

ICSV14

Cairns • Australia

9-12 July, 2007



SMART CONDITION MONITORING BY INTEGRATION OF VIBRATION, OIL AND WEAR PARTICLE ANALYSIS

Stephan Ebersbach¹, Zhongxiao Peng¹ and Nicole Kessissoglou²

¹School of Engineering, James Cook University, Townsville, Qld 4811, Australia

²School of Mechanical and Manufacturing Engineering, University of New South Wales
Sydney, NSW 2052, Australia

Stephan.Ebersbach@jcu.edu.au

Abstract

Vibration, oil and wear particle analyses typically represent the core techniques used for machine condition monitoring. While these techniques have been incorporated in many maintenance programs found throughout industry, the results of each analysis are generally considered independently for machine health assessment. Due to the complexity of condition monitoring and the lack of a successful correlation algorithm, the potential benefits of an integrated condition monitoring program have not been realised.

This paper outlines the development stages of an expert system designed to perform automated machine condition monitoring of gearbox and associated components faults, by using a correlation algorithm to combine the results obtained from vibration, oil and wear particle analysis. The design aspects of the correlation algorithm are presented in detail, including an analysis of the detection abilities of the three condition monitoring techniques. The development also included a rigorous testing phase which included the verification of all implemented reasoning logic, as well as analysis of laboratory and industry derived data. Some testing results are also discussed, outlining the fault identification ability of the algorithm for typically encountered gearbox faults.

The analysis of machine condition data by a correlated approach of vibration, oil and wear particle analysis has a number of benefits compared to conventional condition monitoring practices. These include accurate, efficient and early fault detection of gearbox and bearing faults, as well as the ability to perform root-cause analysis. The automated analysis algorithm permits non-expert personnel to perform routine comprehensive machine condition monitoring, while providing a consistent objective analysis of the machine health.

1. INTRODUCTION

The fault detection and general health monitoring of critical industrial machinery is performed by a machine condition monitoring program, which is typically composed of either vibration, oil or wear particle analysis, or a combination of these. While monitored industrial machinery encompasses many components including internal combustion engines, gearboxes, turbines,

electric motors, fluid pumping as well as bulk material handling equipment, this paper concentrates on power transfer components such as spur and helical gearboxes, couplings and belt-drive systems. Gearboxes lend themselves to condition monitoring using an integrated approach of vibration, oil and wear particle analysis as the required information can be obtained for each technique. This is unlike electric motors and material handling equipment where generally only vibration analysis can be performed. Furthermore, gearboxes are commonly among those machines critical to the operation of a plant, presenting considerable downtime and repair costs should a catastrophic failure occur.

The current use of condition monitoring techniques has resulted in fault detection and tracking being performed with reasonable success. However, due to the complexity of correctly interpreting the monitoring data; taking into account the machine design and operating variations, experts are required for fault diagnosis. Improvements on the current practice in condition monitoring could therefore be realised by enhanced fault detection accuracy and automated data interpretation. This has been confirmed by case studies, such as on fault detection of roller bearings [1,2]. While the benefits of correlated condition monitoring result in a more efficient maintenance program, along with possible gains in plant cost effectiveness, not all fault detection benefited from a correlated case. A scenario where the results from each analysis technique provided conflicting information has also been reported in literature [2]. Therefore there is a need for the development of comprehensive, powerful data interpretation mechanisms to correlate multiple data generated using various techniques, ideally in an automated manner.

Previous developments in automated data interpretation have shown that expert systems can be used successfully for fault detection in condition monitoring programs [3-5]. Existing research on the development of Artificial Intelligent (AI) systems for machine condition monitoring only rely on one technique, resulting in limited fault detection ability [1]. In this work, the algorithms that have been developed provide improved fault detection and diagnosis by incorporating those elements of vibration, oil and wear particle analysis currently used by experts and professionals in industry. The development of an expert system capable of analysing data from multiple condition monitoring techniques was conducted by the design of an individual expert system for vibration analysis, and another for oil and wear particle analysis. The completed expert system referred to as the Combined Analysis Expert System, incorporates the expert systems for vibration, oil and wear particle analysis. The data is therefore pre-processed by the individual expert systems, and the results collated by the combined analysis algorithm into one comprehensive integrated machine condition report. This orientation allowed the project to be divided into a number of sub projects, as well as allowing each algorithm to be tested and verified individually. The testing and verification of the expert systems was a crucial component of each algorithm development to ensure that correct operation of the final expert system outputs.

