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A Case Study for Improving Maintenance Planning of Centrifugal Pumps Using Condition-Based Maintenance

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Abstract: *Centrifugal Pumps (CPs) are one of the most widely used industrial assets globally. Condition-based maintenance (CBM) is one of the maintenance strategies applied for monitoring the operational conditions of CPs. Use of CBM has resulted in improvements in CP performance. However, CBM practice for maintenance planning is suboptimal. This work presents a case study which utilises a CBM approach for monitoring CPs as part of a safety critical Fire Water System aboard an Offshore Production Platform. A CBM approach for CP maintenance was researched, and the best practice identified. This was compared to the practices of the offshore company, and the deficiencies in application and data collection observed. A test programme was simulated which would represent the company's operations. Subsequently, data was collected to assess the ability of CBM to identify various failures for CPs. Vibration data for the CPs was utilised to develop the P-F curve for pump failure as a result of faulty bearings. The results were then used for establishing potential inspection activities. In cases where a single fault was studied, a classification accuracy of 100% was attained from the test programme. In cases where multiple faults were studied, a classification accuracy of 67% was attained. An overall classification accuracy of 76.5% was attained. Furthermore, a P-F interval of five months was obtained, implying that inspections should be performed every two or three months for the bearings compared with the current schedule of one month. The tests demonstrated the possibility for improved fault classification and data driven maintenance planning when a CBM best practice approach is implemented effectively. Future work will investigate the ability of enhanced Artificial Intelligent (AI) techniques to improve the classification accuracies in the face of more complex operational conditions.*

Keywords: *Condition Based Maintenance, Centrifugal Pumps, Vibration Analysis, Failure Modes, Effects and Criticality Analysis, PF Curve*

1. Introduction

Centrifugal Pumps (CPs) are one of the most widely utilised assets in a number of industries globally. These assets are ubiquitous in safety critical systems such as those in Offshore Oil and Gas Production which require high levels of availability and reliability (Farokhzad, 2013; Mahalik et al., 2012). With technological advancements, Condition-based maintenance (CBM) has emerged as the most prevalent type of Preventive Maintenance (PM) activity that is used for CPs. In CBM sensor technology is utilised to monitor the condition of assets and thereby detect failures before they occur (Moubray, 1997; Beebe, 2004). CBM monitors a measured asset condition to determine deterioration with time. It therefore allows for appropriate action to avoid catastrophic failures of CPs. One popular measureable quantity monitored includes equipment vibration. Vibration Analysis (VA) is a CBM technique which measures the vibration levels present with various forms of asset condition (Farokhzad, 2013). The ability of VA to detect a wide range of equipment faults makes it perhaps the most versatile and thus widely applied CBM technique for monitoring most rotational equipment.

While the application of CBM techniques to dynamic equipment is no new task, many organisations fail to realise the full benefits since the execution of a complete CBM best practice approach is not always adhered to. There have also been reports of defects such as cracks, gear defects and other bearing and electrical faults remaining undetected (Mahalik et al., 2012). Current VA methods are unable to detect all incipient faults and therefore there is still a need for frequent Corrective Maintenance (CM) (Albraik et al., 2012). Furthermore, Albraik et al. (2012) and Wang and Gao

(2006) have indicated that vibration levels are dependent on operating parameters such as flow rate, suction pressure, output pressure, drive power, speed, bearing temperatures and others. In some cases, if the CBM approach is not implemented with a full understanding of these conditions, faults may be misclassified. These factors have resulted in the need to investigate whether a properly implemented CBM best practice approach can improve the fault diagnosis and aid maintenance of CPs.

The aim of this work is to improve the maintenance planning process as applied to CPs by utilising a CBM approach. To achieve the aim, the steps of a CBM best practice approach were determined through extensive literature research and compared to industry practice at a collaborating offshore oil and gas company. The gaps in the implementation process were noted and an experimental study was designed and applied to evaluate the extent to which the best practice approach, if properly implemented, can lead to efficient and effective maintenance planning.

In Section 2, this paper describes the common maintenance practices that are employed for CPs. This includes the currently applied CBM approach and the techniques which are applied. Section 3 outlines the research process including the data collection design and analysis process. Section 4 presents and discusses the results. Finally, Section 5 provides concluding remarks and suggestions for future work.

