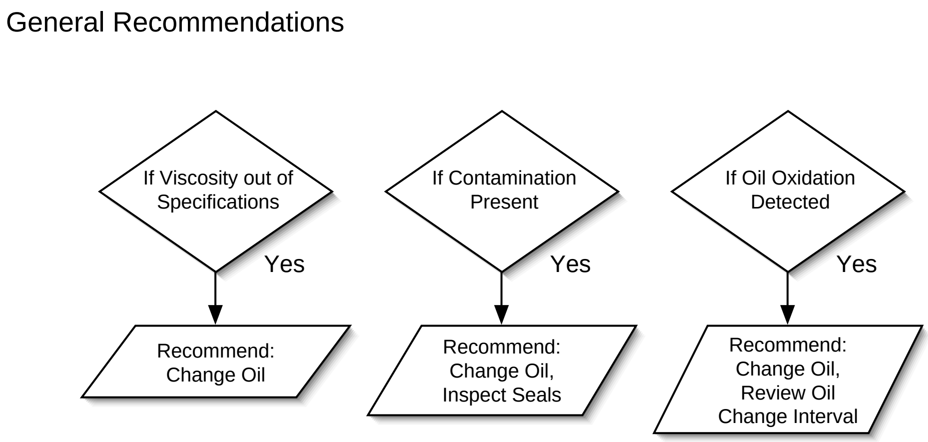

Figure E.8: *General Recommendations.*

Appendix F

OWDES Testing Data

Laboratory Report

Table F.1: *Laboratory Report of Oil Analysis Data from an Industrial Gearbox Used to Test Oil & Wear Debris Analysis Expert System — Part 1.*

Test Condition	Quantity
Sample Date	16-10-2002
Oil Brand	Castrol
New Oil Viscosity (cSt@40°C)	100
Used Oil Viscosity (cSt@40°C)	88
Particle Count: <10 μm	97 %
Particle Count: 10-20 μm	2 %
Particle Count: >20 μm	1 %

Table F.2: *Laboratory Report of Oil Analysis Data from an Industrial Gearbox Used to Test Oil & Wear Debris Analysis Expert System — Part 2.*

Test Condition	Quantity
Rubbing Particles	Low to 50 μm
Cutting Particles	Low to 15 μm
Fatigue Particles	Low to 20 μm
Dark Oxides	Low
Copper Particles	Low to 25 μm
Particle Contamination	Medium
Iron	<1 ppm
Lead	5 ppm
Tin	35 ppm
Copper	3 ppm
Aluminium	1 ppm
Chromium	<1 ppm
Silicon	2 ppm
Sodium	2 ppm
Boron	6 ppm
Calcium	2 ppm
Magnesium	<1 ppm
Phosphorous	3 ppm
Molybdenum	<1 ppm
Zinc	3 ppm
Sulphur	533 ppm
Water	<0.1 ppm

Appendix G

Remaining Lifetime — Cutting Wear Calculations

Quantities that must be known in order to calculate volume removed from cutting wear:

- Gear width, in mm
- Gear addendum radius (R_1), in mm
- Gear deddendum radius, in mm
- Shaft length, in mm
- Position of centre of gear from end of shaft, in mm
- Total clearance at end of shaft (total clearance of both shaft bearings and gear looseness if present), in mm
- Gear interference factor, between 0 and 1
- Volume Removed At Wear Out-Limit, in mm^3

Equations required to calculate volume removed from cutting wear:

The angle of tilt on the gear due to looseness at the shaft support bearings or gear mounting can be determined by:

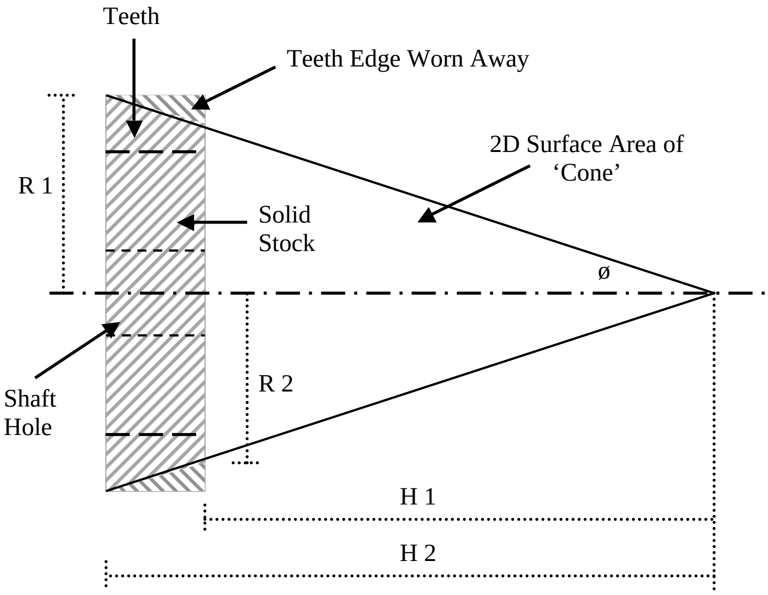

Figure G.1: *Calculation of gear volume wear using conical machining model.*

$$\phi = \mathrm{Tan}^{-1}(\frac{\text{Total Clearance}}{\text{Shaft Length}}) \tag{G.1}$$

The cutting depth of the gear edge is found by:

$$\text{Cutting Depth} = \mathrm{Tan}(\phi) \times \frac{\text{Shaft Length} - \text{Gear Width}}{2} \tag{G.2}$$

The height of the triangle of Figure G.1 is dependent on the misalignment angle as follows:

$$\mathrm{H}_2 = \frac{\mathrm{R}_1}{\mathrm{Tan}(\phi)} \tag{G.3}$$

The height of the inner triangle, whose base is R_2 is:

$$\mathrm{H}_1 = \mathrm{H}_2 - \text{Gear Width} \tag{G.4}$$

Volume 1 is the area of the triangle, whose base is R_2, and whose height is H_1.

$$\mathrm{Vol}_1 = \frac{1}{3}\pi \mathrm{R}_2^2 \mathrm{H}_1 \tag{G.5}$$

Volume 2 is the area of the triangle, whose base is R_1, and whose height is H_2.

$$\mathrm{Vol}_2 = \frac{1}{3}\pi \mathrm{R}_1^2 \mathrm{H}_2 \tag{G.6}$$

The volume of the gear solid stock and shaft hole can be determined by:

$$\text{Gear Stock Volume} = \text{Gear Width} \times \pi \times \text{Gear Deddendum Radius}^2 \tag{G.7}$$

The new teeth volume, which is the volume of the worn teeth, can be calculated by:

$$\begin{aligned}\text{New Teeth Volume} = {} & \frac{1}{2} \times \text{Gear Interference Factor} \times ((\text{Gear Width} \times \pi \times \mathrm{R}_1^2) \\ & - (\text{Gear Width} \times \pi \times \text{Gear Deddendum Radius}^2))\end{aligned} \tag{G.8}$$

The total volume worn off the gear teeth can finally be calculated by:

$$\begin{aligned}\text{Total Worn Volume} = {} & \text{Gear Stock Volume} + \text{New Teeth Volume} - \text{Gear Stock Volume} \\ & + (((\text{Volume}_2 - \text{Volume}_1) - \text{Gear Stock Volume}) \\ & \times \frac{\text{Gear Interference Factor}}{2})\end{aligned} \tag{G.9}$$

The percentage worn off the gear teeth can be determined by:

$$\text{Percent Worn} = \frac{\text{Total Worn Volume}}{\text{Volume Removed At Wear Out-Limit}} \times 100 \tag{G.10}$$

Note: The gear interference factor is the amount of the gears occupying the air space between the tip of a gear tooth and the deddendum of the meshing gear, which is required to allow the gears to come into and out of mesh without the gear tips scratching the flanks of the other gear teeth.

Appendix H

Expert Systems — Menu Structure & Screens

H.1 Main Menu Structure & Screens

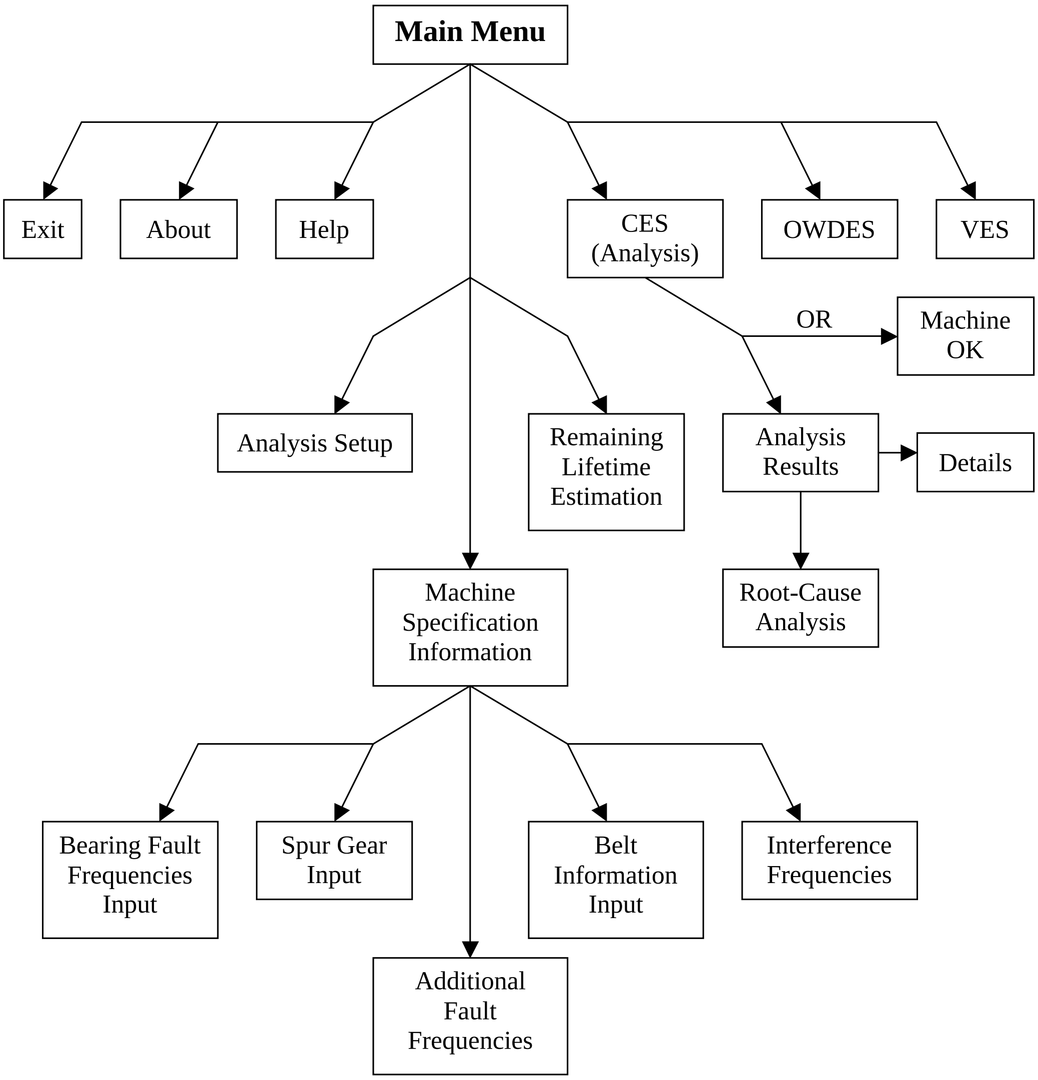

Figure H.1: *Schematic diagram of the Main menu. OWDES and VES have individual schematic diagrams shown in Sections H.3 and H.4.*

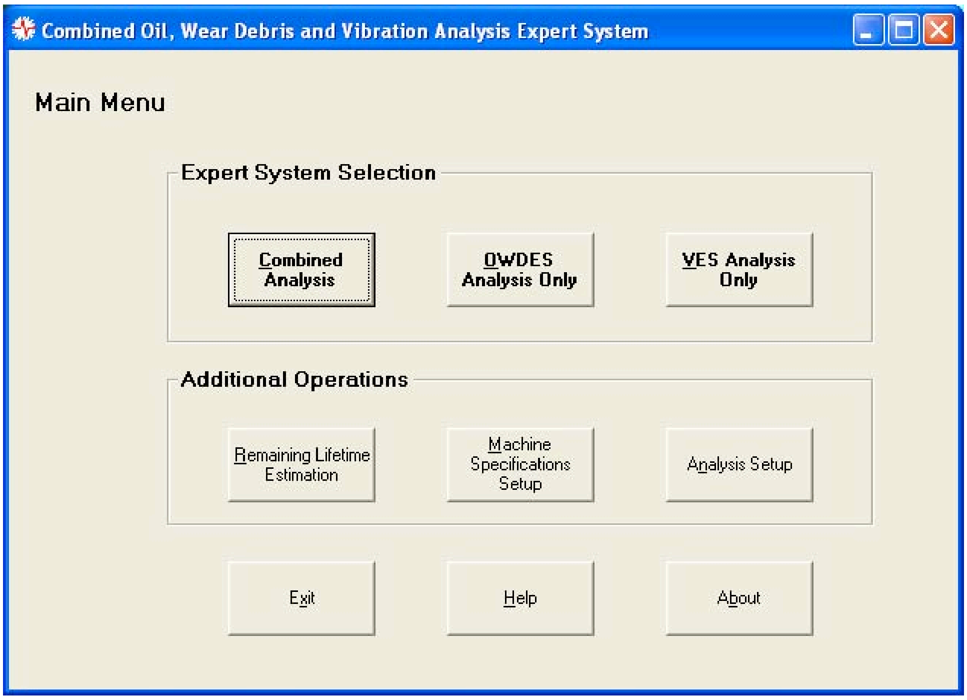

Figure H.2: *The combined analysis expert system main menu. This is the main menu, which is displayed when the software is started. All functions of the combined analysis expert system are available from this main menu including: analysis (the 'CES' button opens the CES analysis screen), machine specifications information, and analysis information.*