The core of this development originates from a comprehensive correlation analysis that allowed the fault detection and diagnostic abilities of the condition monitoring techniques to be evaluated. This was a crucial initial step as an analysis into correlation had not been performed before. The paper discusses the methodology, encountered difficulties and results of the correlation investigation. The benefits of automated data interpretation are that apart from non-expert staff being able to perform comprehensive routine condition monitoring, the analysis is performed quickly in an objective manner.

2. CORRELATION INVESTIGATION

The strategy developed in order to investigate the degree of fault detection overlap between

vibration, oil and wear particle analysis focused on two objectives. These were to firstly perform a comprehensive study to determine the fault detection ability of each technique, and secondly, to examine the type of conflicting results encountered and derive a method to resolve these.

The correlation analysis included an analysis of real condition monitoring data obtained using a laboratory single reduction spur gear test rig, which is shown in Figure 1. The tests conducted using this test rig were normal operation, overload, cyclic load, contamination, and operation with a bent shaft. These faults reflect common abnormal operating conditions encountered by industrial gearboxes, while the normal operation test provided a baseline to determine the life of the gearbox as well as provide normal oil, wear particle and vibration data.

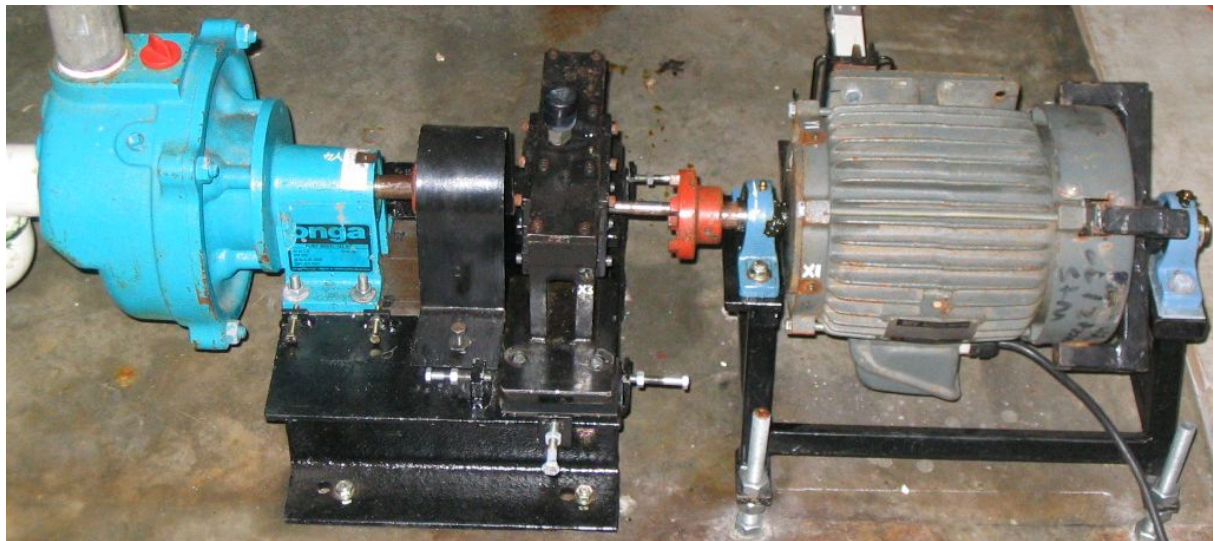


Figure 1. Spur gear test rig

The primary investigation of fault detection ability for gearbox type faults was performed using those techniques typically used in industry. For vibration analysis this included tri-axial frequency spectra, demodulated frequency spectra and time domain spectra used predominately for detecting broken gear teeth. The tests performed for oil and wear particle analysis typically include a particle count to rate the oil according to the ISO4406 cleanliness code, wear particle identification, change in viscosity and chemical index, presence of water, and elemental analysis. The fault indicators from each test were used to assess the information that can be gathered about the health of a gearbox, and compiled into a single table. This table featured machine faults in one column, and the fault indicators for each technique for the corresponding fault in the other columns.