2. Maintenance Practices for CPs

Generally, there are two (2) main types of maintenance which are performed for CPs. These include Corrective Maintenance performed when unplanned breakdown occurs, and Preventive Maintenance. With the dawn of the Information and Communications Technology (ICT) tools, CBM inspections, a type of PM, have become ubiquitous the globe. Figure 1 illustrates the percentage of CBM techniques which have been applied for monitoring pump operation including lubrication analysis, infrared thermography and motor current signature analysis.

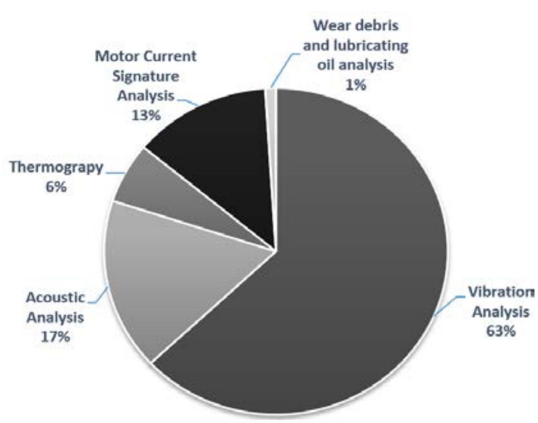

Figure 1. CBM Technologies Applied to CPs in the Literature

However, the most common type of CBM techniques includes Vibration Analysis (VA) (Beebe, 2004). This is because VA is the most versatile of all techniques and it is adaptively useful at detecting a wide range of common failure modes that exist not only for CPs but for most rotating equipment.

2.1 CBM Approach for Fault Diagnosis of CPs

The basic CBM approach is conceived as having three (3) steps including Data Acquisition, Data Processing and Maintenance Decision-Making (Jardine et al., 2006). Over the years, authors have proposed variations to this general approach. Lebold et al. (2003) suggest seven modules in the CBM process including, Data Acquisition, Data Manipulation, Condition Monitoring, Health Assessment, Prognostics, Automatic Decision Reasoning and Human Computer Interface. Mohsen (2017) suggests four phases of CBM including Data Processing, Diagnostics, Prognostics and Maintenance Operation.

In addition to these commonly applied stages, past applications of the CBM approach to CPs included proper definitions of the system boundaries and significant failure analysis. Failure analysis is a critical aspect prior to implementation of CBM since an abundance of different failures are possible for these assets. Although this is the case, researchers and practitioners note that only some of these failures are highly critical and require significant focus over others. Thus, failure analysis is essential in determining these failures prior to testing the capability of CBM for detection of incipient failures (Selvakumar and Natarajan, 2015).

2.2 Failure Analysis of CPs

CPs consist of many interconnected components which may fail in numerous ways. Each failure can impact the overall operation of the CP differently. Since maintenance resources must be wisely distributed, a Failure Mode, Effects and Criticality Analysis (FMECA) aids in scoping the analysis to only include those failure modes which are most critical for pump operation. Several common failure mechanisms are noted in the literature as pertaining to CPs, including unbalance, misalignment, bearing failure, seal failure, resonance, bent shaft, blade pass, vane pass vibrations, and cavitation (Mahmood, 2011).

Due to the large number of possible failure modes it is impractical to use Condition Monitoring for testing the ability of CBM to detect all of them. In such cases, techniques have been proposed and utilised which have aided practitioners and the authors to narrow these failure modes to a much more manageable level that can be tested. The Pareto technique (20/80) is an effective method which can be used to narrow the scope of these failure modes. It involves of acquiring data for each failure mode such as frequency of occurrence and plotting this data (in descending order) against the failure modes. The method is hinged on the basis of 20% of critical failure modes which causes 80% of failures. The modes can then be extracted from the graphical plot. Bejger et al. (2012) and Sheikh et al. (2002) have illustrated the use of Pareto for such analyses.

Besides, several commonly applied techniques have been identified for performing failure analysis. These included FMECA, Root Cause Analysis (RCA), Fault Tree Analysis (FTA), the 5 Whys and Weibull Analysis. The most popularly applied technique was found to be FMECA, appearing in 55% of all reviewed studies.