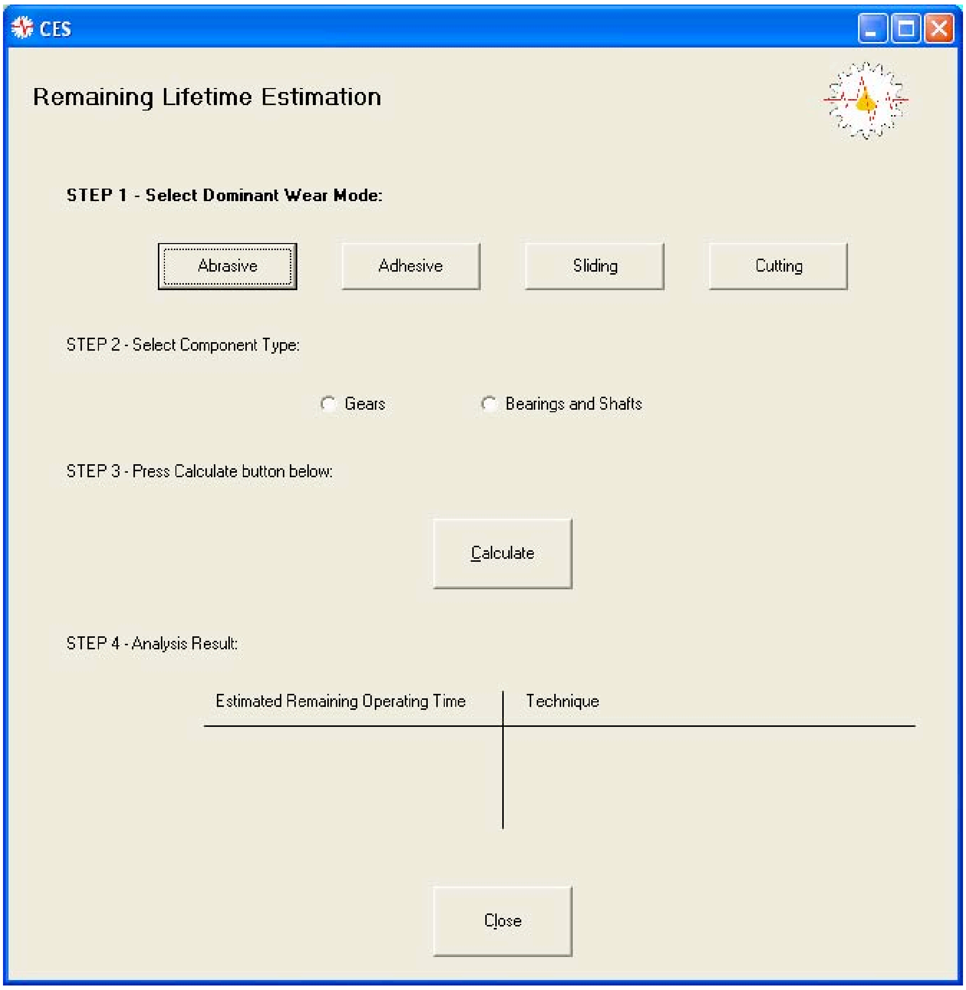

Figure H.3: *The Remaining Lifetime Estimation menu.*

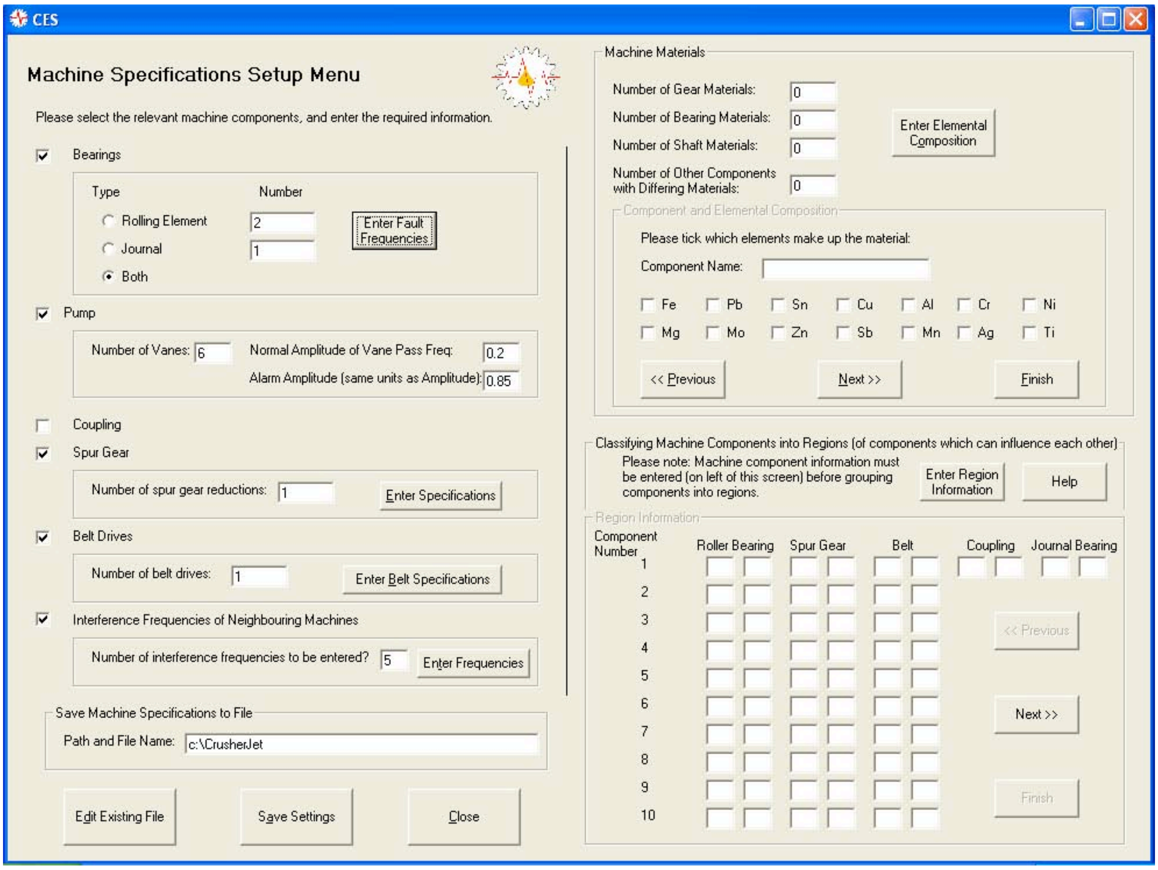

Figure H.4: *The Machine Specifications Setup menu. The sub-menus for entering bearing fault frequencies, spur gear specifications, belt drive specifications, and interference frequencies, as well as the menu for additional fault frequencies are identical to those of the VES With Machine Historical Data case (Figures in Section H.4.2), except for differences in logo and application icon.*

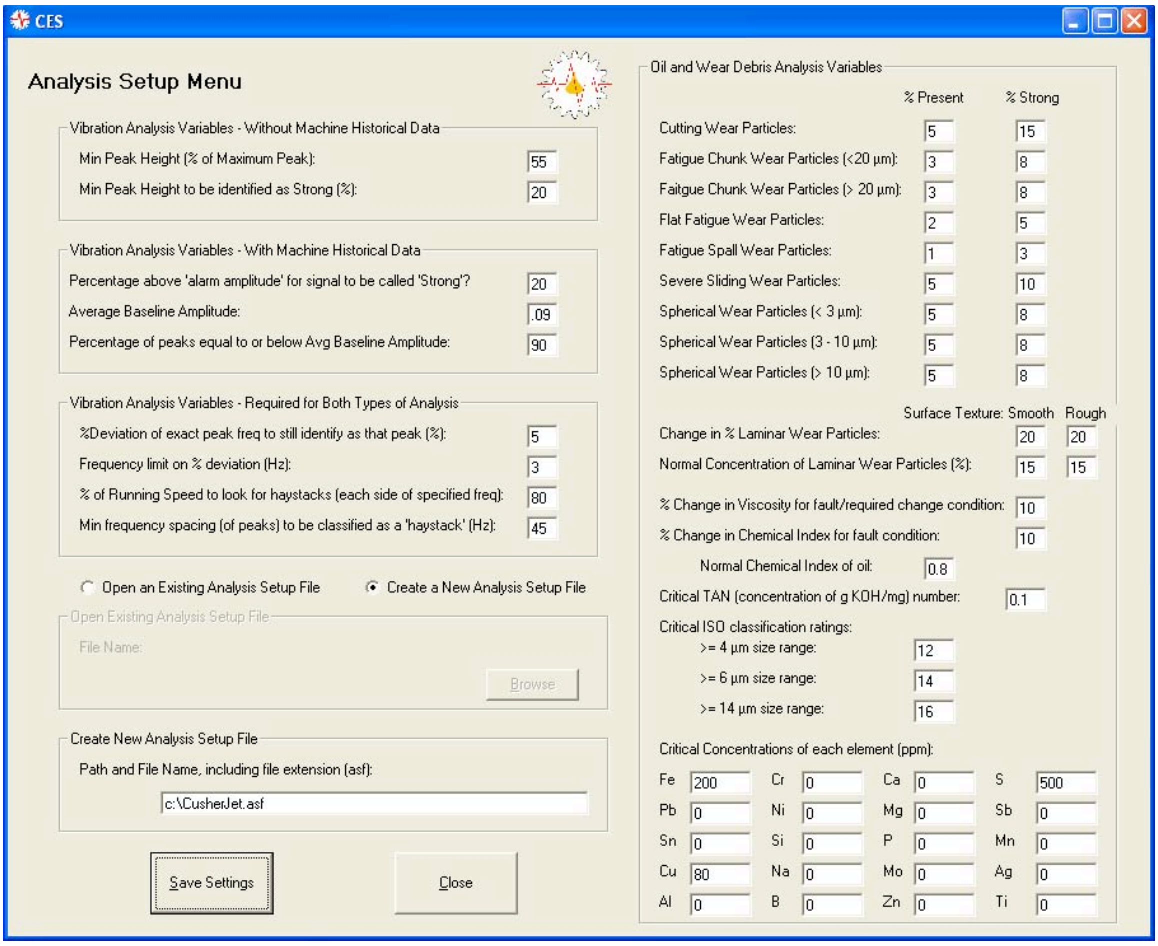

Figure H.5: *The Analysis Information menu.*

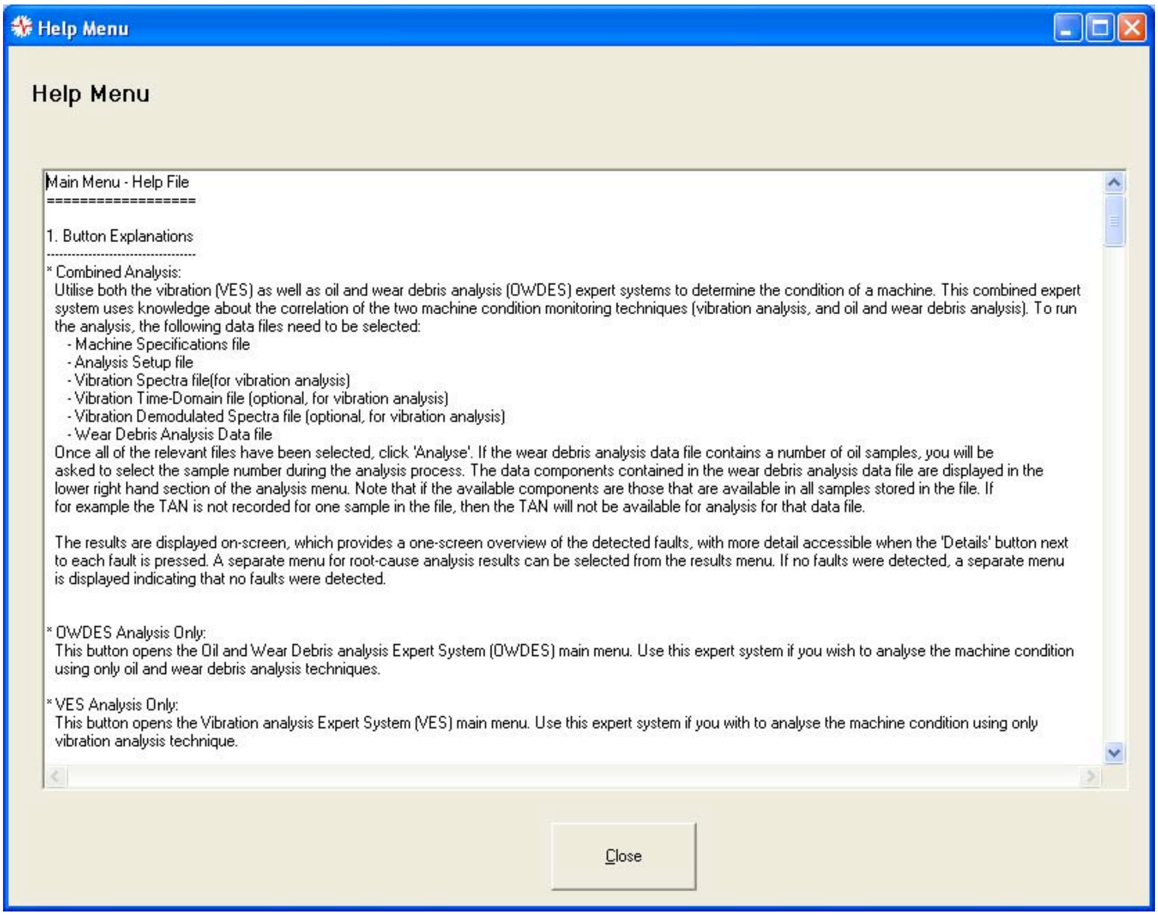

Figure H.6: *The CES Help menu.*

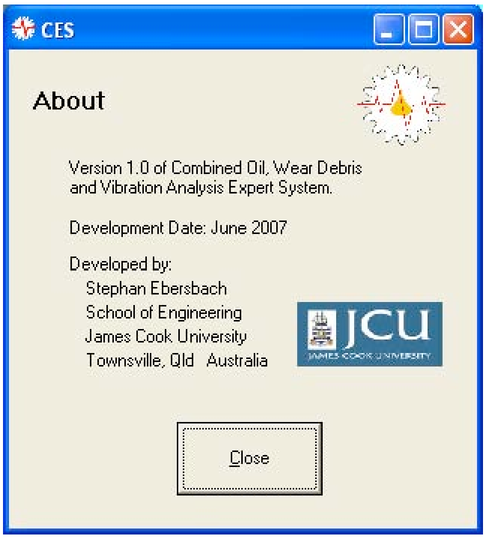

Figure H.7: *The CES About menu.*

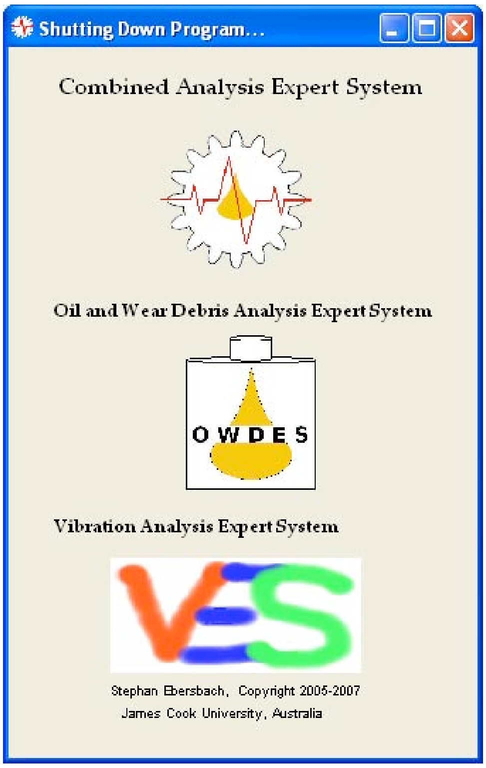

Figure H.8: *The Exit menu. This menu is displayed when the 'Exit' button is pressed.*