The use of techniques currently performed in industry for correlation analysis has a number of benefits, which include that data acquisition practices do not need to be altered as sufficient data is collected, and that the elements of each technique have provided reasonable results. The effectiveness of each element of vibration, oil and wear particle analysis has therefore been proven, and the fault indicators provided by each element has been verified. The elements above were therefore chosen due to their popularity in condition monitoring.

The assessment of machine health when various faults are present in the machine can lead to different conclusions being obtained from each condition monitoring technique. The table compiled in the previous step was used to investigate the possible outputs from each technique for every machine fault. It was observed that due to very limited detection overlap between vibration, oil and wear particle analysis techniques, three scenarios could occur

where the output results of the techniques differed. The encountered scenarios are shown in Figure 2.

These scenarios originate from the differing fault detection ability of vibration, oil and wear particle analysis. A technique capable of detecting a certain fault at an early stage is referred to as the primary indicator, while a secondary indicator will detect the fault after it has progressed further. The occurrence of the first scenario can be observed when a fault is in the early developing stages, and therefore only detected by the primary indicator as shown in Figure 2. Similarly, the second scenario can occur when the primary indicator returns a more severe fault condition than that determined by the secondary indicator. When the fault categories as shown in Table 1 were analysed for fault detection overlap during the correlation analysis, it was noted that the first two scenarios do not occur for the chosen categories. This means that for example, if roller “bearing fatigue” is detected by wear particle analysis, vibration analysis can detect a “bearing fault” such as outer race damage, but not fatigue directly. Using these fault categories, only one fault resulted in an overlap, being gear misalignment. Misalignment can be detected by wear particle analysis as cutting wear particles (2 body wear), and by a strong 2 and 3 times gear mesh frequency in vibration frequency spectra analysis.

The third scenario occurs when each technique detects a different fault. This will occur when a machine has numerous faults. This complementing action, indicating the deterioration of the machine in the form of secondary faults, can be used to categorise faults according to primary and secondary faults and hence construct the possible failure mechanism.