FMECA has the capability of examining potential failure modes as well as functional failures within a system and is able to analyse failure causes and effects, identify potential weak critical areas, and propose improvement measures (Ravi Sankar and Bantwal, 2001). FMECAs can be both qualitative and quantitative in its examination of systems faults. Quantitative methods make use of a Risk Priority Number (RPN) which is the product of the occurrence, severity, and detection of the failure mode. Mathematically, this is formulated as:

$$\text{RPN} = \text{Occurrence x Severity x Detection} \quad (1)$$

Singh and Suhane (2015) applied a quantitative FMECA to examine CP faults and found the most critical (highest RPN) components to be bearings, the mechanical seal, impeller and shaft. Utilisation of the FMECA allowed for improvements in the selection of maintenance strategies. This meant an increase in the overall profit by 36.74% per year through reductions in labor, downtime and part replacement costs.

3. Research Framework

This research was guided by the framework as developed and illustrated in Figure 2. It was developed subsequent to the literature research which identified the necessary factors such as data requirements and the application setting for CBM. The framework begins by determining and comparing the steps in CBM that are proposed as part of best practice as opposed to that implemented in the industry. This would indicate shortfalls in the maintenance system.

3.1 Determine the Steps in a CBM Best Practice Approach

The literature research involved the initial gathering of publications within eighteen (18) years from 2000-2018. These included sources such as journal and conference papers, PhD and Masters theses and books. The publication search focused on finding work related to the following title areas ‘Vibration Analysis’, ‘Centrifugal Pumps’, and ‘CBM Approach’.

A total of fifty (50) publications were eventually obtained which were found to be relevant and current. Over the years, several authors have proposed variations to the CBM approach that have been applied to maintenance of CPs as discussed in Section 2. In this study, the analysis of reviewed literature has highlighted the following steps in the CBM approach that have been adopted for testing and validation purposes. These are depicted in Figure 3.

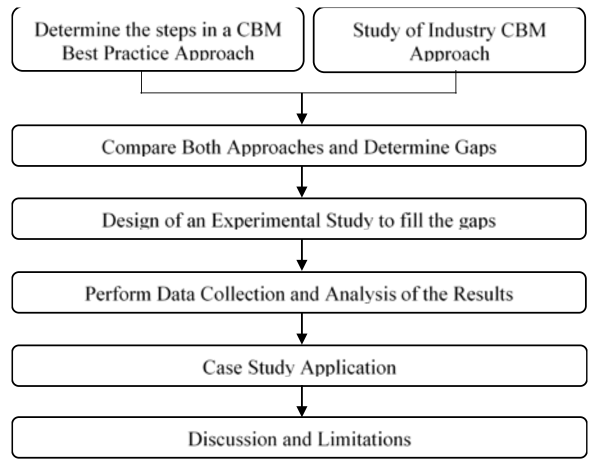

Figure 2. The Research Process Stages Adopted in this Study

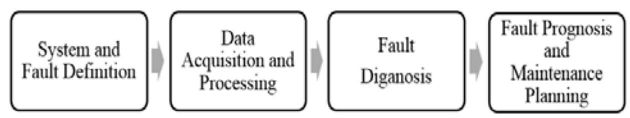

Figure 3. Steps of the CBM Approach

3.1.1 System and Fault Definition

The first step in the approach involves System and Fault Definition. One application of CPs involves utilisation as part of a Fire Water Pump (FWP) safety system for most offshore platforms (Pettersen, 2009). In this work, the operation of CPs in this context was investigated since pump vibration data from an offshore oil and gas company will also be available for further collection and analysis purposes. The typical CP system comprises of a driver-driven series configuration with the driver unit being an electric motor in most cases which drives the pump. Failures of either the driver or driven units result in complete failure and downtime of the entire system and thus the boundaries that were assigned for the current study include both the motor and pump units.

As mentioned in the literature research, it is often impractical to test and examine the effectiveness of CBM for detection of all potential failure modes of CPs because of their abundance. Thus, in step two, techniques were used to determine the most critical failure modes for the current study. The first included a Pareto 20/80 as identified in literature to be useful when identifying the few most critical failure modes which contribute to 80% of the failures. The Offshore Reliability Data Handbook (OREDA, 2002) lists a total of 16 critical failure modes for CPs as spurious stop, external leakage-process medium, overheating, vibration, external leakage-utility medium, low output, breakdown, parameter deviation, high output, other, structural deficiency, noise, internal leakage, failure to start on demand, failure to stop on demand and erratic output. These were utilised in the Pareto Analysis to identify the most critical failure modes. Subsequently, to effectively rank the criticality of these failures modes and identify faults which should be the focus of experimental testing, a quantitative FMECA technique was implemented. Figure 3 illustrates the process of Failure Analysis used. It illustrates the scoping of all failures for CPs down to 5 CP faults with the highest RPN values.