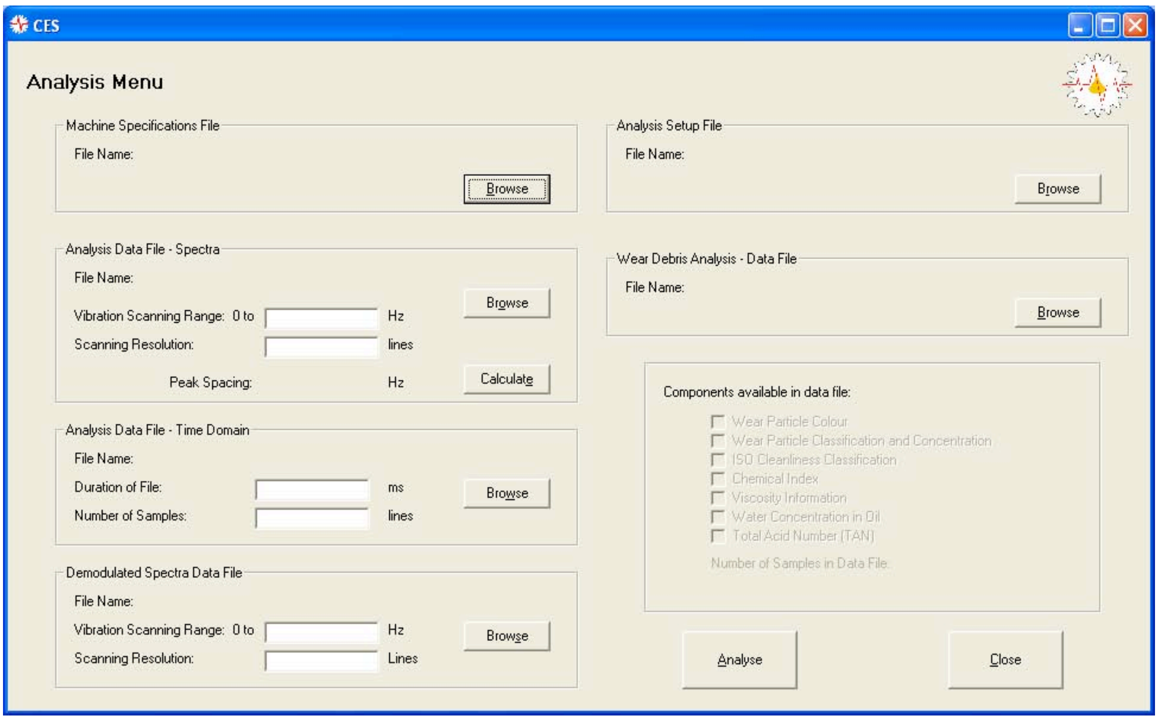

Figure H.9: *The CES Analysis menu.*

H.2 CES Results Menu Screens

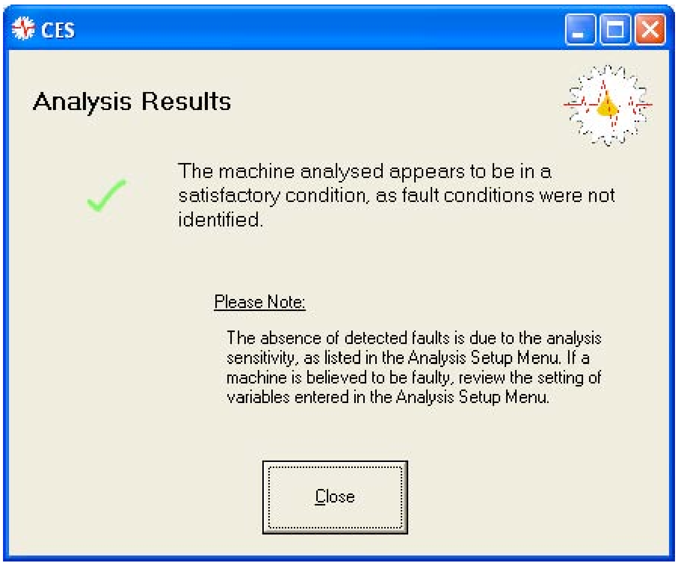

Figure H.10: *Alternative Analysis Results menu when no faults are detected.*

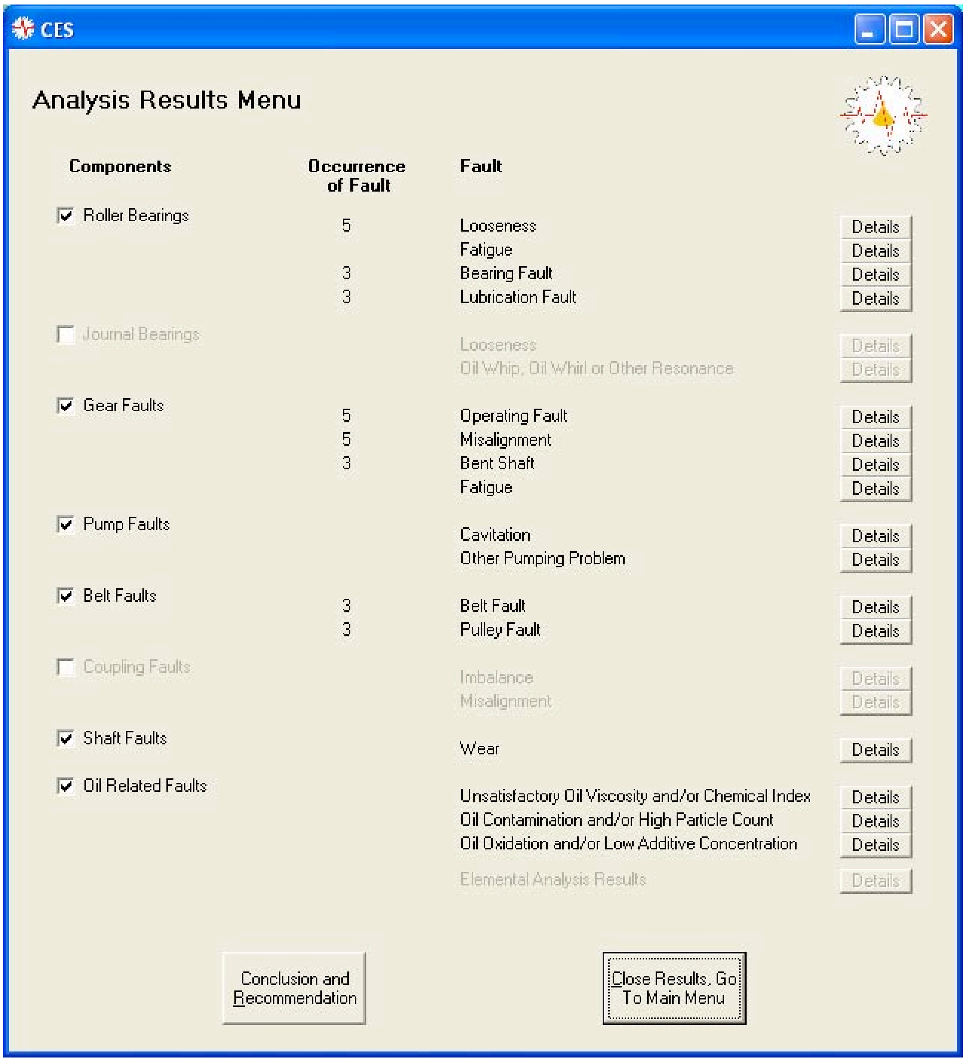

Figure H.11: *The Analysis Results menu of the Combined Analysis Expert System.*

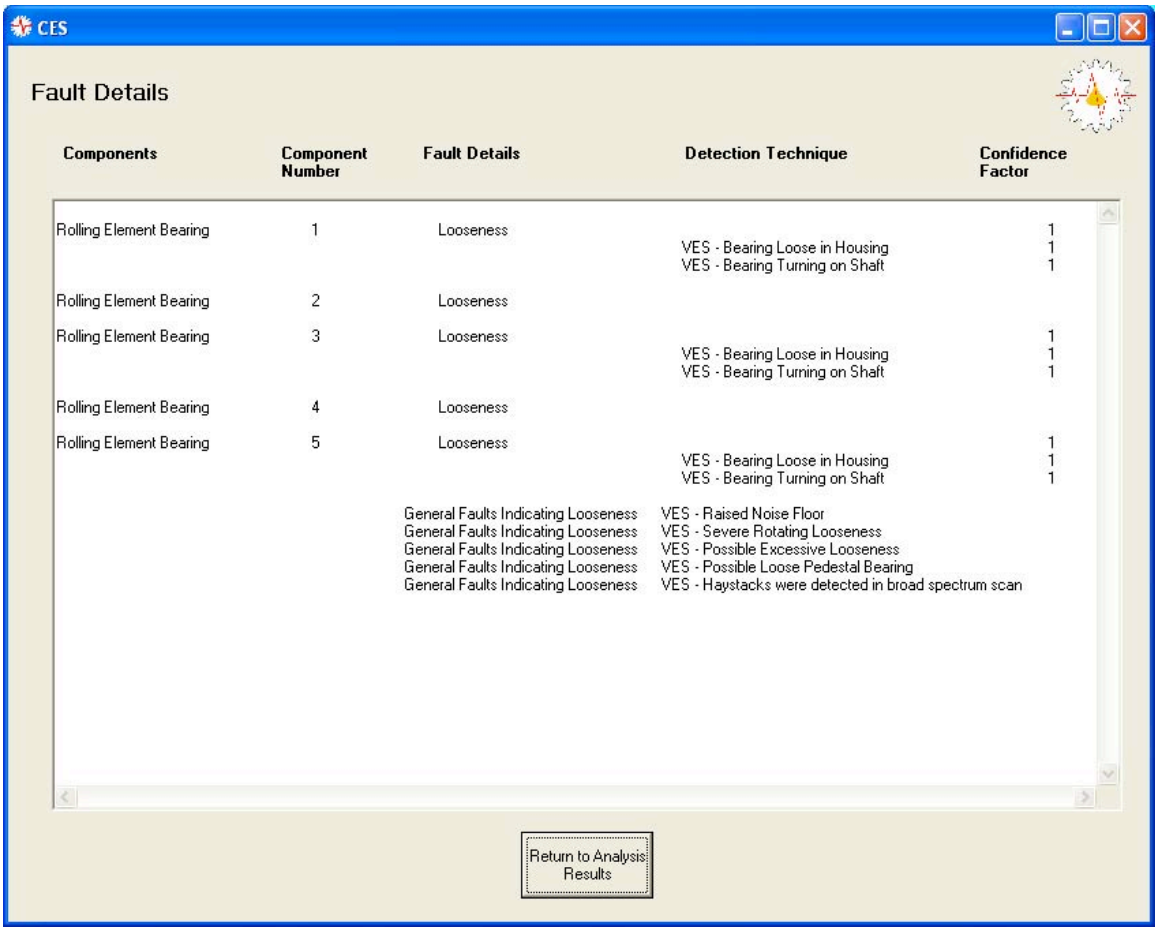

Figure H.12: *The Analysis Results — Details menu of the Combined Analysis Expert System.*

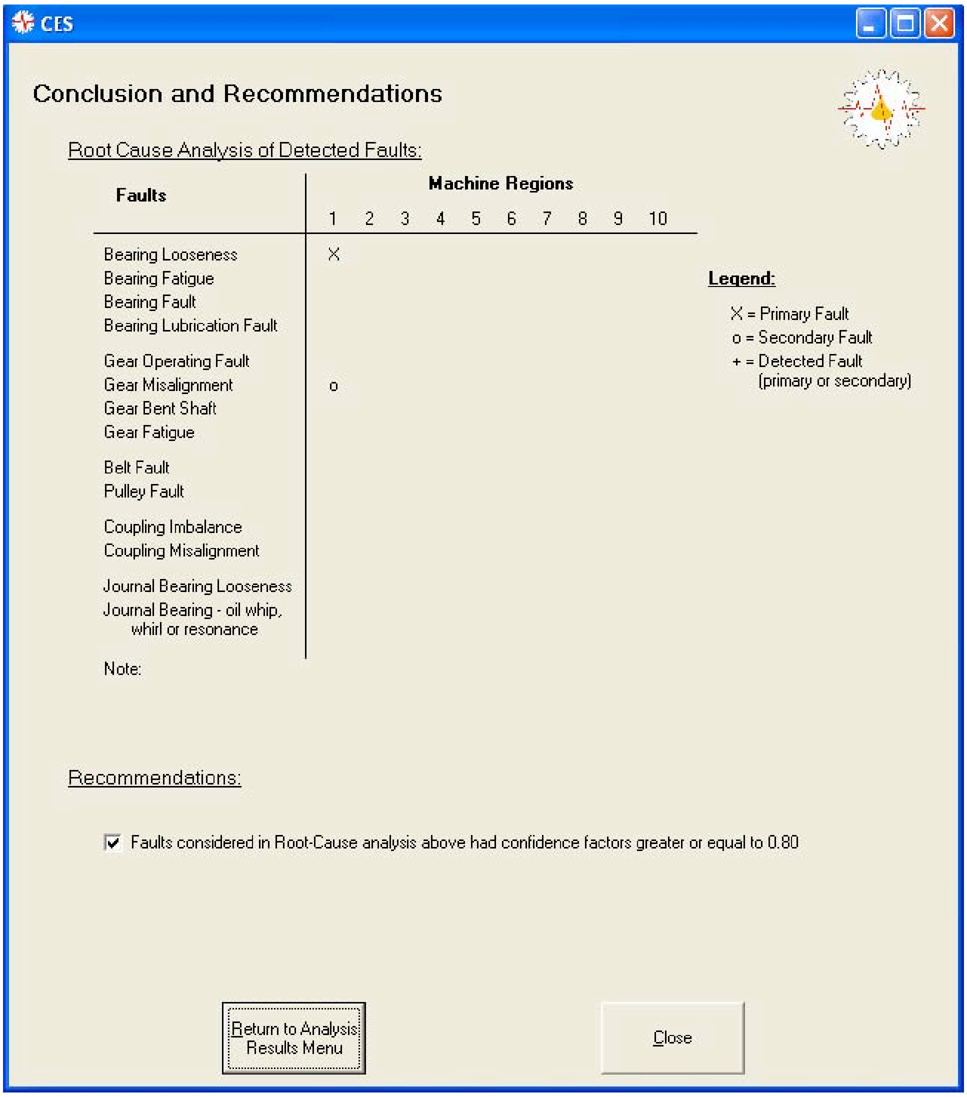

Figure H.13: *The Root-Cause Analysis results window, showing an example where bearing looseness caused gear misalignment.*

H.3 OWDES Menu Structure & Screens

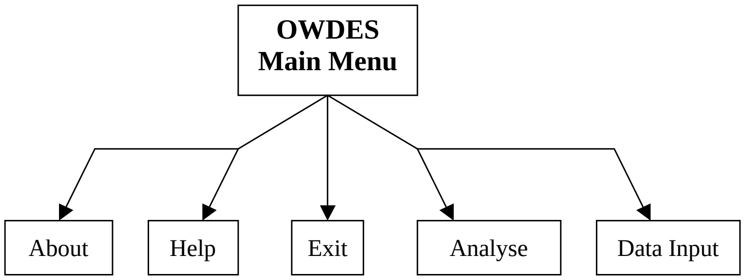

Figure H.14: *Schematic diagram of the OWDES menu structure.*

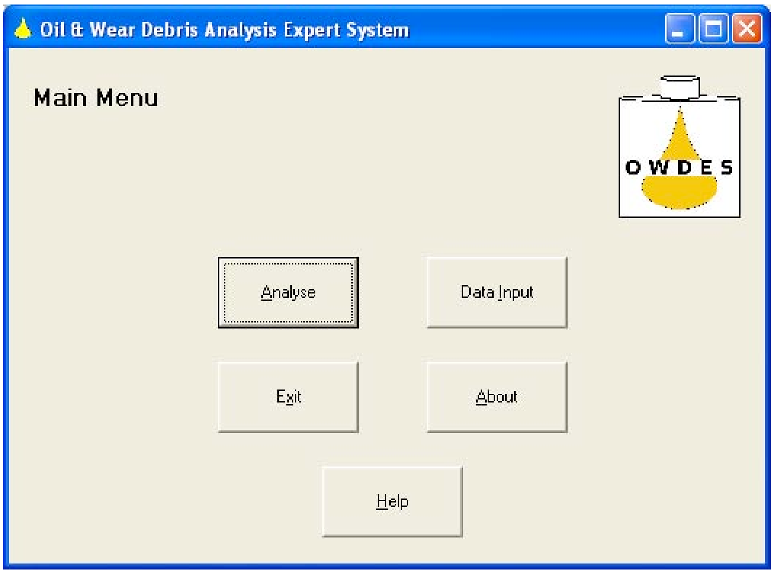

Figure H.15: *The OWDES Main menu.*

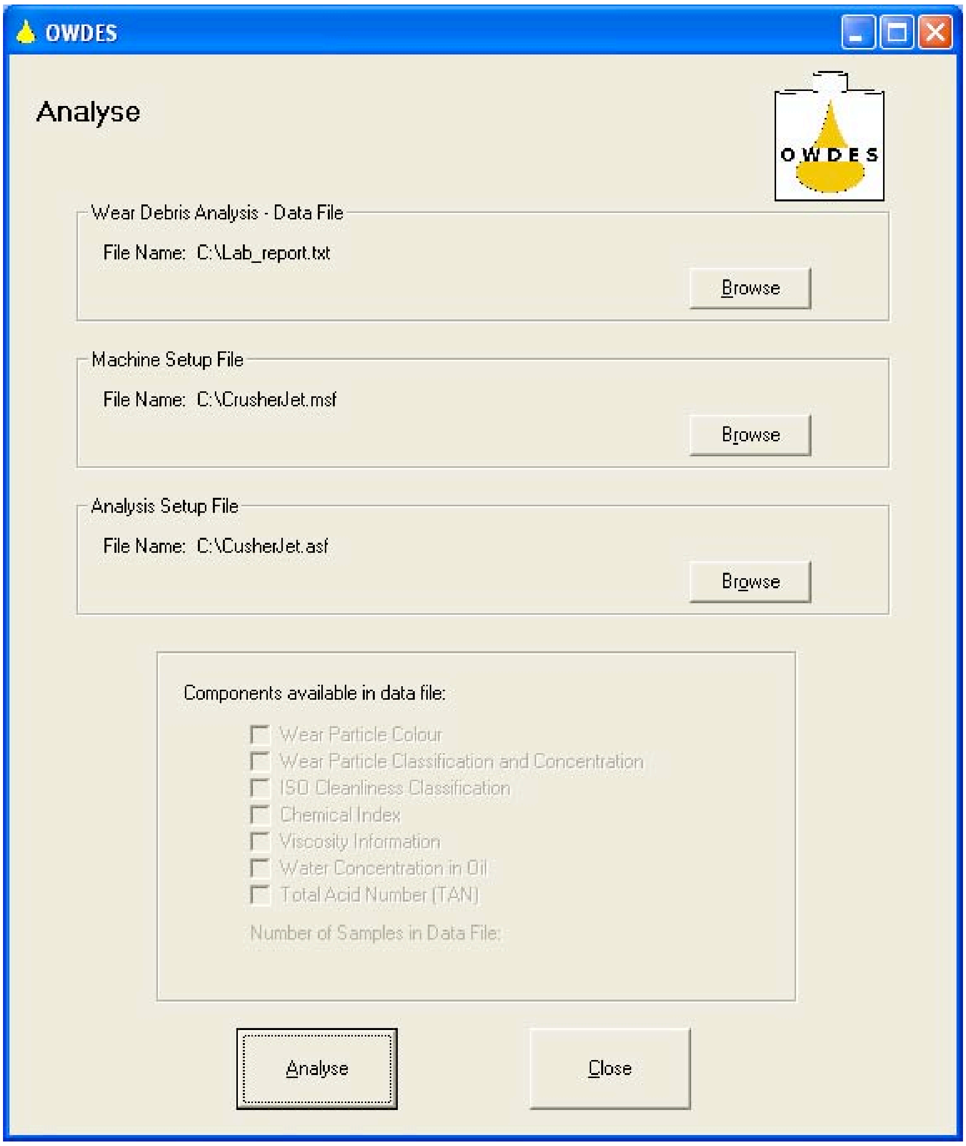

Figure H.16: *The OWDES Analyse menu.*

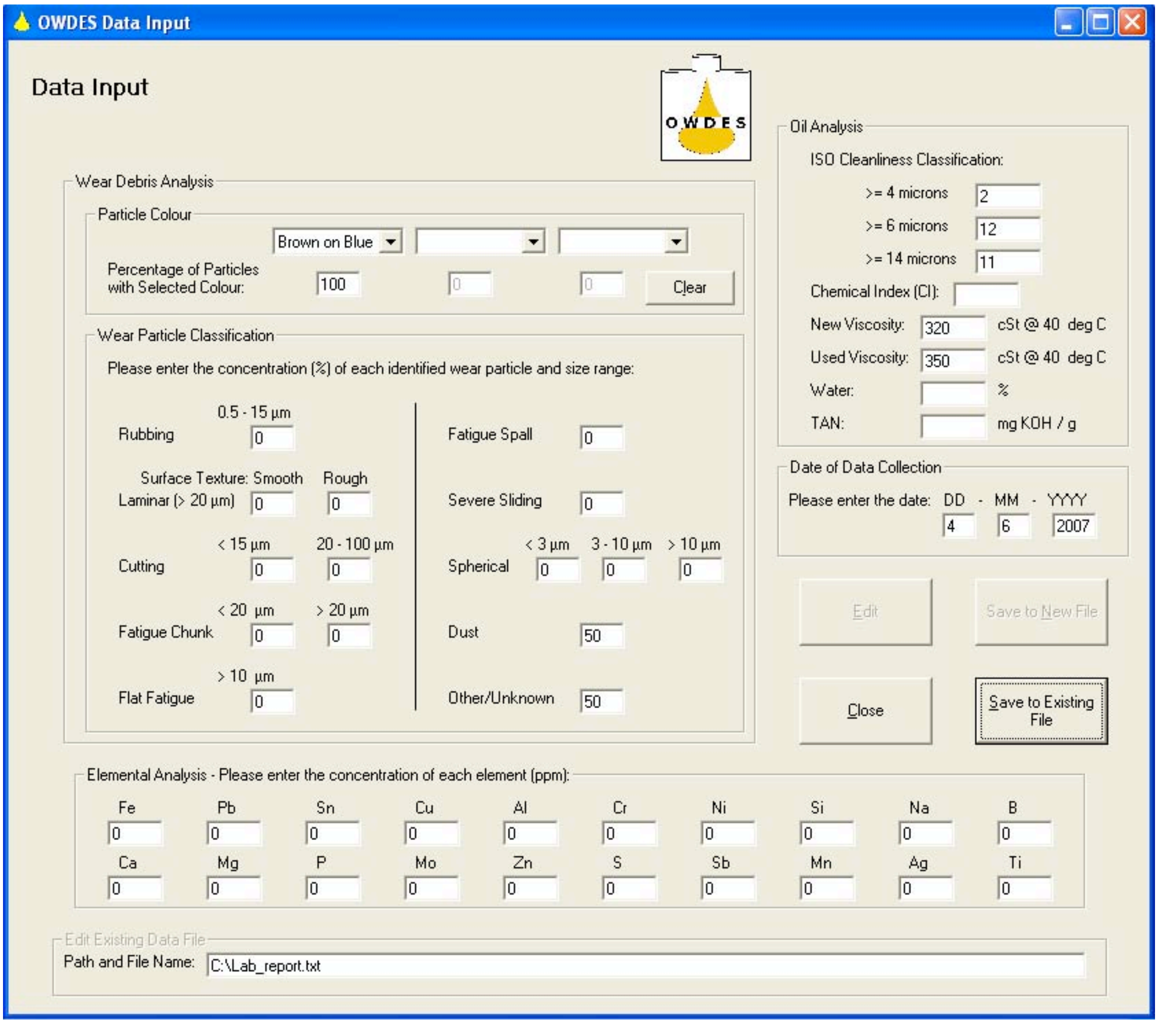

Figure H.17: *The OWDES Data Input menu. This menu is used to input oil analysis data (from a laboratory report) into a text file compatible with the Oil & Wear Debris Analysis Expert system.*