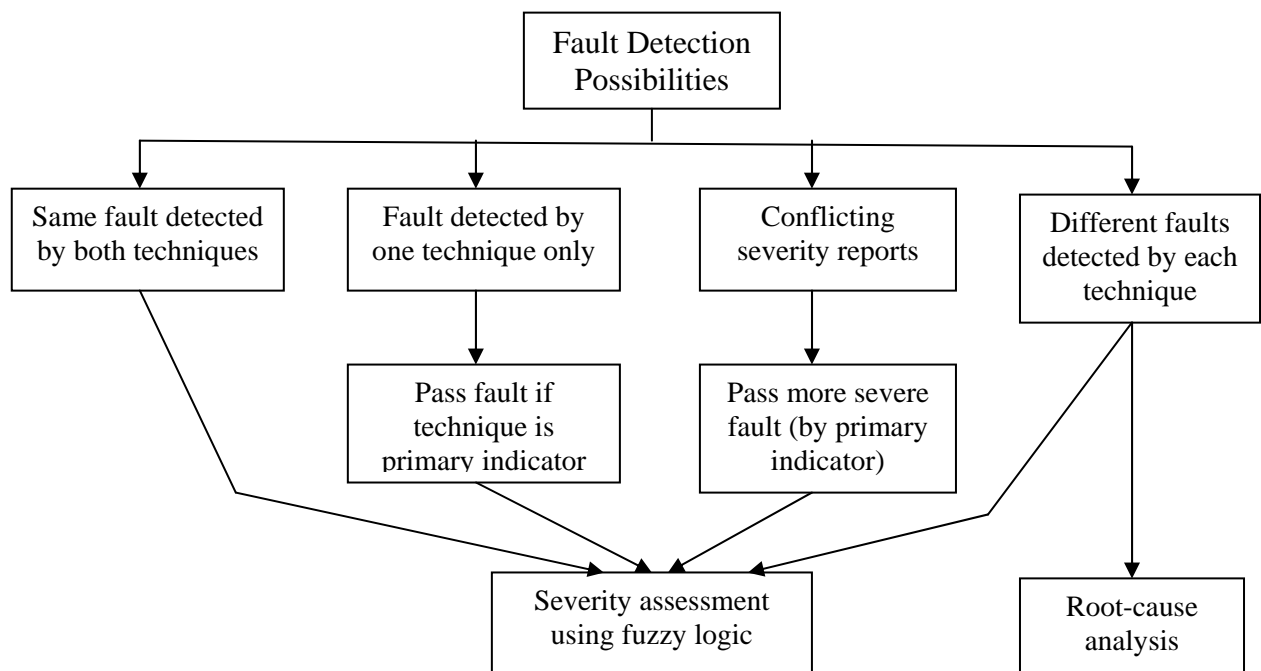


Figure 2. Fault detection scenarios

3. VIBRATION ANALYSIS EXPERT SYSTEM FEATURES

The vibration analysis expert system was developed primarily to operate as a pre-processor for the combined analysis expert system, by analysing and interpreting the vibration analysis machine condition data. While designed as a module of the completed combined analysis expert system, a user interface was also included in the development to allow the system to be used for stand-alone use. This facilitated the testing of the analysis algorithm for verification

purposes, as well as providing additional functionality for the combined system.

The surveying of 3 companies performing vibration analysis for the mining and mineral processing industries in Queensland, Australia, revealed that the preferred methods of vibration analysis include tri-axial frequency spectra analysis, time domain analysis and demodulated spectra analysis. These techniques were incorporated in the analysis algorithm, as well as a haystack detection algorithm [6] for identification of broad areas of distinguishable peaks over a frequency range, typical for severe rotating looseness. The inclusion of additional analysis algorithm capabilities beyond single axis frequency spectra analysis presented a new level of sophistication in expert systems for vibration analysis [6]. The knowledge base, which contains the data analysis rules for these techniques was initially established using literature knowledge, and refined by consulting with the experts from the surveyed companies. This ensured that the design objective relating to the use of techniques currently used in industry was complied with.

The analysis algorithm was thoroughly tested using data obtained from a laboratory test rig as well as industry sourced data. The gearbox faults were successfully detected in all cases, with the detected faults being verified by visual inspection in each case. The developed expert system allows the automated analysis and interpretation of vibration analysis condition monitoring data using techniques that are performed in industry practice. While stand-alone operation is possible by using the text based output file, the output results are also presented in a numeric format suitable to be used by the combined analysis expert system for correlation.

4. OIL & WEAR PARTICLE ANALYSIS EXPERT SYSTEM FEATURES

The oil and wear particle analysis expert system was developed to allow oil analysis and wear particle analysis to be performed in an automated system. Similarly to the vibration analysis expert system, this expert system was also designed to output the results in a format suitable to be used by the combined analysis expert system.

This expert system was designed to interpret all of the information that is generally contained in the oil laboratory report from an oil sample. This required an algorithm for oil analysis and one for wear particle analysis. Oil analysis is typically concerned with the physical and chemical properties of the oil including viscosity, chemical index, contaminants such as water, and a particle count according to the ISO4406:1999 standard. The wear particle analysis algorithm is concerned with the type and origin of the worn off particles, including elemental analysis and wear particle identification. The wear particle identification component was designed to allow quantitative particle concentration calculation methods to be used. By utilising a wear particle identification algorithm [7], wear particle analysis can be performed in a quantitative manner, not previously possible due to the high dependence on manual particle identification.

The development of the expert system also included the design of a user interface to allow the algorithm to be used as a stand-alone program as well as being part of the combined analysis expert system. The user interface included a data input screen to allow the information contained in oil laboratory reports to be entered into a digital format. This allows reports to be used from laboratories that only issue printed material. This feature was not required for the vibration analysis expert system as the data is already in a digital format that can be used by the expert system.

The expert system algorithm was tested using the oil samples taken from the spur gearbox test rig for the same tests as used in the vibration analysis expert system verification procedure. Industry data obtained from gearboxes operating in a mineral processing plant

were also used to verify the algorithm. The algorithm correctly identified the occurring wear modes, oil condition and contaminant levels in the verification data. The completion of the oil and wear particle analysis expert system allowed the development of an algorithm designed to link the output reports of the vibration analysis expert system, and the oil and wear particle analysis expert system.