3.1.2 Data Acquisition and Processing

Collection of the right data types is of paramount importance for such an application, since the ability of CBM to monitor faults with sufficient time before failure depends on the nature of the data collected. The selection of appropriate data collection instrumentation, allocation of data collection points and directions are all critical decisions for this stage.

3.1.3 Fault Diagnosis

In this study, time and frequency signal analysis was performed on the raw data to aid in detection of the faults. A classification accuracy performance metric was calculated and utilised to determine the accuracy of CBM for fault detection. This metric is estimated only to illustrate the effectiveness of the current detection methods with respect to all the faults considered.

3.1.4 Fault Prognosis and Maintenance Planning

The P-F interval curve as defined in literature was constructed using a combination of theoretical and practical data. The data obtained from the P-F interval curve aids in planning inspection intervals for the asset.

3.2 Study of Industry CBM Approach

The literature research was conducted alongside the study of CP operation aboard an Offshore Production platform utilised as part of a fire water safety system. In the industry however, it was found that while the infrastructure for CBM implementation is in place, not all the stages of a CBM Best Practice are followed. Instead CBM is used simply to indicate that CP components are approaching an alarm limit of wear and degradation. Such alarm limits are typically established by experienced personnel over time who were able to identify marginal vibration levels beyond which failure was imminent.

3.3 Compare Both Approaches and Determine Gaps

Subsequent to understanding the approaches proposed as ‘Best Practice’, and those used in the industry, both were compared and analysed to identify areas for improvement. These are:

- Since CBM was not employed in the initial stages of CP operation, initial baseline data is missing for certain components.
- The failure vibration frequencies for certain components are missing, and as such faults in such cases remain undetected until it is too late.
- While data were used to create alarm limits which dictate repair or replacement points for CP components, they are not used further for fault prognosis and maintenance planning.

3.4 Design of an Experimental Study to close the gaps

An experimental procedure was subsequently designed for appropriate data to be collected and for validation of the best practice approach. The factors which influenced the experimental test size are listed in Table 1. Other factors which did not affect the number of experiments conducted but were considered for each test includes the number of lines, resolution, frequency span and window type.

Table 1. The Controlled Parameters in the Experiments

Parameters	Designed Values
Operating speeds	25Hz, 40Hz and 55Hz
Measurement/Transducer location	Vertical, Horizontal, Axial
Number of Experimental Trials/test	3

The testing procedure was performed in two phases. The first phase tested the capability of the CBM approach to detect a single fault at a point in time. The system was set up in five (5) different configurations each consisting of a single fault. Each faulted setting was labelled as unknown faults 1-5. The second phase tested the ability of the CBM approach to detect multiple failures within the system which is not uncommon in the industry. The system was set up in three different configurations with each consisting of multiple faults. In addition, a baseline test for the system as it exists in ‘good working condition’ was also included in the procedure.

This resulted in a total of nine (including one baseline setting and eight faulted settings) settings of the system for which data were collected. Considering the factors of operating speed, measurement directions and number of replications, the total number of trials conducted to collect data was calculated as:

3 replications x 3 measurement directions x
3 operating speeds x 9 experiments = 243 tests.

3.5 Perform Data Collection and Analyze the Results

To collect data for testing s, an experimental test rig namely the Machinery Fault Simulator (MFS) was utilised. For this experimental apparatus set-up (to be similar to a practical pump set-up in industry), modifications were made to the MFS system. For the purpose of this investigation, the accelerometer was mounted via a magnet at the horizontal and vertical locations on the bearing centerline to sense vibrations from radial forces. In the case of vibrations from axially-directed forces, the accelerometer was placed in the axial direction. The VibExpert II Data Analyser was utilised to collect data from the test rig and transmit to the PC. OMNITREND software was utilised for the data collection process (Pruftechnik, 2017).