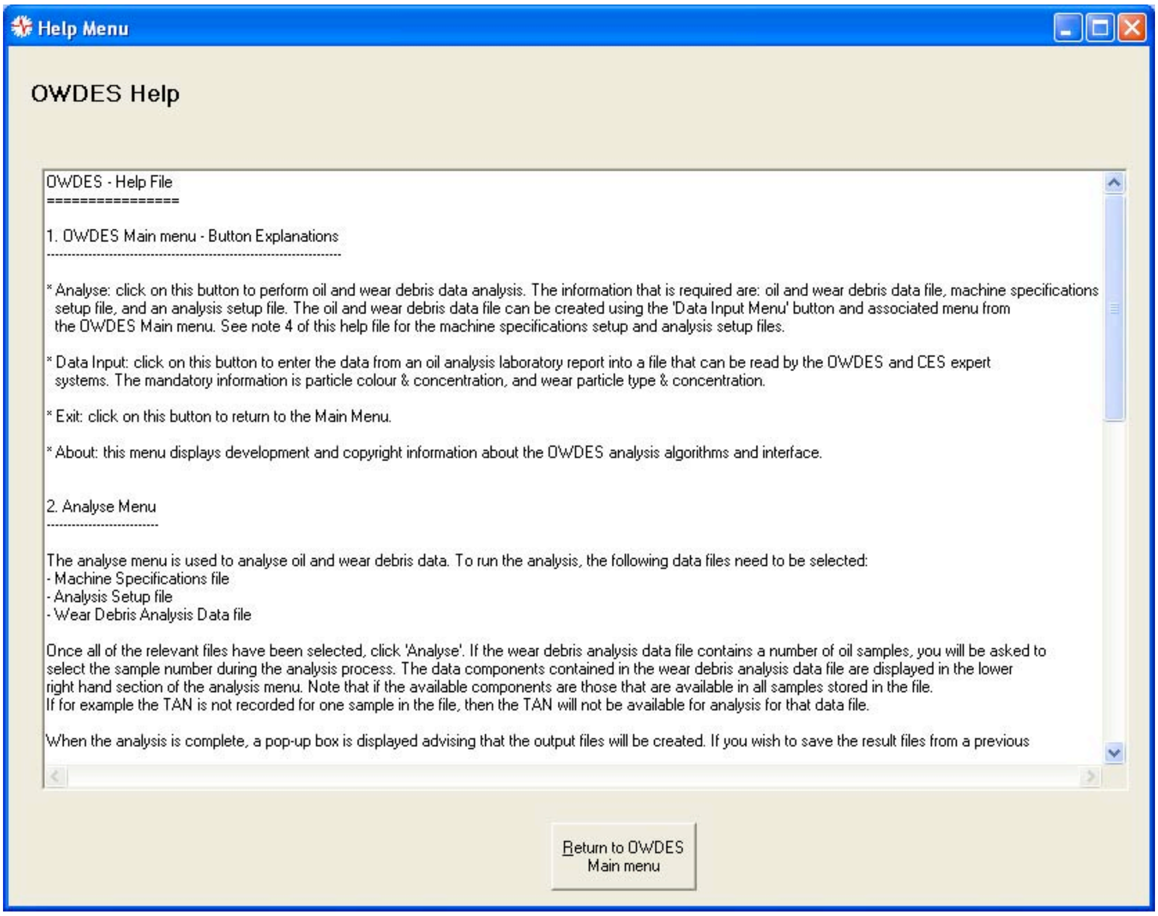

Figure H.18: *The OWDES Help menu.*

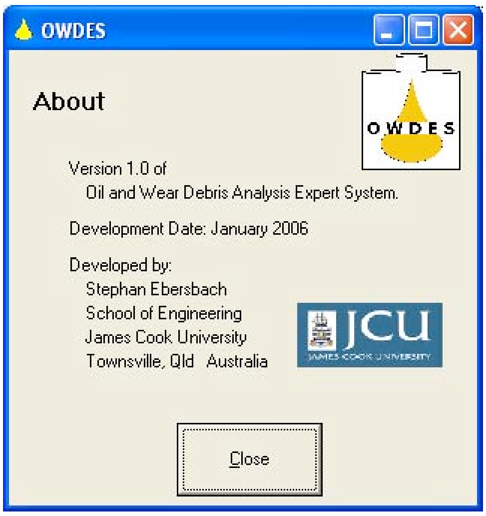

Figure H.19: *The OWDES About menu.*

H.4 VES Menu Structure & Screens

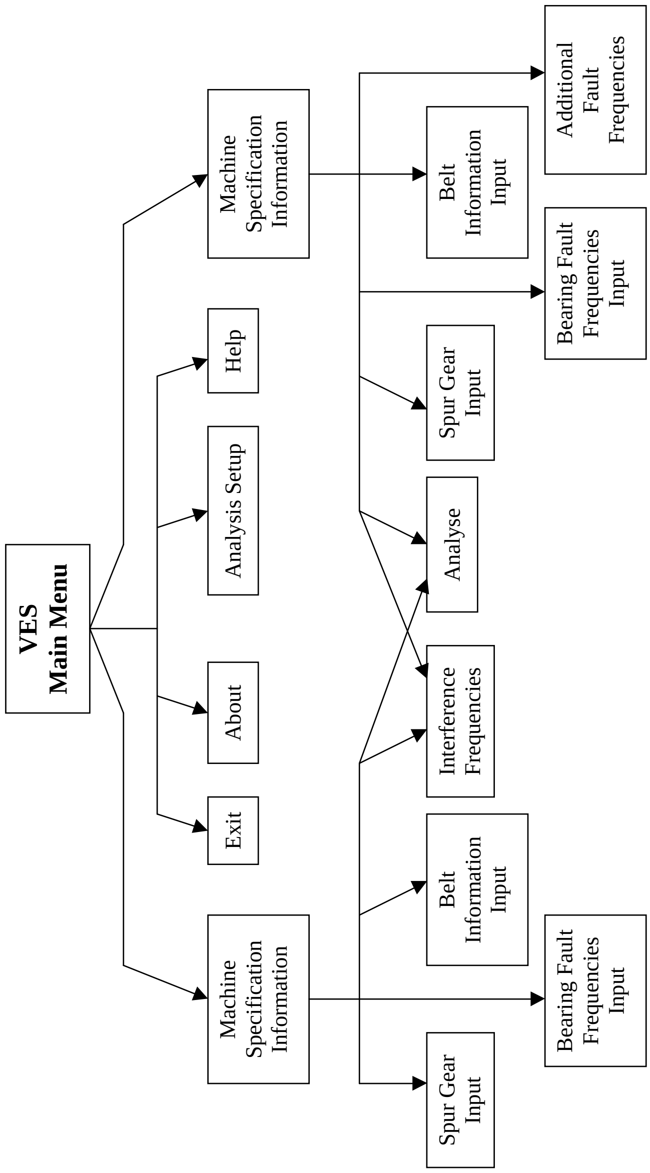

Figure H.20: *Schematic diagram of the VES menu structure.*

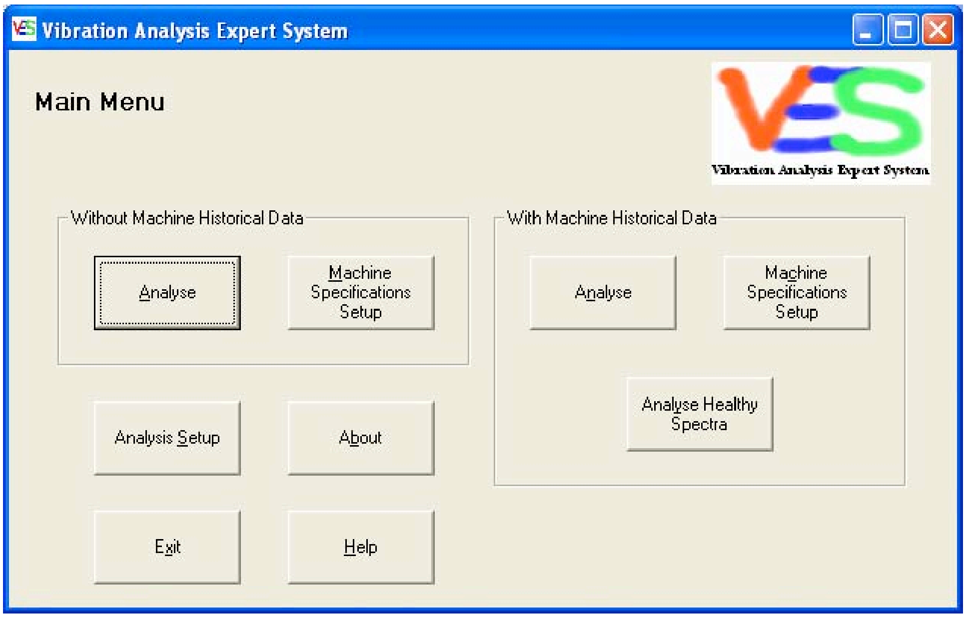

Figure H.21: *The VES Main menu.*

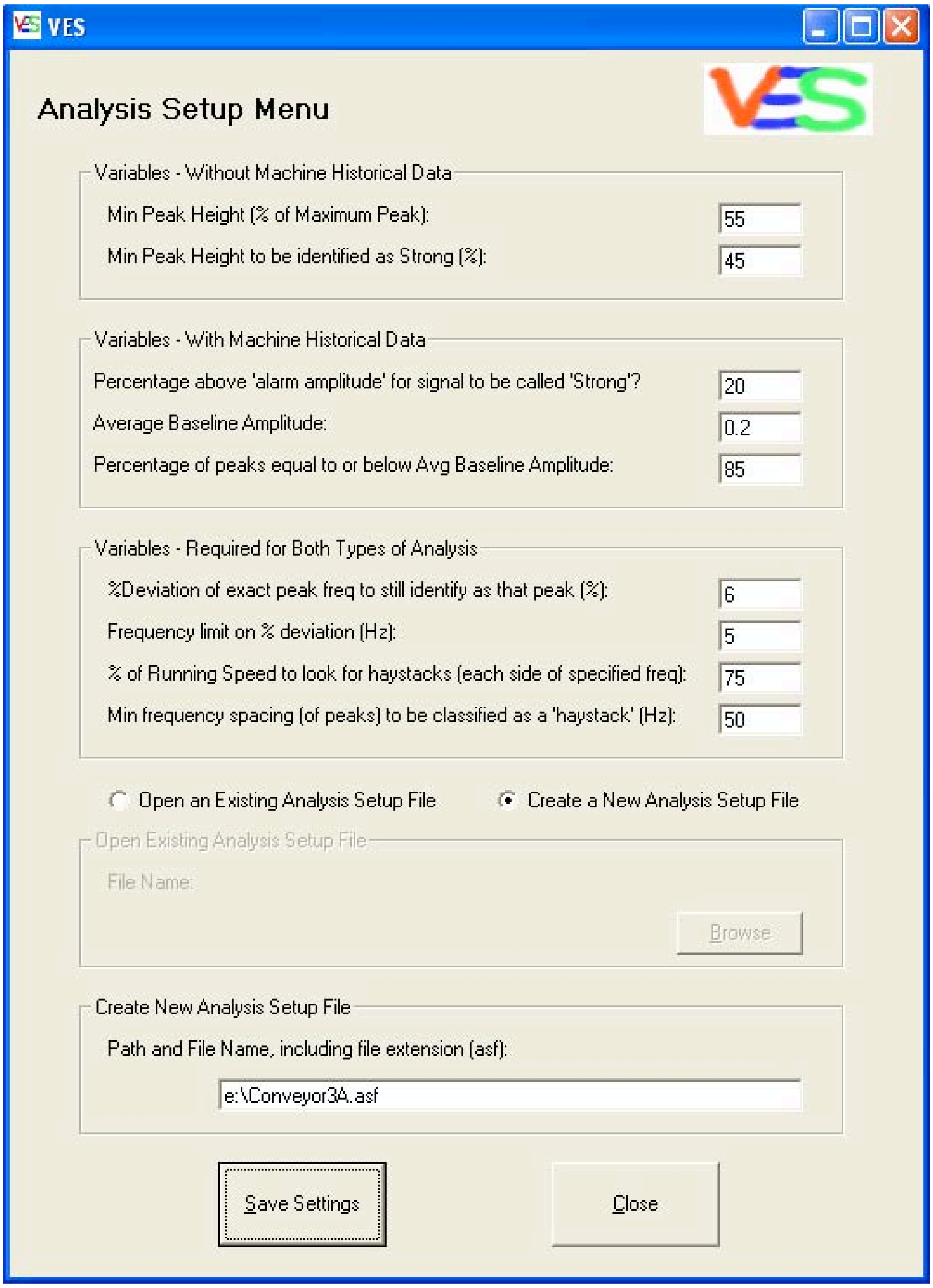

Figure H.22: *The VES Analysis Setup menu.*

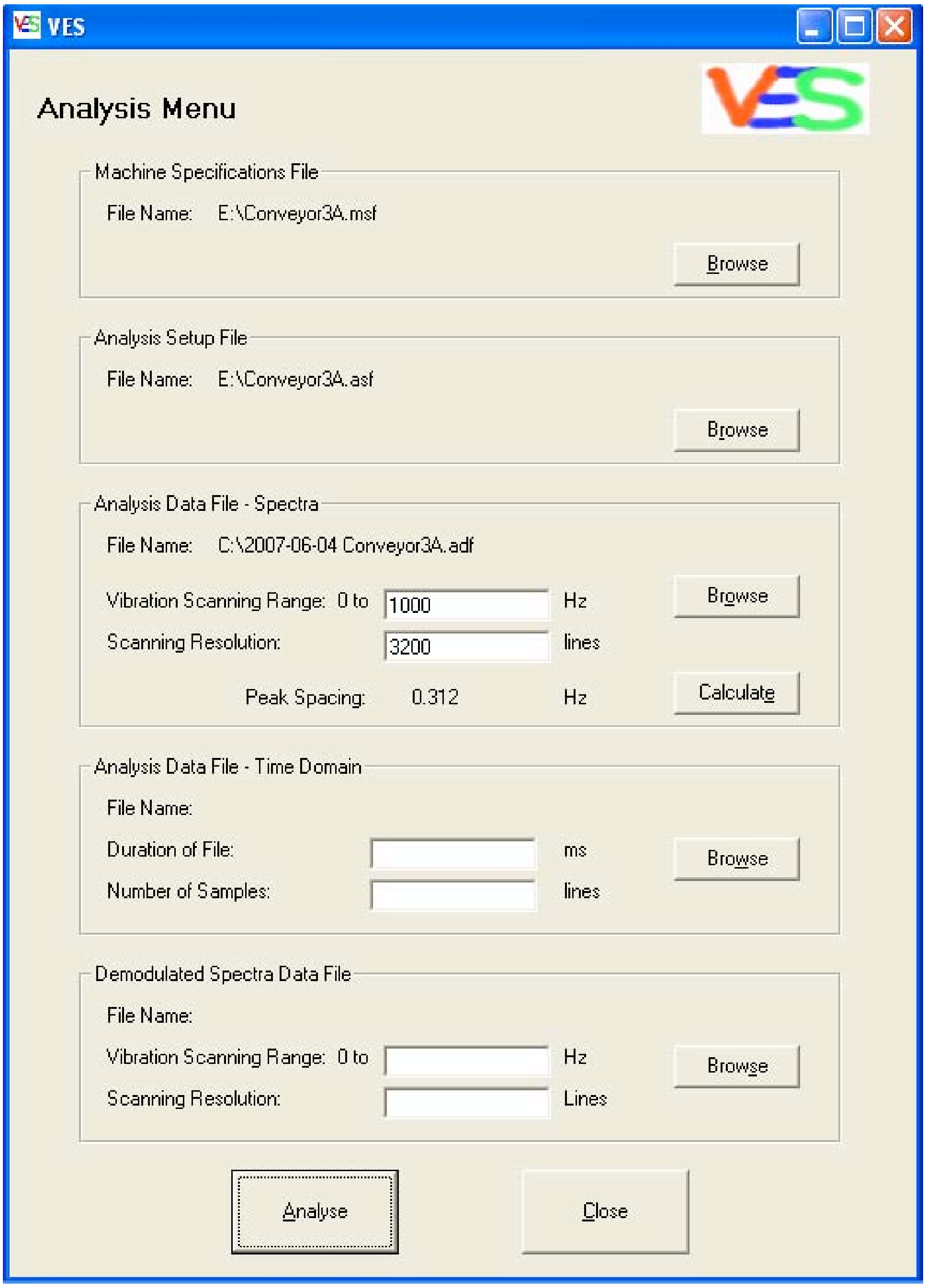

Figure H.23: *The VES Analyse menu. The menu shown here looks identical for both analysis methods (With or Without Machine Historical Data), however the software code varies in the peak detection algorithm.*