5. COMBINED ANALYSIS EXPERT SYSTEM FEATURES

The combined analysis expert system consists of the individual expert system algorithms for vibration, and oil and wear particle analysis, the algorithm for correlating the outputs of these two expert system modules, as well as a root-cause analysis algorithm and user interface. The core component is the correlation algorithm, which incorporates the knowledge of the correlation investigation.

The correlation is performed by combining all of the fault indicators from the pre-processing expert system modules (the individual expert systems discussed in sections 3 and 4) into a list of machine faults. This organizes the information into a fault based structure rather than the fault indicator structure. Fault indicators are provided by the machine condition monitoring techniques and include information such as bearing cage fault, gear eccentricity, and gear backlash. The fault based structure relates to the faults in general categories such as bearing fault, with the indicator being bearing cage fault, or gear meshing fault with indicators like gear eccentricity and gear backlash. In order for a machine health report to be constructed, faults need to be in the fault-based structure.

Once the faults are organised in the required fault-based structure, the faults are sorted by decreasing confidence factor. The confidence factor for vibration analysis data is calculated by:

$$\text{Confidence Factor} = \frac{1}{2} \times \left[1 - \frac{|\text{Theoretical Hz} - \text{Actual Hz}|}{(\text{Allowable Frequency Difference Hz})} \right] + \frac{1}{2} \times \left[\frac{(\text{Actual Amplitude} - \text{Alarm Amplitude})}{(\text{Severe Alarm Amplitude} - \text{Alarm Amplitude})} \right]$$

The confidence factor for oil and wear debris analysis is calculated by using:

$$\text{Confidence Factor} = \frac{(\text{Actual Concentration} - \text{Normal Concentration})}{(\text{Alarm Concentration} - \text{Normal Concentration})}$$

where concentrations represent the percentage of each particle type that were found on the filtergram slide. The alarm amplitudes and particle concentrations can be determined from the relevant standards and/or industry experience.

The resulting information is therefore summarised as shown in Table 1, which allows the operator to view the type of faults present on the gearbox while also containing detailed fault specifications. The fault indicators in Table 1 were marked by using different bullet points, an 'o' denoting indicators from oil and wear particle analysis, while a '-' designates an indicator from vibration analysis.

The categorisation operation of faults detected by the individual expert system modules also includes the mechanism for resolving different faults being detected by the respective analysis techniques. As discussed previously, the only scenario of where the conclusions of the two individual expert modules results can deviate is in the type of fault detected. In this scenario, all of the detected faults can be considered to occur, and are ordered by descending confidence factor. In this way, the confidence factor of the fault is used to determine which of the numerous detected faults is most dominant and established.

The correlation between vibration, oil and wear particle analysis is achieved by categorising the fault indicators of these techniques into a fault-based structure, and resolving any conflicts in results by applying the strategy as discussed. The fault categories for gearbox faults as shown in Table 1 were used successfully to correlate the condition monitoring results from the spur gearbox test rig. As indicated by Table 1, the fault detection of vibration, oil and wear particle analysis do not overlap significantly, demonstrating the benefits of utilising vibration analysis in conjunction with oil and wear particle analysis for complete fault detection. This confirms the conclusions of previous case studies of a correlated approach to condition monitoring [1]. Additional fault categories also incorporated in the correlation algorithm included journal bearing looseness and lubrication faults, pump cavitation and other hydraulic faults, coupling misalignment and imbalance, belt and pulley faults as well as drive shaft wear. Lubricant specific faults that were included by utilising oil analysis information included oil contamination, additive depletion, and oil oxidation.