3.6 Case Study Application

The procedure was subsequently applied to establish the PF curve for a practical case study. Data were obtained from a collaborating company for motor bearings in two (2) firewater pumps A and B, where pump A is the stand-by pump that remains inactive unless otherwise switched on. This type of inspection used vibration analysis techniques to measure the RMS velocity of motors A and B over a period of time. The operating speed of the pump was recorded as 3,500 rpm. Using practical RMS velocity data for the inspection of motor bearings experimental RMS velocity data via the MFS system, the P-F curve was plotted to determine the point of potential failure (P) and hence the P-F interval.

The results were gathered and analysed to assess the effectiveness of the CBM approach for fault classification.

4. Results and Findings

4.1 Failure Analysis

From the Pareto analysis, the most severe and frequent failure modes (refer to Figure 4) were found to be vibration, overheating, external leakage-process medium, failure to start on demand and spurious stops. Consequently, these five failure modes were further analysed in a FMECA. From the FMECA, most critical causes of failure are misalignment, imbalance, defective bearings, cavitation and mechanical looseness.

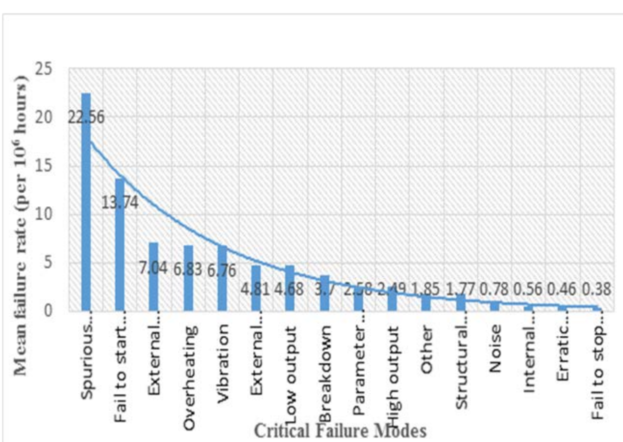

Figure 4. Pareto plot for CP Failure Modes

4.2 Singular Fault Testing

The vibration spectrum obtained from measurements in three perpendicular directions at each operating speed were obtained and then analysed. Key frequencies for faults pertaining to bearing and gearbox failures were calculated, and their presence was used as indication of specific types of fault in the system.

Figures 5 and 6 show some of these results. For an operating speed of 25Hz, the vibration spectrum in Figure 5 shows high axial vibration at 1X, 2X and 3X, indicating angular misalignment. At higher operating speeds, the machine tended to produce stronger vibrations. This is also the case when the system operates at 40 Hz and 55 Hz. The spectrum showed a high increase the RMS velocity from 4.88 mm/s to 5.64 mm/s at 1X followed by a small 2X and 3X peak.

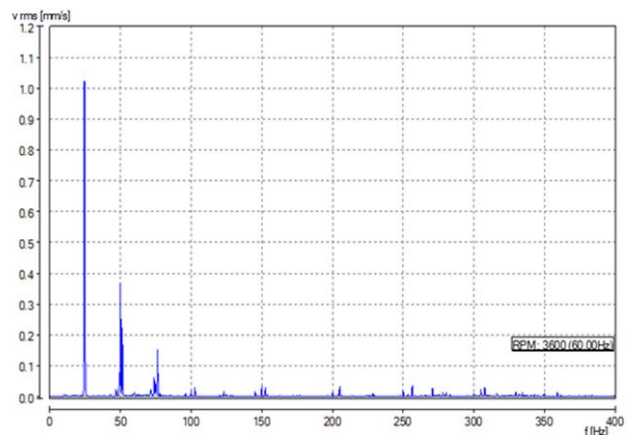

Figure 5. Vibration Spectrum in the Axial Direction at an Operating Speed of 25Hz Depicting the Presence of Angular Misalignment in the Motor

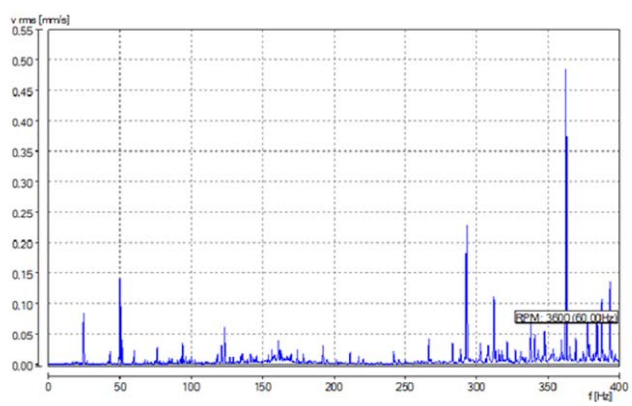

Figure 6. Vibration spectrum for the vertical direction at an operating speed of 25Hz depicting the presence of inner and outer race bearing defect with respect to the motor