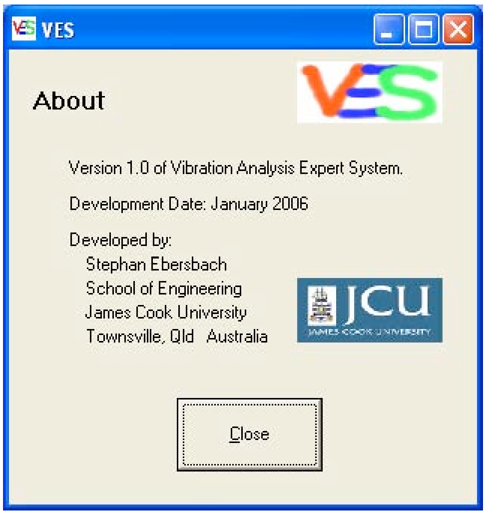

Figure H.24: *The VES About menu.*

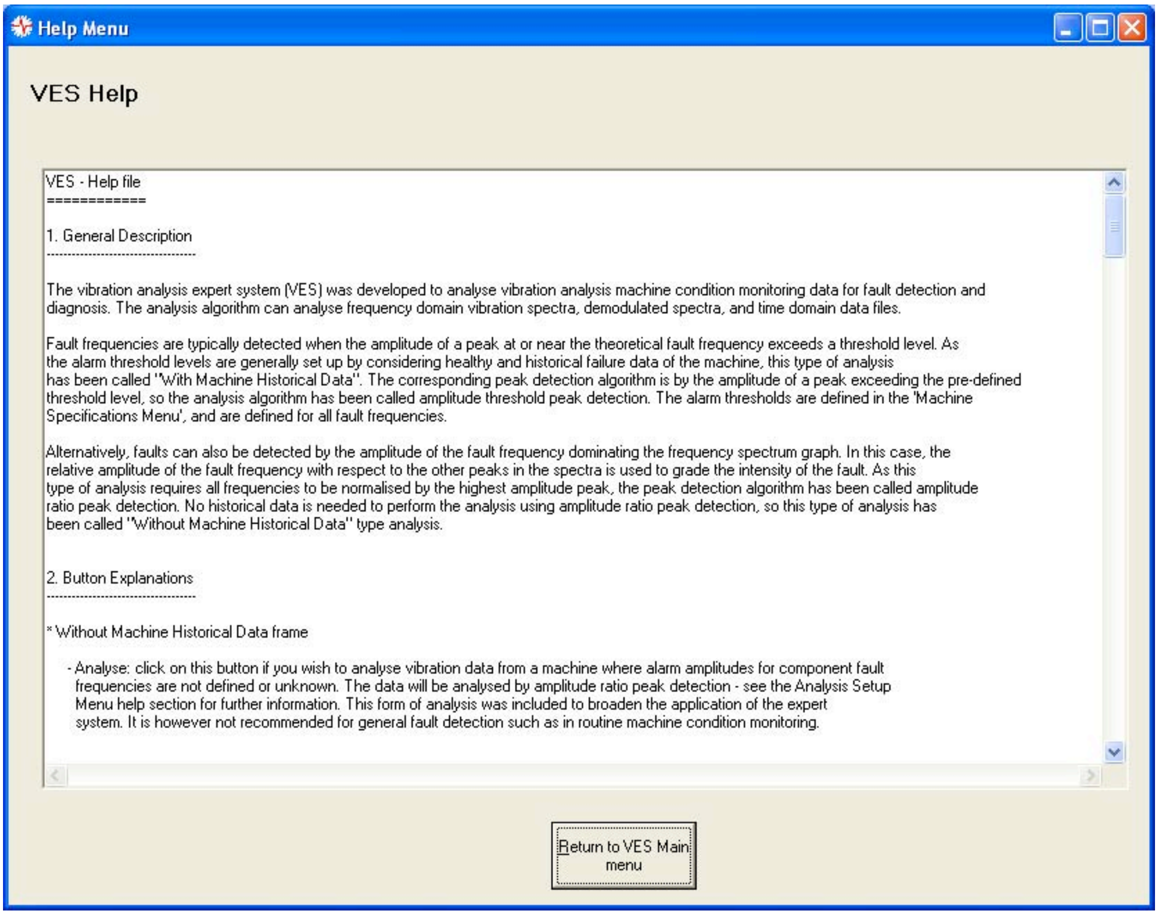

Figure H.25: *The VES Help menu.*

H.4.1 Analysis Without Machine Historical Data

The menus in this part of the VES main menu are used to enter machine specifications information and perform the analysis for the scenario when alarm amplitudes are not established for the machine. The fault frequencies are detected using the amplitude ratio peak detection algorithm as discussed in Section 5.2.2.1.

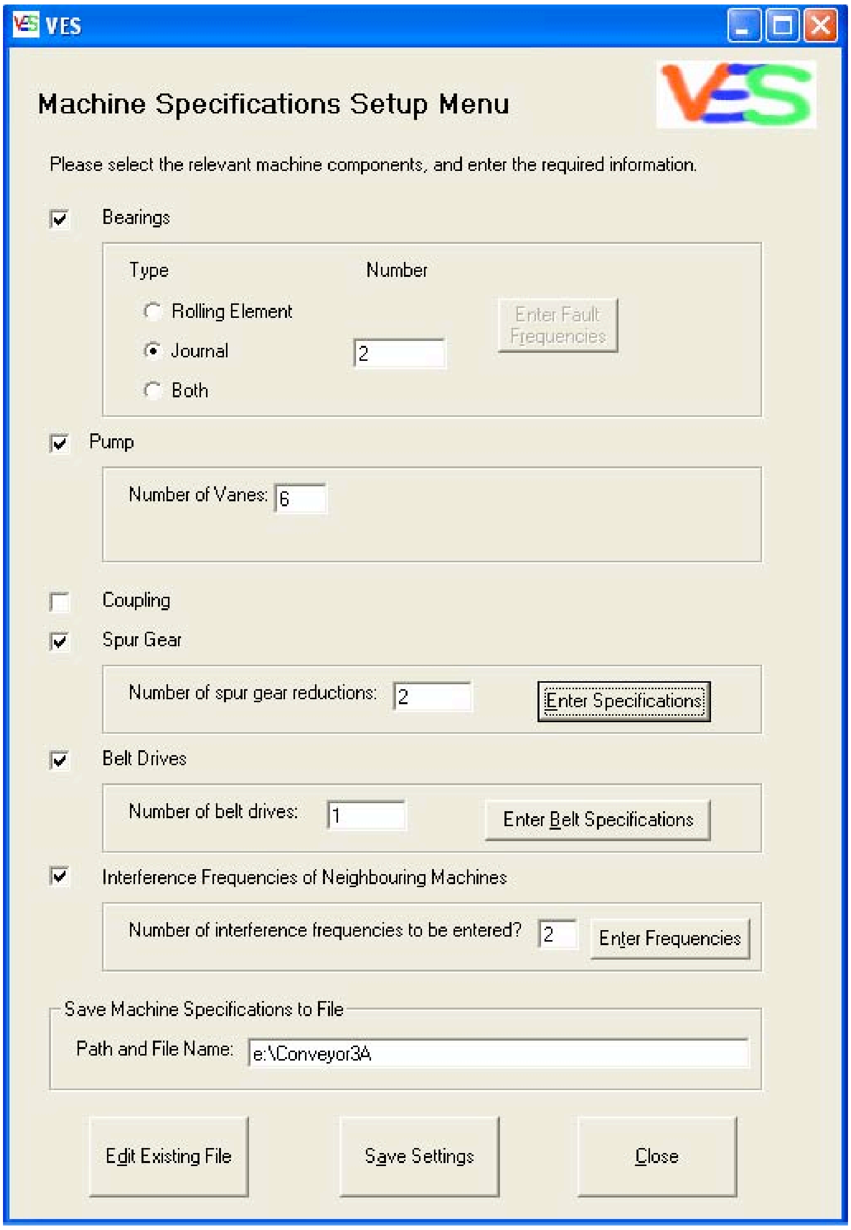

Figure H.26: *The VES Machine Specification Setup menu (using amplitude ratio peak detection).*

H.4.1.1 Sub Menus of the Machine Specifications Menu

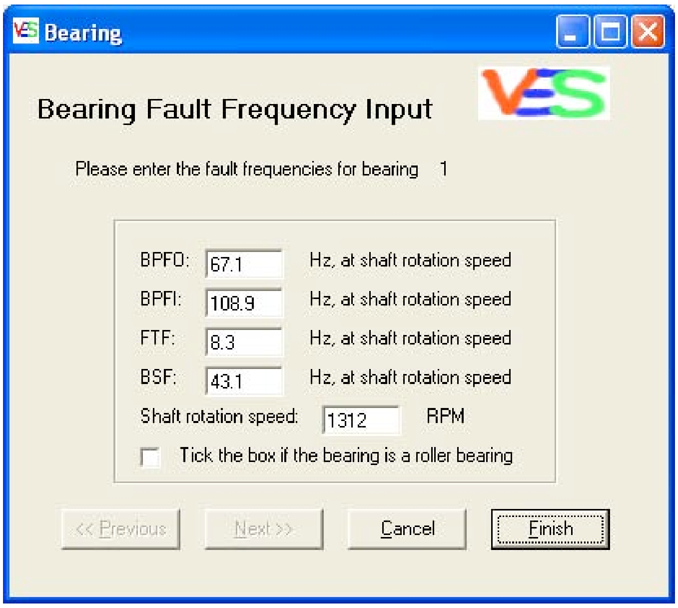

Figure H.27: *The VES Bearing Fault Frequency Input menu (for amplitude ratio peak detection).*

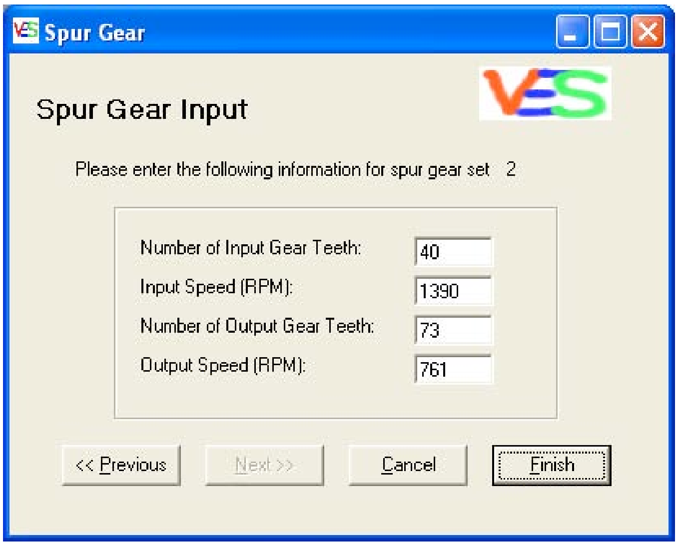

Figure H.28: *The VES Spur Gear Data Input menu (for amplitude ratio peak detection).*

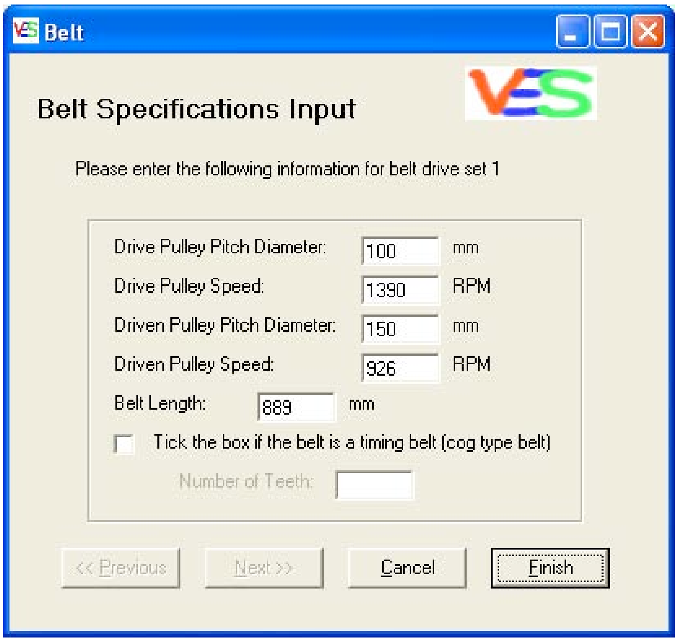

Figure H.29: *The VES Belt Specifications Input menu (for amplitude ratio peak detection).*

H.4.2 Analysis With Machine Historical Data

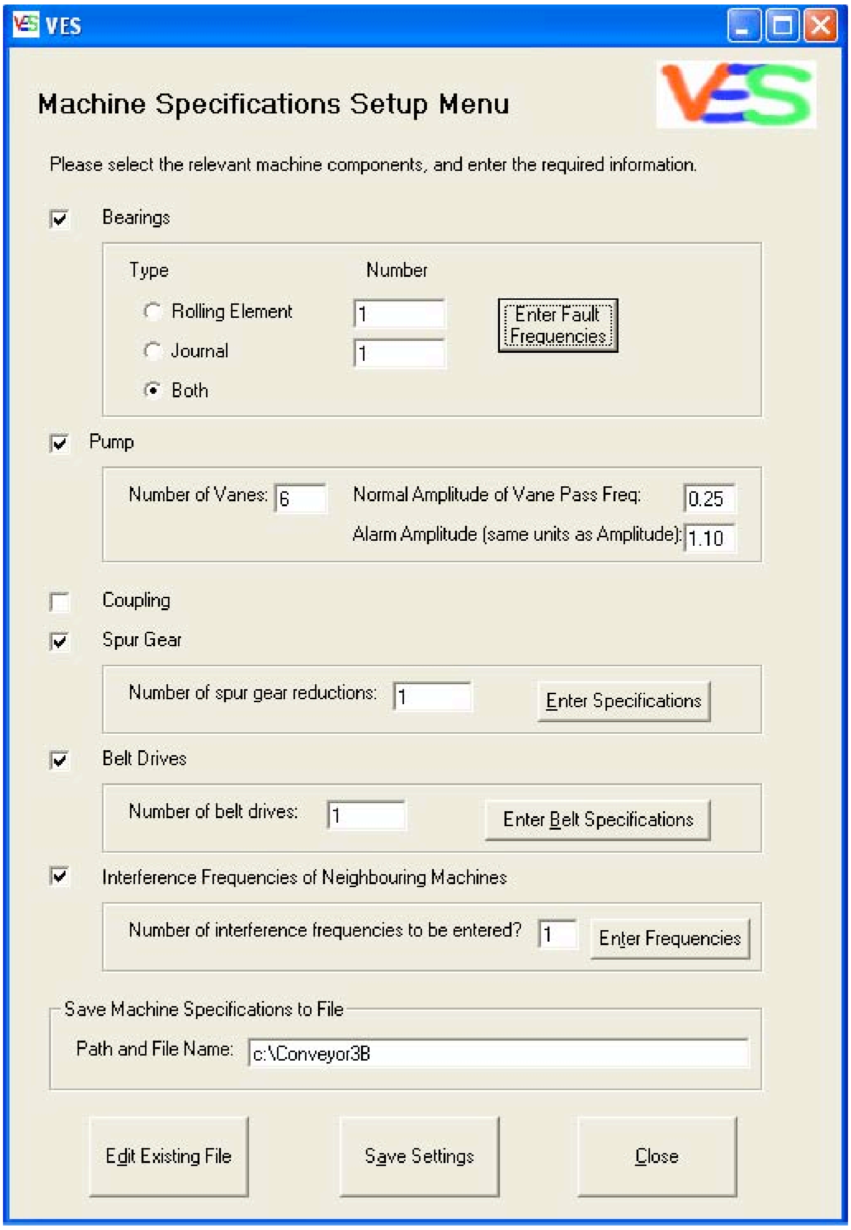

Figure H.30: *The VES Machine Specification menu (using amplitude threshold peak detection).*