Table 1. Reporting structure of faults

Bearing Faults	
Looseness	<ul style="list-style-type: none"> - Loose in housing - Turning on shaft - Generally loose (Severe Rotating Looseness - raised noise floor, haystacks)
Fatigue	<ul style="list-style-type: none"> o Mild - micro cracking o Medium - macro cracking o Severe - severe macro cracking
Fault	<ul style="list-style-type: none"> - Cage fault or cage loading - Ball/Roller fault - Race defect - Possible installation fault
Lubrication Fault	<ul style="list-style-type: none"> o Inadequate lubrication o Lubrication fault (contamination, begin of inadequate lubrication, over-lubrication)
Gear Faults	
Operating Fault	<ul style="list-style-type: none"> - 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 (due to meshing gears having multiple common factors) o Welding (adhesive wear)
Misalignment	<ul style="list-style-type: none"> - Misalignment (gear misalignment due to shaft misalignment) o Misalignment (gear misalignment due to shaft misalignment)
Bent Shaft	<ul style="list-style-type: none"> - Input shaft bent - Output shaft bent
Fatigue	<ul style="list-style-type: none"> o Gear fatigue (including pitting)

Information of what faults exist in a gearbox and how well these are established is useful for performing root cause analysis, which is concerned with identifying primary faults that are responsible for causing secondary faults. An individual algorithm was developed that aimed at identifying primary faults by considering the types of faults detected. This algorithm

was developed by investigating common failure modes and mechanisms of gearbox components, as well as the influence that a component defect has on the other gearbox components.

The development of the completed expert system including pre-processing, correlation and root cause analysis algorithms is a novel approach for integrated condition monitoring. This expert system facilitates non-expert staff to perform comprehensive condition monitoring using sophisticated algorithms that ensure an objective analysis of the input data, and leads to reliable machine health report. Although the expert system development focused on the health monitoring of power transmission devices including spur and helical gearboxes, couplings and power transmission belts, other machinery including pump and fans was also included. With successful implementation of correlation for these types of machines, integrated health monitoring can now be expanded to include other common equipment such as turbines, electric motors, and internal combustion engines.

6. SUMMARY

An integrated condition monitoring strategy consisting of vibration, oil and wear particle analysis was successfully developed for improved accuracy in health monitoring of power transmission equipment. The correlation strategy consists of categorising the fault indicators of each technique into a fault-based structure, and resolving conflicting results from the vibration, oil and wear particle analysis techniques. The detected faults can then be organized according to decreasing confidence factor.

The development of the expert system for automated data interpretation allowed the results of the correlation investigation to be implemented in a novel stand-alone system. The strategy was implemented in an expert system to allow automated data analysis and interpretation of the vibration, oil and wear particle analysis information. The underlying analysis algorithms permit condition monitoring and root-cause analysis to be performed by technical personnel who are non-experts at the condition monitoring techniques. Another benefit of the expert system is that analysis is performed in an objective manner ensuring reliable results. The algorithms were tested using laboratory as well as industry sourced condition monitoring data to verify correct operation and to demonstrate the ability of an integrated condition monitoring strategy.

ACKNOWLEDGMENTS

Thanks go to the Australian Research Council (linkage grant LP0348873) and Industrial and Technical Services for funding of this research project.

REFERENCES

- [1] H. Maxwell and B. Johnson, "Vibration and lube oil analysis in an integrated predictive maintenance program", *Proceedings of the 21st Annual Meeting at the Vibration Institute*, New Orleans, Louisiana, 17-19 June 1997, pp. 117-124.
- [2] D.D. Troyer, "Effective integration of vibration analysis and oil analysis", *Condition Monitoring '99*, Swansea, UK, 12-15 April 1999, pp. 411-420.
- [3] B.S. Yang, B.S. Lib and A.C. Chiow Tanc, "VIBEX: an expert system for vibration fault diagnosis of rotating machinery using decision tree and decision table", *Expert Systems with Applications* **28**, 735-742 (2005).

- [4] X.P. Yan, C.H. Zhao, Z.Y. Lu, X.C. Zhou and H.L. Xiao, "A study of information technology used in oil monitoring", *Tribology International* **38**, 879-886 (2005).
- [5] S. Chen, Z. Li and Q. Xu, "Grey target theory based equipment condition monitoring and wear mode recognition", *Wear* **260**, 438-449 (2006).
- [6] S. Ebersbach and Z. Peng, "Expert system development for vibration analysis in machine condition monitoring", *Expert Systems with Applications* **34**, 291-299 (2008).
- [7] Z. Peng and T.B. Kirk, "Computer image analysis of wear particles in 3 dimensions for machine condition monitoring", *Wear* **223**, 157-166 (1998).