The vibration spectrum for vertical measurements at an operating speed of 25Hz shows the inner race defect frequency (BPFI) and its multiples, as well as the four times the outer race defect frequency (BPFO) (See

Figure 6). This indicates a bearing defect with respect to the inner and outer races of the bearing. At an operating speed of 40Hz, the defective rolling element frequency (BSF) and its multiples are visible on the vibration spectrum in the radial directions The defective rolling element frequency and its multiples are also visible in the vibration spectrum for the radial directions at an operating speed of 55 Hz..

Phase 1 of the testing and validation investigated singularly tested faults. Table 2 lists the results for these tests. Root Mean Square (RMS) velocities and Fast Fourier Transform (FFT) analysis were utilised to diagnose the faults. The Table lists the predicted and true faults allowing for comparison . The results show a total classification accuracy of 100% for this phase of testing.

Table 2. Results Obtained for Phase 1 of the Testing and Validation for Singular Faults

Fault #	Predicted Fault(s)	True Fault(s)
1	Inner race bearing defect with respect to motor	Inner race bearing defect with respect to motor
2	Angular misalignment of shaft	Angular misalignment of shaft
3	Defective rolling element bearings (motor)	Defective rolling element bearings (motor)
4	Cavitation in pump Unbalanced motor	Cavitation in pump Unbalanced motor
5	Bowed rotor which may have been caused by a broken rotor bar	Broken rotor bar in motor
Classification Accuracy:100%		

4.3 Multiple Fault Testing

The second phase of tests involved combinations of up to four (4) faults within a single run. The classification accuracy attained was 67%. The results are shown in Table 3.

Table 3. Results Obtained from Combinational Fault Testing

Fault #	**Predicted Fault(s)**	**True Fault(s)**
6	Bowed rotor which may have been caused by a broken rotor bar	Broken rotor bar in motor
	Unable to Detect Fault	Misalignment between pump and motor
	Base plate of pump loose	Base plate of pump loose
7	Cavitation in pump	Cavitation in pump
	Defective rolling element bearings (motor)	Defective rolling element bearings (motor)
	Unable to Detect Fault	Misalignment between pump and motor
	Unable to Detect Fault	Defective blade fan in motor
8	Cavitation in pump	Cavitation in pump
	Unbalanced motor	Unbalanced motor
	Unable to Detect Fault	Defective blade fan in motor
	Base plate of pump loose	Base plate of pump loose
Classification Accuracy: 76.5 %		

It is noted although that misalignment and defective blade fans were the two faults that were undetected in cases where others within the combination were found. From both phases 1 and 2 of testing, the final overall classification accuracy was 76.5%.

4.4 P-F Interval Determination

One of the key steps subsequent to fault diagnosis is utilising the machine condition covariate data to aid in fault prognosis and maintenance planning efforts. To illustrate that this was possible, vibration condition data were collected from the organisation for the CPs operation for a period of twelve (12) months. The operational speed provided was 3,500 RPM.

To develop the P-F curve required, the baseline and fault condition readings would be required. Since vibration analysis began on the CP system only subsequent to a few years of pump operation, precise vibration readings with respect to the 'Good Operating Condition' were not stored. Data records of vibration readings were not specified for a 'roller element bearing failure condition'. To obtain this data for the P-F curve, the MFS was set up to operate at 3,500 RPM (the same running speed as the CPs in the industry) and the vibration condition readings observed under 'good working condition' and 'a roller element bearing faulted condition'. These readings were plotted on P-F curve shown in Figure 7.