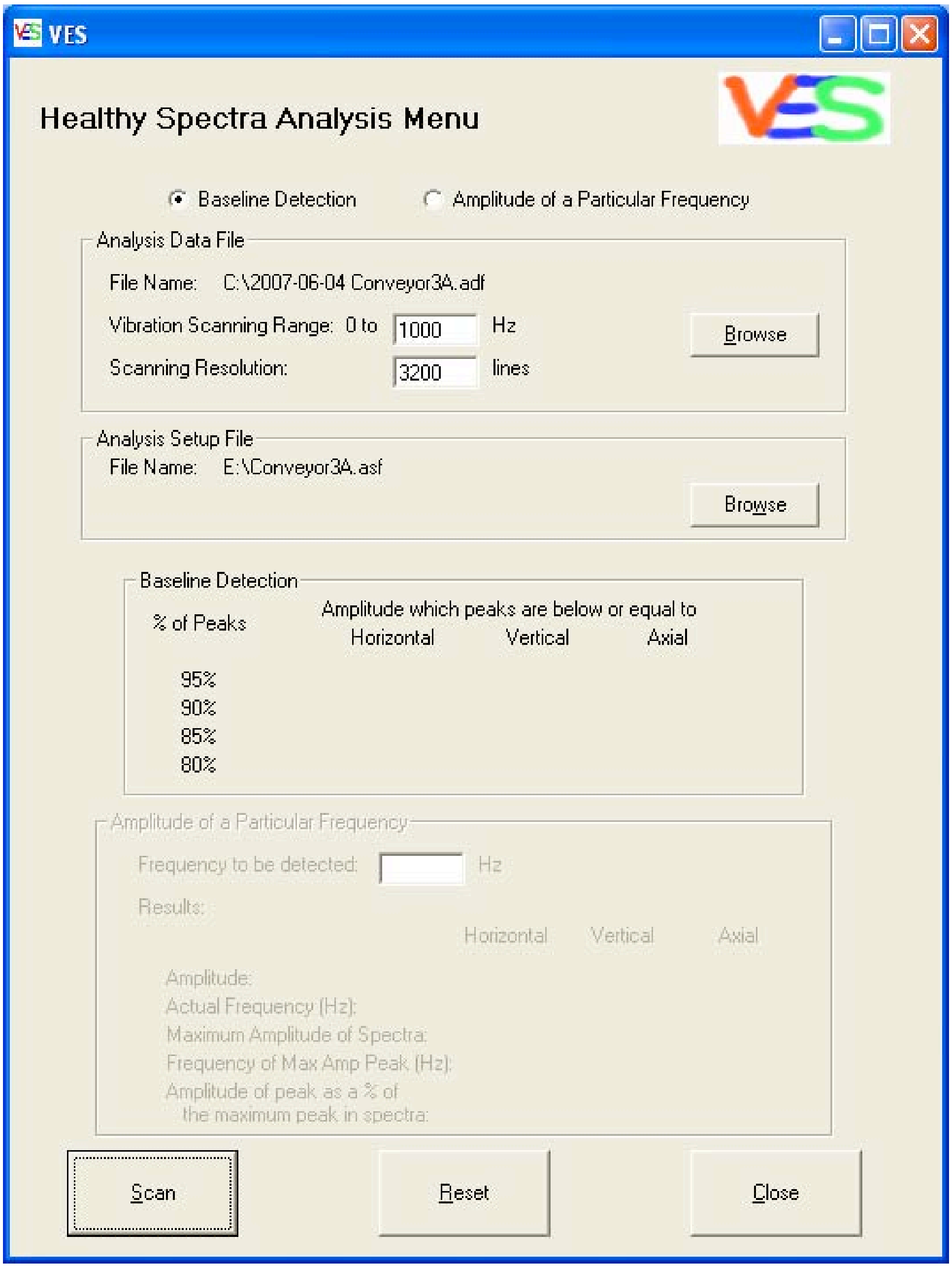

Figure H.31: *The VES Healthy Spectra Analysis menu. This menu allows (a) Amplitude detection of a particular frequency (selected in figure), (b) Baseline analysis.*

H.4.2.1 Sub Menus of the Machine Specifications Menu

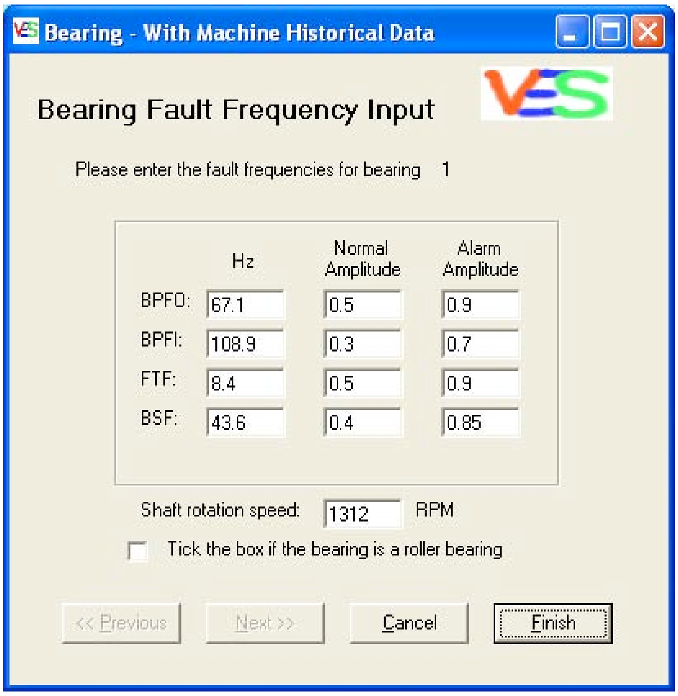

Figure H.32: *The VES Bearing Fault Frequency Input menu (for amplitude threshold peak detection).*

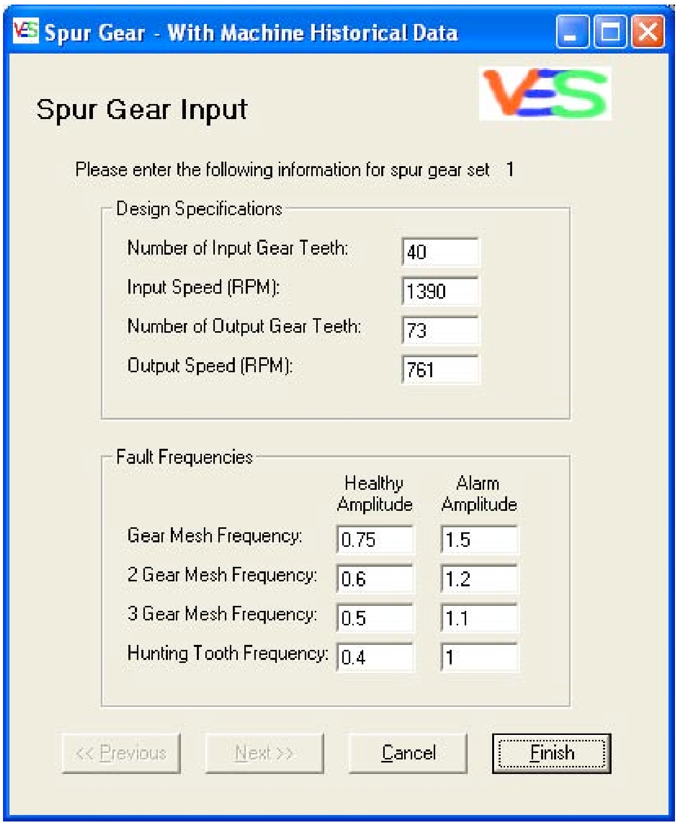

Figure H.33: *The VES Spur Gear Data Input menu (for amplitude threshold peak detection).*

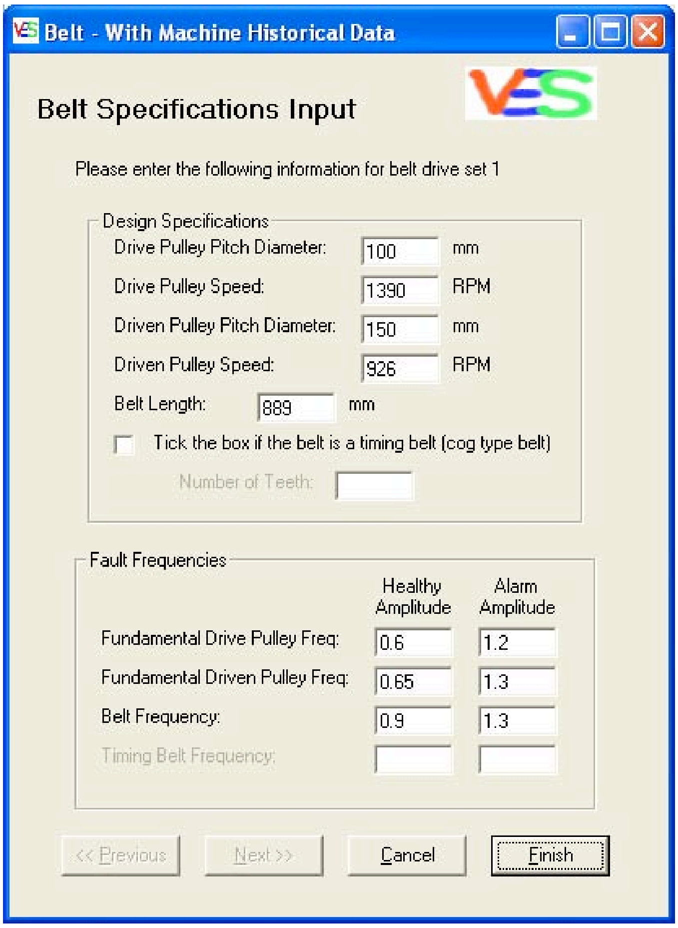

Figure H.34: *The VES Belt Specifications Input menu (for amplitude threshold peak detection).*

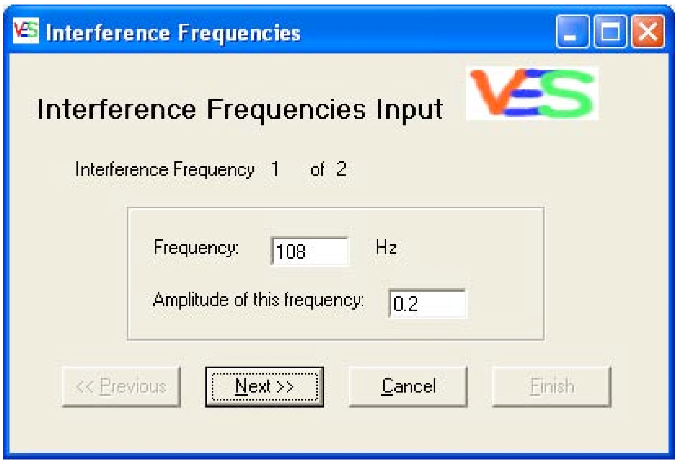

Figure H.35: *The VES Interference Frequencies menu. The interference frequencies menu is the same menu as available through the Machine Specifications menu without historical data case.*

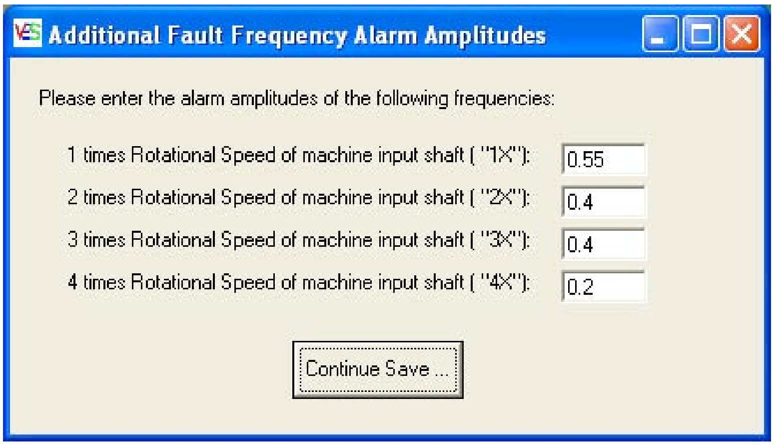

Figure H.36: *The VES Additional Fault Frequency Alarm Amplitude menu. This menu is displayed when the Save button is pressed.*

Appendix I

Expert Systems — Help Files

I.1 Main Menu - Help File

1. Button Explanations

    - **Combined Analysis:** Utilise both the vibration (VES) as well as oil and wear debris analysis (OWDES) expert systems to determine the condition of a machine. This combined expert system uses knowledge about the correlation of the two machine condition monitoring techniques (vibration analysis, and oil and wear debris analysis). To run the analysis, the following data files need to be selected:

        - Machine Specifications file
        - Analysis Setup file
        - Vibration Spectra file (for vibration analysis)
        - Vibration Time-Domain file (optional, for vibration analysis)
        - Vibration Demodulated Spectra file (optional, for vibration analysis)
        - Wear Debris Analysis Data file

      Once all of the relevant files have been selected, click ‘Analyse’. If the wear debris analysis data file contains a number of oil samples, you will be asked to select the sample number to analyse during the analysis process. The data components contained in the wear debris analysis data file are displayed in the lower right hand section of the analysis menu. Note that if the displayed available components are those that are available in all samples stored in the file. If for example the TAN is not recorded for one sample in the file, then the TAN will not be available for analysis for all samples in that data file.

The results are displayed on-screen, which provides a one-screen overview of the detected faults, with more detail accessible when the 'Details' button next to each fault is pressed. A separate menu for root-cause analysis results can be selected from the results menu. If no faults were detected, a separate menu is displayed indicating that no faults were detected.

- **OWDES Analysis Only:** This button opens the Oil and Wear Debris analysis Expert System (OWDES) main menu. Use this expert system if you wish to analyse the machine condition using only oil and wear debris analysis techniques.
- **VES Analysis Only:** This button opens the Vibration analysis Expert System (VES) main menu. Use this expert system if you with to analyse the machine condition using only the vibration analysis technique.
- **Remaining Lifetime Estimation:** This button opens the Remaining Lifetime Estimation menu.
- **Machine Specifications Setup:** The machine specifications setup menu is used to enter the components contained on the machine that is monitored. The information entered varies from broad component selection, such as whether bearings or gears are present on the machine, to specific information including the types of chemical elements found in the various components of the machine.
- **Analysis Setup:** The analysis setup menu is used to adjust the analysis sensitivity, and to fine tune the analysis operation for the particular machine.
- **Exit:** Clicking on the exit button will result in the program being closed.
- **About:** This menu displays development and copyright information about the CES analysis algorithms and interface.

2. General Information About CES

   The CES (Combined Analysis Expert System) operates the VES and OWDES analysis algorithms for data analysis, then employs its own algorithms for correlation and root-cause analysis. CES therefore requires the full machine specifications and analysis setup data for both expert systems.

3. Remaining Lifetime Estimation - Operation

   This menu is used to estimate the remaining lifetime of a machine, by considering the wear rate, and the amount of material that can be worn off the component before it is deemed as 'failed'. The amount of material that can be worn off a component is the difference between the dimensions of the current component, minus the dimensions of the wear-out limit as published by many manufacturers (the wear-out limit is typically used for judging component condition during machine rebuilds). The remaining lifetime estimation requires 4 steps to be completed.

   Step 1 — Dominant Wear Mode. This information is available from the results of the combined analysis expert system (or from oil analysis report directly). Either select Abrasive, Adhesive, Sliding or Cutting wear.

   Step 2 - Select whether the component you are estimating the remaining operating life for is a gear, or a bearing or shaft. Note that only plain bearings can be used for analysis as their internal clearances can be approximated. The internal clearances of rolling element bearings generally depends on the fit between the bearing, shaft and housing, and can therefore be different for each installation.

   Step 3 - Press the 'Calculate' button. At this stage, the required information about the machine needs to be entered. This is facilitated through pop-up type boxes. The required information is dependent on the dominant wear mode selected in step 1. Information required for every analysis includes:

Abrasive Wear:

- Wear Volume (in mm^3)
- Load (in kg)
- Speed — the sliding speed of the wearing surfaces (m/s)
- Brinell Hardness of the Abrasive
- Brinell Hardness of the Component
- Abrasive Concentration (ppm)
- Abrasive Wear Constant

Adhesive & Sliding Wear:

- Wear Volume (in mm^3)
- Load (in kg)
- Speed — the sliding speed of the wearing surfaces (m/s)
- Brinell Hardness of Component 1
- Brinell Hardness of Component 2
- Adhesive Wear Constant

Cutting Wear:

- Wear Volume (in mm^3)
- Load (in kg)
- Speed — the sliding speed of the wearing surfaces (m/s)
- Brinell Hardness of Component 1
- Brinell Hardness of Component 2
- Total Clearance (including at bearings and looseness of gear if present)
- Shaft Length (mm)
- Gear width (mm)
- Position of centre of gear from end of shaft (mm)

- Gear Adendum Radius (mm)
- Gear Dedendum Radius (mm)
- Gear Interference Factor — the volume of gear meshing zone not occupied by gear teeth. This is the volume of air between the top of a tooth (adendum radius of gear 1) and the bottom of the corresponding gear teeth (dedendum radius of gear 2). Expressed as a decimal, eg 95% vol. is occupied by gear teeth and 5% vol is air. In this example, factor = 0.95.

Step 4 - The results are displayed.

4. Machine Specifications Setup Variables

This menu contains all of the information about the machine to be monitored, to allow the expert system to perform fault detection and diagnosis on the input data. The data fields and a short description follow. The menu has been divided into 2 sections: the left half is for vibration analysis, and the right half is for oil and wear particle analysis, and root-cause analysis.

To edit an existing file, click the 'Edit Existing File' button at the bottom left hand corner of the menu, browse and select the desired file in the pop-up menu. To start a new file, just enter the components and specifications by clicking the tick box next to the component type you wish to enter.

Vibration Analysis Part:

- Bearings: select the number and type of bearings. For rolling element bearings (ball bearings and roller bearings), the fault frequencies and their normal and alarm amplitudes must be entered. This is done via the separate menu which is displayed when the 'Enter Fault Frequencies' button is pressed. If more than 1 bearing was entered, click 'Next' to enter the specifications of the other bearings called '2' etc. You can view what was already entered by clicking 'Previous'. When the last bearing information was entered, the 'Finish' button will become active. Click 'Finish' to return to the Machine Specifications Setup menu to continue with the other components, and save the entered data to a file. Up to 50 rolling element bearings can be entered. Please note that every bearing with different fault frequencies must be defined as a separate bearing. Differences in fault frequencies could be due to the use of a different bearing size/design, or two identical bearings operating at different rotational speeds.

- Pump: Enter the number of vanes on the pump impeller, as well as the normal and alarm amplitudes of the vane pass frequency.
- Coupling: Tick this box if the machine has a coupling. The analysis algorithm will then test for coupling misalignment.
- Spur Gear: Enter the number of reductions that the gearbox has, and press the 'Enter Specifications' button to enter the specifications of each spur gear reduction. You will need to enter the number of teeth and rotational speed (RPM) of each gear. The normal and alarm amplitudes will also be required for the typical frequencies produced by gears (gear mesh frequency - GMF, 2 GMF, 3 GMF, and hunting tooth frequency - HTF). If more than 1 reduction was selected, click 'Next' to enter the specifications of the reduction called '2' etc. You can view what was already entered by clicking 'Previous'. When the last reduction was entered, the 'Finish' button will become active. Click 'Finish' to return to the Machine Specifications Setup menu to continue with the other components, and save the entered data to a file. Up to 50 spur gear reductions can be entered.
- Belt Drives: Enter the number of belt drive reductions present on the machine to be monitored. Belt specifications also need to be entered via the pop-up menu displayed when the 'Enter Belt Specifications' button is pressed. The information required is: Drive pulley pitch diameter and rotational speed (RPM), Driven pulley pitch diameter and RPM, belt length (in mm), and whether the belt is a cog type belt, such as a timing belt. The

normal and alarm amplitudes of common belt frequencies are also required (fundamental drive pulley frequency, fundamental driven pulley frequency, belt frequency, and timing belt frequency if the 'timing belt' tick box was selected). If more than 1 reduction was selected, click 'Next' to enter the specifications of the reduction called '2' etc. You can view what was already entered by clicking 'Previous'. When the last reduction was entered, the 'Finish' button will become active. Click 'Finish' to return to the Machine Specifications Setup menu to continue with the other components, and save the entered data to a file. Up to 50 belt reductions can be entered.

- Interference Frequencies of Neighbouring Machines: This feature allows you to enter strong frequencies of machines near by that can be induced into the machine to be monitored via the mounting structure. Enter the number of frequencies you wish to register, and click the 'Enter Frequencies' button to enter the frequencies (in Hz) and their expected amplitude, using the displayed menu. Use the 'Next' and 'Previous' buttons to toggle between the entered frequencies (if more than 1 was entered) and click 'Finish' when complete. Up to 50 interference frequencies can be entered.
- Saving File: Save the file by entering the path and file name in the text box. The path is the drive which you wish to save to as well as the folder. Eg: to save to the Conveyor folder on E-drive, using Gearbox5 as a file name, enter 'E:\Conveyor\Gearbox5' in the textbox. The file will be given the extension '.msf'. Make sure that the file name is unique, otherwise the existing file will be over-written!

Oil & Wear Particle Analysis Part:

- Machine Materials: This menu allows you to enter the elemental compositions of component materials, such as bearings, gears, shafts, and other components. Enter the number of different material compositions you wish to enter for these 4 material categories, and click the 'Enter Elemental Composition' button. You may now enter the elements present in each component by selecting the elements from the selection, and using the 'Previous' and 'Next' buttons to toggle between components. The bearing, gear and shaft materials are numbered automatically. If you selected to enter the composition of 'other materials', you are also prompted for a unique name for each one, as well as the elemental composition. Once all of the information has been entered, click 'Finish'.

- Machine Regions Analysis: This information is required for the expert system to perform root-cause analysis. The machine components that influence each other must be grouped into a 'Region'. Components that should be grouped together are those where the failure of one component can lead to the failure of another component - the failure of a bearing leading to abnormal gear wear for example. Each component can be part of two 'Regions', which allows 'Regions' to overlap. Eg: A single reduction gearbox driving a conveyor. The gears, shafts and bearings would be grouped into 'Region 1', while the output shaft and bearings, and conveyor drive roller and bearings would be grouped into 'Region 2'. To enter the regions information, click on the 'Enter Regions Information' button, and enter the component number positioned in each 'Region'. Before entering the regions information, the components present on the machine need to be entered by clicking on the tick boxes of the relevant components on the left side of this menu. Each component can be part of up to 2 Regions. The component numbers are those of the previously entered components. For example, the menus allow up to 50 rolling element bearings to be entered in the 'Bearings' section in the top left side of this menu. The bearings are therefore numbered from 1 to 50. Hence, if 50 rolling element bearings have been entered, then all 50 need to be assigned into 'Regions'. The expert system allows up to 10 machine 'Regions' to be assigned. To progress to the next set of 10 components, click the 'Next' button. You can review entered information by clicking on the

'Previous' button, or once complete, clicking 'Finish'.

- To save the information to file, click the 'Save Settings' button. Then 'Close' to exit the menu.

Notes:

- To de-select a component, just click on the tick box before the type of component you wish to de-select. Then click 'Yes' to the question.
- To delete the entries for a component so that the information can be re-entered, de-select the component and click 'Yes' to the question. Then click on the tick box again to re-enter the information.
- If the alarm amplitude data is not available, combined analysis using vibration, oil and wear particle analysis cannot be performed. You can however analyse the vibration data using only the VES, and setting up the machine in the 'Without Machine Historical Data' section.
- The units of the alarm amplitudes must be the same as those used in the vibration analysis data files. If you have acceleration vibration data, then you must use acceleration units (m/s^2).

5. Analysis Setup Menu

The Analysis Setup menu allows the information required by the expert systems to perform the analysis, to be entered and saved to a text file. The menu has been divided into 2 sides: the left side for vibration analysis information, and the right side for oil and wear particle analysis.

In order to run an analysis using the OWDES, an Analysis Setup File (ASF) needs to be selected. There are two options to establish an ASF file: by selecting the 'Analysis Setup Menu' from the Main menu, or from the VES Main menu (clicking the 'VES Analysis Only' button on the Main menu displays the VES Main menu). The saved files, although having the same extension (.asf) are not identical however.

- ASF files saved under the VES ‘Analysis Setup Menu’ button can only be used by the VES, not the CES or OWDES.
- ASF files saved under the ‘Analysis Setup Menu’ button from the Main menu can be used for the analysis by all expert systems (ie CES, VES and OWDES). It is therefore recommended that when a machine is set up, the ‘Analysis Setup Menu’ button on the Main menu is selected.

To edit an existing file, click the ‘Open an Existing Analysis Setup File’ option button at the lower left hand side of the menu, browse and select the desired file in the pop-up menu. To start a new file, just click the ‘Create a New Analysis Setup File’ option button. For a new file, you will need to enter the path and file name (including extension). Eg: to save to the Conveyor folder on E-drive, using Gearbox5 as a file name, enter ‘E:\Conveyor\Gearbox5.asf’ in the textbox. Make sure that this file is unique, otherwise the existing file will be over-written!

Vibration Analysis Part:

The VES analysis algorithm utilises nine user changeable variables to determine the peak detection sensibility, which the operator can edit using the Analysis Setup menu. These variables have been categorised into three groups, depending on whether the variables are required for analysis with machine historical data, without, or both. The variables and their functions are as follows:

- Variables used for Without Machine Historical Data type analysis:
  - Min Peak Height — the minimum height of a peak, relative to the highest peak in the spectra, to be classified as a ‘Present’ peak
  - Min Peak Height to be identified as Strong — the minimum height of a peak, relative to the highest peak in the spectra, to be classified as a ‘Strong’ (or distinctive) peak
- Variables used for With Machine Historical Data type analysis:
  - Percentage in amplitude above ‘alarm amplitude’ (entered for each fault frequency) for peak to be called strong

  - Average Baseline Amplitude (this can be calculated using the Analyse Healthy Spectra menu accessible from the VES main menu)
  - Percentage of peaks with an amplitude below or equal to the average baseline amplitude (this can be calculated using the Analyse Healthy Spectra menu)

- Variables required for both analysis types:
  - Percentage Deviation — the percentage deviation in frequency of a peak
  - Frequency Limit — a frequency limit (in hertz) on the percentage deviation
  - Min Haystack Width — the minimum width of haystack, in hertz
  - Haystack Search %Run Speed — The width of searching for a haystack around a specific frequency, in percent of running speed

The Min Peak Height variable sets the minimum height of a peak so that the algorithm accepts that a peak exists at the specific frequency. This variable is therefore used to adjust the peak detection sensitivity. The 'Min Peak Height to be identified as Strong' variable is similar to the Min Peak Height variable, in that it sets the detection sensitivity for distinctive peaks.

The variables used for analysis when machine historical data is available are concerned with identifying distinctive peaks relative to the entered alarm limit, and detect a raised baseline. The Average Baseline Amplitude and Percentage variables are used in detecting a raised baseline, as is often the case for severe looseness type faults.

The Percentage Deviation and Frequency Limit variables were incorporated to allow the VES to search the vibration data file for specific frequencies, and allow for measurement inaccuracies, where the particular peaks can be several hertz off their theoretical frequency. The combination of a percentage and a frequency deviation has been used as a fixed 'error' frequency may be too large for low frequency detection, and a percentage 'error' too large for high frequency detection (while a 5 % error may be ok for frequencies under 1000 Hz, it is probably too large for spectra ranging to 6000 Hz). The software therefore evaluates the 'error' using both the Percentage Deviation and Frequency Limit, and uses the smaller of the two.

The haystack detection algorithm searches for regions of consecutive Present or Strong peaks. The minimum width of such a region before it is classified as a haystack can be adjusted using the Min Haystack Width variable.

The Haystack Search % Run Speed variable can be used to adjust how far on each side of a specific frequency the algorithm searches for a haystack. In order to reduce the likelihood of a one times running speed harmonic being mistakenly detected as a haystack, this variable allows the width of spectra which is searched to be limited to a percentage of the running speed.

Oil & Wear Debris Analysis Part:

- Wear Particle Concentrations: enter the % limits of each wear particle to detect that type of particle as 'Present' or 'Strong'. These are both alarm limits, where the 'Present' concentration will generally be used to detect a fault, while the 'Strong' concentration will return a severe fault condition. Laminar particles require the normal concentrations to be entered, as well as the change in concentration which triggers a fault.
- Oil Analysis Parameters: parameters including viscosity, ISO4406 cleanliness codes and TAN can be entered using limits discussed in draft ISO standard ISO/TC 108/SC 5/WG 4 (titled 'Condition monitoring and diagnostics of machines — Tribology - based monitoring and diagnostics of machines. — General guidelines', 2000). Some recommendations on critical changes for viscosity are:
  - Critical Viscosity Increase: +20%
  - Critical Viscosity Decrease: -10%

- Elemental Analysis: enter the critical concentrations of each element, in parts per million (ppm). If any concentration is exceeded, the expert system will perform elemental analysis.

6. System Requirements

- Pentium type PC running Microsoft Windows based operating system.
- Recommendations:
  - Windows 98 or later
  - Screen resolution of at least 1024 by 768 pixels
  - At least 15 MB of free hard disk space
  - Mouse or equivalent pointing device is recommended, although most buttons can be accessed using 'Alt' and corresponding letter shortcut keys and using 'Tab' to move between text boxes.

7. Installation Requirements

The expert system .exe file can be positioned anywhere on the hard drives accessible to the PC. However, the expert expects several files and folders positioned on c-drive for correct operation. To install the expert system on the PC, follow these steps:

(a) Copy the .exe file to the desired folder

(b) Create the folder C:\Temp. This folder is used by the CES to store the result files accessible when pressing on the 'Details' button beside the detected faults, from the CES Analysis Results menu.

(c) Copy the 'CES_Help.txt', 'VES_Help.txt' and 'OWDES_Help.txt' files to the C-drive (C:\) root-folder.

(d) Copy the Visual Basic file to the Windows System folder.

The output files will be written to the C-drive root-folder (C:\).

8. Program Development Information and Disclaimer

   This program is made up of three expert systems, in a hierarchical structure where one expert system utilises the analysis of the other two. The high level expert system is the combined analysis expert system (CES), which utilises the analysis performed by the two lower level expert system, and additional correlation knowledge in order to determine the condition of the machine. The two lower level expert systems were developed to utilise the vibration analysis (VES), and the oil and wear debris analysis (OWDES) machine condition monitoring techniques. The two lower level expert systems can either be used independently, or in combination, by running the high level expert system.

   The development of these expert systems was for research purposes, in order to investigate the correlation between the vibration and oil and wear debris analysis techniques, and to develop an interface which could be used as a basis for a commercial system. While the three expert systems were thouroughly tested using either data obtained from laboratory tests, industry, or hypothetical results, or a combination of these, the developers are not responsible for any losses, direct or indirect, which may arise as a result of using this program.

I.2 OWDES - Help File

1. OWDES Main menu - Button Explanations

   - **Analyse:** click on this button to perform oil and wear debris data analysis. The information that is required are: oil and wear debris data file, machine specifications setup file, and an analysis setup file. The oil and wear debris data file can be created using the 'Data Input Menu' button and associated menu from the OWDES Main menu. See note 4 of this help file for the machine specifications setup and analysis setup files.
   - **Data Input:** click on this button to enter the data from an oil analysis laboratory report into a file that can be read by the OWDES and CES expert

systems. The mandatory information is particle colour & concentration, and wear particle type & concentration.

- **Exit:** click on this button to return to the Main Menu.
- **About:** this menu displays development and copyright information about the OWDES analysis algorithms and interface.

2. Analyse Menu

The analyse menu is used to analyse oil and wear debris data. To run the analysis, the following data files need to be selected:

- Machine Specifications file
- Analysis Setup file
- Wear Debris Analysis Data file

Once all of the relevant files have been selected, click 'Analyse'. If the wear debris analysis data file contains a number of oil samples, you will be asked to select the sample number to analyse during the analysis process. The data components contained in the wear debris analysis data file are displayed in the lower right hand section of the analysis menu. Note that if the displayed available components are those that are available in all samples stored in the file. If for example the TAN is not recorded for one sample in the file, then the TAN will not be available for analysis for all samples in that data file.

When the analysis is complete, a pop-up box is displayed advising that the output files will be created. If you wish to save the result files from a previous analysis, rename the files otherwise they will be overwritten. Once the files have been created successfully, another pop-up box is displayed advising that the analysis is complete. Press 'OK', then the 'Close' button to return to the OWDES Main menu. The results are listed in a text file saved to the C-drive. The file is called 'OWDESAnalysisOutput.txt'.

3. Data Input Menu

   When the Data Input menu has loaded, you have 3 options:

   - Edit an existing file (but do not enter any new samples)
   - Create a new data file
   - Amend an existing data file, and add another sample.

   The samples refer to the data from a laboratory report that you have received from the analysis of an oil sample. Every machine that is monitored via oil and wear debris analysis should therefore have an individual 'Wear Debris' file. Every time an oil sample analysis report is received from the oil analysis laboratory for the particular machine, the data is input to the Wear Debris file as another 'sample'. It is therefore necessary in the 'Analyse' menu to specify the sample number that you wish to analyse. The data in the 'Wear Debris Analysis' frame is mandatory, while all other data is optional.

   To edit an existing file, in order to include additional data for an existing sample, or to make corrections to an existing sample, click the 'Edit' button. If you have already entered some data before pressing 'Edit', a warning message is displayed. Browse and select the relevant file to edit. Use the 'Next', 'Previous' buttons to navigate between samples, and click 'Finish' when completed. Save the modifications, and 'Close' to return to the OWDES Main menu.

   To create a new data file, just enter all of the information including the desired file name and path, and click on the 'Save to New File' button. Eg: to save to the Conveyor folder on E-drive, using Gearbox5 as a file name, enter 'E:\Conveyor\Gearbox5' in the textbox. The file will be given the extension '.txt'. Make sure that the file name is unique, otherwise the existing file will be over-written!

   To amend an existing file and add another oil sample, enter all of the information and then click on the 'Save to Existing File' button. Browse and select the relevant file which you wish to amend. The data will be saved to a new sample, which will automatically be given the number immediately above the highest numbered sample existing in the file.

If you wish to cancel the data input at any stage, click on the 'Close' button, and 'Yes' to the pop-up box warning that all entered data will be lost.

4. Machine Specifications & Analysis Setup Information

   In order to perform data analysis using the OWDES 'Analyse' button, machine specifications and analysis setup information must be available. To enter this information and produce '.msf' and '.asf' files respectively, use the 'Machine Specifications Setup' and 'Analysis Setup' buttons from the Main menu. For help with the Machine Specifications Setup menu or Analysis Setup menu, see sections 4 or 5 in the help menu of the Main menu respectively.

5. Other Information

   For additional information, and how the OWDES links together with the CES, see the help file located in the 'Main Menu'.

I.3 VES - Help file

1. General Description

   The vibration analysis expert system (VES) was developed to analyse vibration analysis machine condition monitoring data for fault detection and diagnosis. The analysis algorithm can analyse frequency domain vibration spectra, demodulated spectra, and time domain data files.