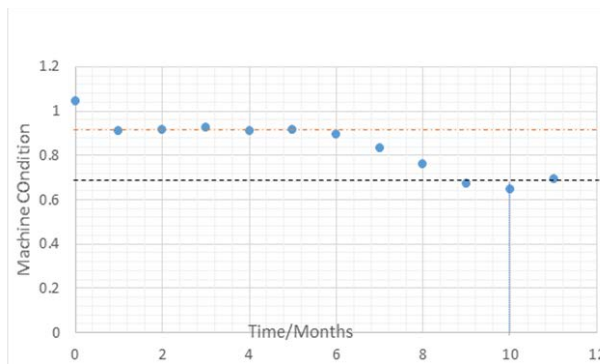

Figure 7. The PF Curve for Motor A

The theoretical baseline and failure condition readings were superimposed on the trending data obtained from the organisation. The baseline conditions and faulted conditions were obtained from the experimental study as well as projected baseline and machine fault conditions for the company. Although these values were close, there were slight differences as shown in Figure 7.

These differences can be attributable to the difference in operating conditions, since the MFS produced values in a relatively controlled environment as opposed to the industrial setting. The motor-pump system used at the company had different specifications and capacity and the operating environment itself was different. The general baseline readings observed from the company data was found to be 1.1 mm/s. This is 0.14 mm/s greater than 0.96 mm/s found from the experimental study.

The machine fault condition for a roller element bearing fault from the organisation data was found to be 1.55 mm/s, while 1.44 mm/s was obtained from the theoretical tests. With the general curve plotted, it was noted that the deterioration condition for the roller element faulted bearings began at 1.12 mm/s. This was taken as the potential failure point P and thus the P-F interval calculated as 5 months. This implies that from this potential failure point P, the company can then plan maintenance inspections to a suitable interval to avoid corrective maintenance on the bearing.

As a rule of thumb the inspection interval is utilised as half or one-third of the P-F interval in some cases (e.g., Blann, (2013), and Moubray (1997)). The results illustrate that the organisation should perform inspections on the bearings every two or three months. Currently, inspections are done on a monthly basis. Considering the cost of inspections, there could be a potential cost savings..

5. Conclusions

The benefits of applying a CBM Best Practice approach have been well reported in the literature. Although this is the case, many companies fail to realise these benefits due to improper application of the approach. This study sought to investigate improvements in fault diagnosis and maintenance planning when a CBM approach is applied to CPs. Initially, the steps in the best practice approach were identified from the literature, and compared with that applied to a set of CPs used in the fire water system aboard an offshore production platform. Subsequently, the gaps were found, and an experimental procedure designed and implemented to fill these gaps and illustrate the applicability and benefits of applying the approach in full.

Although the CBM data was collected by the organisation, it is not always analysed in a manner which would facilitate efficient fault diagnosis and maintenance planning. The experimental tests produced data which would aid fault diagnosis capabilities for prognostic decisions of CPs.

A fault classification accuracy (FCA) of 100% was obtained for fault diagnosis of singular faults, 67% for multiple combinations of faults and an overall Classification Accuracy of 76.5%. In addition, the P-F curve for the FWP motor was obtained from which a PF interval of 6 months was attained. This could potentially be utilised to plan maintenance activities for the motor. It should be noted that the classification accuracy is based on the number of trials undertaken in this study which were three (3) trials per failure for this work.

The work performed has introduced several key innovative contributions:

1. The use of two failure analysis techniques including a Pareto technique and a FMECA for determination of the most prevalent failure modes and ranking the criticality of those faults. Although the failure analysis technique has been applied extensively in the past, the combination of Pareto and FMECA proved to appropriately scope the large numbers of failures and allow for focusing of the experimental testing procedure whilst maintaining the effectiveness of the CBM approach.
2. The approach was tested using two phases. The second phase incorporated multiple combinations of faults which allowed for a much more realistic representation of the work conducted.
3. The approach has uniquely combined both the theoretical data and practically collected industry data to plot the PF interval curve which can aid the company in planning maintenance in a much more evidence-based manner.
4. While the current method represents a pragmatic approach towards P-F interval estimation, the method is best suited for cases where the uncertainty in the P-F interval of failures is negligible. It should be noted that alternative methods such as the use of Proportional Hazards Modeling (PHM) in combination with covariate data and Delay-Time models could be utilised when this uncertainty cannot be ignored.

The use of other vibration analysis techniques such as phase analysis and orbital analysis could potentially increase the classification accuracy from 76.5 % significantly. As a result, future work could investigate 1) the use of a combination of vibration techniques in fault diagnosis of other types of pumps, turbines or generators, 2) the use of oil and acoustic analysis in pump maintenance, and 3) the vibration and flow in cavitation in pumps.

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