   Fault frequencies are typically detected when the amplitude of a peak at or near the theoretical fault frequency exceeds a threshold level. As the alarm threshold levels are generally set up by considering healthy and historical failure data of the machine, this type of analysis has been called 'With Machine Historical Data'. The corresponding peak detection algorithm is by the amplitude of a peak exceeding the pre-defined threshold level, so the analysis algorithm has been called amplitude threshold peak detection. The alarm thresholds are defined in the 'Machine Specifications Menu', and are defined for all fault frequencies.

Alternatively, faults can also be detected by the amplitude of the fault frequency dominating the frequency spectrum graph. In this case, the relative amplitude of the fault frequency with respect to the other peaks in the spectra is used to grade the intensity of the fault. As this type of analysis requires all frequencies to be normalised by the highest amplitude peak, the peak detection algorithm has been called amplitude ratio peak detection. No historical data is needed to perform the analysis using amplitude ratio peak detection, so this type of analysis has been called 'Without Machine Historical Data' type analysis.

2. Button Explanations

- Without Machine Historical Data frame
  - **Analyse:** click on this button if you wish to analyse vibration data from a machine where alarm amplitudes for component fault frequencies are not defined or unknown. The data will be analysed by amplitude ratio peak detection — see the Analysis Setup Menu help section for further information. This form of analysis was included to broaden the application of the expert system. It is however not recommended for general fault detection such as in routine machine condition monitoring.
  - **Machine Specifications Setup:** click on this button to set up a machine for analysis using amplitude ratio peak detection. Choose this option if you do not have any amplitude alarm thresholds for the fault frequencies emitted by the machine.
- With Machine Historical Data frame
  - **Analyse:** click on this button if you wish to analyse vibration data from a machine where alarm amplitudes for component fault frequencies are defined. As traditionally, historical condition monitoring data is used in setting up alarm amplitude levels, this type of analysis has been called

'Analysis With Historical Data'. See the Analysis Setup Menu help section for further information. This analysis mode is recommended for routine machine condition monitoring, and is the only analysis type performed by the CES.

  - **Machine Specifications Setup:** click on this button to set up a machine for analysis, by including both fault frequencies as well as their normal (healthy) and alarm amplitudes. This style of analysis is recommended for general routine machine condition monitoring.
  - **Analyse Healthy Spectra:** click on this button to analyse a vibration spectra (frequency) file for either analysing the baseline characteristics, or finding the amplitude of a frequeny.

- **Analysis Setup:** The analysis setup menu is used to adjust the analysis sensitivity, and to fine tune the analysis operation for the particular machine. Click on this button to set up the parameters to analyse the vibration data of a machine.
- **About:** this menu displays development and copyright information about the VES analysis algorithms and interface.
- **Exit:** click on this button to return to the Main Menu.

3. <u>Minimum Data Required to Run Analysis</u>

   In order to run the analysis algorithm of the VES, at least three files are required. These are:

   - Machine Specifications File (containing information about the design of the machine including fault frequencies)
   - Analysis Setup File (containing information on how the peaks are to be detected in the vibration spectra)
   - The vibration spectra file (containing the raw vibration data of the machine)

The vibration spectra file must have the following format:

- The first line of the file must list the rotational speed of the machine (or input shaft), in RPM.
- The successive lines of the file must be the frequency (in Hz) and the amplitude of the vibration data, separated by a space or tab. There must be three axes of data, in the order of Horizontal, Vertical and Axial. Horizontal and vertical can be alternated, as it is assumed that the direction with the highest vibration reading is listed first. The number of lines of each vibration data set must be the same, and is required to be listed in the 'Scanning Resolution' text field of the Analysis menu. The frequencies listed in the file must also be increasing in equal increments.
- The maximum number of lines per axis is 4096.
- The recommended file extension is '.adf' which allows easy identification from other data file. To convert from '.txt' to '.adf' simply change the file extension (eg by using Windows Explorer).

When the analysis is complete, a pop-up box is displayed advising that the output files will be created. If you wish to save the result files from a previous analysis, rename the files otherwise they will be overwritten. Once the files have been created successfully, another pop-up box is displayed advising that the analysis is complete. Press 'OK', then the 'Close' button to return to the VES Main menu. The results are listed in a text file saved to the C-drive. The file is called 'VESAnalysisOutput.txt'.

4. Optional Data for Advanced Analysis

For a broader fault detection, time domain and demodulated spectra files can also be selected and analysed by the VES analysis algorithm. Time domain data can be useful in detecting cracked or chipped gear teeth, while demodulated spectra data can aid in the early detection of bearing faults. The required file formats are as follows:

- Time Domain Date File: The time domain data file can be up to 8192 lines long, where each line is made up of the sample time (in milli seconds) and amplitude, separated by a space or tab.
- Demodulated Spectra Data File: this file can be up to 4096 lines long, and should have an identical file format as the Vibration Spectra File, except for omitting the first line (rotational speed).

5. Machine Specifications Setup Menu

This menu contains all of the information about the machine to be monitored, to allow the expert system to perform fault detection and diagnosis on the input data. The data fields and a short description follow. Please note that if you set up a machine using the Machine Specifications Setup menu selected from the VES Main menu, this file can only be read by VES, not by CES or OWDES.

To edit an existing file, click the 'Edit Existing File' button at the bottom of the menu, browse and select the desired file in the pop-up menu. To start a new file, just enter the components and specifications by clicking the tick box next to the component type you wish to enter.

- Bearings: select the number and type of bearings. For rolling element bearings (ball bearings and roller bearings), the fault frequencies and their normal and alarm amplitudes must be entered (only fault frequencies need to be entered if Without Machine Historical Data was selected). This is done via the separate menu which is displayed when the 'Enter Fault Frequencies' button is pressed. If more than 1 bearing was entered, click 'Next' to enter the specifications of the other bearings called '2' etc. You can view what was already entered by clicking 'Previous'. When the last bearing information was entered, the 'Finish' button will become active. Click 'Finish' to return to the Machine Specifications Setup menu to continue with the other components, and save the entered data to a file. Up to 50 rolling element bearings can be entered. Please note that every bearing with different fault frequencies must be defined as a separate bearing. Differences in fault frequencies could be due to the use of a different bearing size/design, or two identical bearings operating at different rotational speeds.

- Pump: Enter the number of vanes on the pump impeller. The normal and alarm amplitudes of the vane pass frequency must also be entered if the menu was launched from the With Machine Historical Data frame.
- Coupling: Tick this box if the machine has a coupling. The analysis algorithm will then test for coupling misalignment.
- Spur Gear: Enter the number of reductions that the gearbox has, and press the 'Enter Specifications' button to enter the specifications of each spur gear reduction. You will need to enter the number of teeth and rotational speed (RPM) of each gear. For the case With Machine Historical Data, the normal and alarm amplitudes will also be required for the typical frequencies produced by gears (gear mesh frequency - GMF, 2 GMF, 3 GMF, and hunting tooth frequency - HTF). If more than 1 reduction was selected, click 'Next' to enter the specifications of the reduction called '2' etc. You can view what was already entered by clicking 'Previous'. When the last reduction was entered, the 'Finish' button will become active. Click 'Finish' to return to the Machine Specifications Setup menu to continue with the other components, and save the entered data to a file. Up to 50 spur gear reductions can be entered.
- Belt Drives: Enter the number of belt drive reductions present on the machine to be monitored. Belt specifications also need to be entered via the pop-up menu displayed when the 'Enter Belt Specifications' button is pressed. The information required is: Drive pulley pitch diameter and rotational speed (RPM), Driven pulley pitch diameter and RPM, belt length (in mm), and whether the belt is a cog type belt, such as a timing belt. The normal and alarm amplitudes of common belt frequencies are also required (fundamental drive pulley frequency, fundamental driven pulley frequency,

belt frequency, and timing belt frequency if the 'timing belt' tick box was selected), for the With Machine Historical Data case. If more than 1 reduction was selected, click 'Next' to enter the specifications of the reduction called '2' etc. You can view what was already entered by clicking 'Previous'. When the last reduction was entered, the 'Finish' button will become active. Click 'Finish' to return to the Machine Specifications Setup menu to continue with the other components, and save the entered data to a file. Up to 50 belt reductions can be entered.

- Interference Frequencies of Neighbouring Machines: This feature allows you to enter strong frequencies of machines near by that can be induced into the machine to be monitored via the mounting structure. Enter the number of frequencies you wish to register, and click the 'Enter Frequencies' button to enter the frequencies (in Hz) and their expected amplitude, using the displayed menu. Use the 'Next' and 'Previous' buttons to toggle between the entered frequencies (if more than 1 was entered) and click 'Finish' when complete. Up to 50 interference frequencies can be entered. This feature can be entered in both With and Without Machine Historical Data modes, but interference frequencies are only taken into account when vibration data is analysed using the With Machine Historical Data analysis.

Saving File: Save the file by entering the path and file name in the text box. The path is the drive which you wish to save to as well as the folder. Eg: to save to the Conveyor folder on E-drive, using Gearbox5 as a file name, enter 'E:\Conveyor\Gearbox5' in the textbox. The file will be given the extension '.msf'. Make sure that the file name is unique, otherwise the existing file will be over-written! For the case With Machine Historical Data, you will also be prompted to enter the alarm amplitudes of the 1X, 2X, 3X and 4X running speed frequencies. Enter the amplitudes and press 'Continue Save...'. You will then be warned to make sure that the file name is unique, and that the file will be overwritten if it already exists. Click 'Yes' to acknowledge the warning, then

'Close' to return to the VES Main menu.

6. Analysis Setup

   The Analysis Setup menu allows the information required by the expert system to perform the analysis, to be entered and saved to a text file. Please note that if you set up a machine using the Analysis Setup menu selected from the VES Main menu, this file can only be read by VES, not by CES or OWDES.

   To edit an existing file, click the 'Open an Existing Analysis Setup File' option button, browse and select the desired file in the pop-up menu. To start a new file, just click the 'Create a New Analysis Setup File' option button. For a new file, you will need to enter the path and file name (including extension). Eg: to save to the Conveyor folder on E-drive, using Gearbox5 as a file name, enter 'E:\Conveyor\Gearbox5.asf' in the textbox. Make sure that this file is unique, otherwise the existing file will be over-written!

   The VES analysis algorithm utilises nine user changeable variables to determine the peak detection sensibility, which the operator can edit using the Analysis Setup menu. These variables have been categorised into three groups, depending on whether the variables are required for analysis with machine historical data, without, or both. The variables and their functions are as follows:

   - Variables used for Without Machine Historical Data type analysis:
     - Min Peak Height — the minimum height of a peak, relative to the highest peak in the spectra, to be classified as a 'Present' peak
     - Min Peak Height to be identified as Strong — the minimum height of a peak, relative to the highest peak in the spectra, to be classified as a 'Strong' (or distinctive) peak
   - Variables used for With Machine Historical Data type analysis:
     - Percentage in amplitude above 'alarm amplitude' (entered for each fault frequency) for peak to be called strong

  - Average Baseline Amplitude (this can be calculated using the Analyse Healthy Spectra menu accessible from the VES main menu)
  - Percentage of peaks with an amplitude below or equal to the average baseline amplitude (this can be calculated using the Analyse Healthy Spectra menu)

- Variables required for both analysis types:
  - Percentage Deviation — the percentage deviation in frequency of a peak
  - Frequency Limit — a frequency limit (in hertz) on the percentage deviation
  - Min Haystack Width — the minimum width of haystack, in hertz
  - Haystack Search %Run Speed — The width of searching for a haystack around a specific frequency, in percent of running speed

The Min Peak Height variable sets the minimum height of a peak so that the algorithm accepts that a peak exists at the specific frequency. This variable is therefore used to adjust the peak detection sensitivity. The 'Min Peak Height to be identified as Strong' variable is similar to the Min Peak Height variable, in that it sets the detection sensitivity for distinctive peaks.

The variables used for analysis when machine historical data is available are concerned with identifying distinctive peaks relative to the entered alarm limit, and detect a raised baseline. The Average Baseline Amplitude and Percentage variables are used in detecting a raised baseline, as is often the case for severe looseness type faults.

The Percentage Deviation and Frequency Limit variables were incorporated to allow the VES to search the vibration data file for specific frequencies, and allow for measurement inaccuracies, where the particular peaks can be several hertz off their theoretical frequency. The combination of a percentage and a frequency deviation has been used as a fixed 'error' frequency may be too large for low frequency detection, and a percentage 'error' too large for high frequency detection (while a 5 % error may be ok for frequencies under 1000 Hz, it is probably too large for spectra ranging to 6000 Hz). The software therefore evaluates the 'error' using both the Percentage Deviation and Frequency Limit, and uses the smaller of the two.

The haystack detection algorithm searches for regions of consecutive Present or Strong peaks. The minimum width of such a region before it is classified as a haystack can be adjusted using the Min Haystack Width variable.

The Haystack Search % Run Speed variable can be used to adjust how far on each side of a specific frequency the algorithm searches for a haystack. In order to reduce the likelihood of a one times running speed harmonic being mistakenly detected as a haystack, this variable allows the width of spectra which is searched to be limited to a percentage of the running speed.

7. Analyse Healthy Spectra Menu

The Analyse Healthy Spectra menu has 2 functions, for Baseline Detection, and Amplitude of a Particular Frequency. The desired function can be selected by clicking on the appropriate option button.

Regardless of which function is selected, the desired file must be selected (vibration frequency spectra file), and the frequency range covered by the spectra (maximum Hz) as well as the number of lines in the file must be entered. The analysis setup file also needs to be selected.

The baseline Detection function was included in the software to allow the 'Average Baseline Amplitude' and '% of peaks equal to or below Average Baseline Amplitude' in the Analysis Setup Menu to be evaluated. These two variables are required to allow the detection of a raised baseline, which is an indicator of excessive looseness.

The 'Amplitude of a Particular Frequency' feature allows the amplitude of the selected frequency to be determined, as detected in the selected vibration data file. This feature is useful in determining the amplitude of a fault frequency present in the vibration spectra of a healthy machine. As the amplitude of the detected peak is the maximum in the frequency window, the frequency of the maximum peak in the frequency window (around the desired frequency) is displayed. For analysis Without Machine Historical Data, the maximum amplitude in the spectra is displayed, and the amplitude of the peak as a percentage of the maximum peak amplitude in the spectra is also shown in the results part of the bottom of the menu.

Once the two required data files and the desired option is selected, click 'Scan' to perform the analysis. To run another analysis, click 'Reset'. When finished, press 'Close' to exit to the VES Main menu.

8. FAQ's:

Q: How long does the analysis take?

A: This depends on numerous factors including:

- Number of components (ie: roller bearings, spur gears, belt reductions, and interference frequencies)
- Whether time domain and demodulated spectra files are also analysed
- The sensitivity of analysis (as set in the Analysis Setup Menu)
- The complexity of the data (how many peaks are present in the spectra files)

Q: Why do I get an error message when pressing 'Analyse' or 'Scan'?

A: The data file does not have the right format. Analysis Data File (ADF) must have the rotational speed as the first line, then three sets of vibration data of equal number of lines and frequency (eg: all 3200 lines, and 0 to 1000 Hz). For Machine Setup and Analysis Setup files, see below

Q: Why do I get an error message saying 'Not Machine Specifications Setup file', or 'Not Analysis Setup file'?

A: The file you entered as the MSF or ASF is not of the correct type. If the file was created using the functions from the VES Main menu, then these files cannot be used by the CES or OWDES.

Q: What is the file format for the Vibration Spectra File (Analysis Data File)?

A:

- 1st Line: RPM of input shaft
- 2 columns of Hz and Amplitude of vibration spectra - Horizontal (or primary vibration) direction
- 2 columns of Hz and Amplitude of vibration spectra - Vertical (or lower vibration amplitude) direction
- 2 columns of Hz and Amplitude of vibration spectra - Axial direction

Q: What is the file format for the Time Domain Data File?

A: 2 columns of Time (ms) and Amplitude

Q: What is the file format for the Demodulated Vibration Spectra File?

A:

- 2 columns of Hz and Amplitude of demodulated vibration spectra - Horizontal direction
- 2 columns of Hz and Amplitude of demodulated vibration spectra - Vertical direction
- 2 columns of Hz and Amplitude of demodulated vibration spectra - Axial direction

Appendix J

Time Capsule

The computer used throughout this PhD project was an Apple iBook G4, running the Mac OS X operating system. Some specifications are shown below:

- Mac OS X version 10.3.9
- 1 GHz PowerPC G4 processor
- 640 MB DDR SDRAM
- 55.89 GB Hitachi hard disk
- AirPort Extreme
- 14 inch LCD monitor, 1024 x 768 resolution @ 60Hz

Software used during this project includes:

- Microsoft Word (for Mac)
- Microsoft Excel (for Mac)
- Microsoft Powerpoint (for Mac)
- OmniGraffle
- Gimp
- BibDesk

- TexShop
- LaTex
- iTunes (for motivation and procrastination!)
- Microsoft Visual Basic 6 (used on a PC)
- Matlab (used on a PC)
- Optimas (used on a PC)

The iBook has proven to be quite a reliable machine, being very portable thanks to good battery charge providing 3 to 4 hours of use. During the project I have worked on it in some awkward places including in a car, airport, hospital, caravan, and in the open under a shady tree (I found a change of scenery inspiring and thought provoking)!

During the project duration repairs consisted of a motherboard and cd drive replacement at just short of 3 years, and a complete re-install after the second and third years of the project. Some disadvantages were the keyboard becoming quite warm in summer due to the heat emitted by the motherboard so I used an external Microsoft USB keyboard. The base also became quite warm which is a drawback when resting on your lap! Apart from these few complaints, it has been a joy to use.

Figure J.1: *Photo of Apple iBook used throughout the PhD project.*