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Enabling condition based maintenance in a precious metal processing plant

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Abstract

In precious metal processing plants, suitable maintenance systems should be deployed to provide the necessary plant operating conditions, ensure plant availability and provide critical fume extraction and filtration systems for health and safety. A key focus for this work was use of sensors to monitor and predict abnormal equipment behaviour and examining how the data obtained could be processed into information and better inform the condition monitoring systems. The requirement for this research was driven by escalating maintenance costs in an industrial case study in South Africa. Historical records on equipment failure and was used in Pareto analysis to define the critical assets and failure modes for equipment that dominated the escalating maintenance costs for the industrial case study. Vibration data from mounted sensors was then collected the identified critical assets, analysed and used to infer condition of critical assets. Statistical tools based on process capability index values for processes in control and out of control were defined for tracking system deterioration and enabling predictive maintenance. The results show that sensors and thresholds based on process capability index can be used in predictive maintenance to alert maintenance teams to attend to vacuum pumps and fans pre-failure and hence improve plant availability and operation and reduces cost.

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Keywords: Maintenance; Vacuum Pumps; Sensors; Process capability Index

1. Introduction

Safety and throughput are important for precious metal processing plants. Ventilation and vacuum systems are key systems in a processing plant. Any stoppages in the operation of ventilation and vacuum systems can lead to fume accumulation and inhalation by staff and production delays. The focus of this industrial research was on improving maintenance on fans, and pumps motors (scrubbing systems) and hence promote plant availability, safety, throughput and reduced maintenance costs. The aim of the study was thus, to reduce the escalating costs of maintenance and to develop condition monitoring capability.

Proper maintenance requires techniques and methods to properly utilize assets supported by appropriate technical skills (Velmurugan and Dhingra, 2015) and knowledge. The key objective of maintenance is to ensure system function (availability, efficiency and product quality), systems life (asset management) and system safety with low-energy consumption. Researchers such as Al-Najjar et al., 2001, saw the role of maintenance in improving performance and profitability of manufacturing processes. Companies are looking for improvements in condition monitoring, fault diagnostics, reliability analysis and maintenance planning.

Liyanage and Badurdeen, 2010 noted that ill-defined maintenance practices led to environmental problems, such as hazardous emissions, production waste due to system malfunctions, inefficient energy usage, ineffective resource consumption and waste of stored materials. In the context of platinum processing skin and respiratory exposures to soluble platinum (Pt) were both positively correlated with urinary Pt excretion, and both exposure routes were recommended to be

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considered when investigating occupational exposure to soluble Pt (Stephanus et al, 2018). Franciosi et al., 2020 pointed out that maintenance processes affect the technical condition of target systems, in particular their reliability and availability, but also affect sustainability for example, safety performance, environmental damage, high consumption of energy and resources and indirect impacts, due to its effect on assets/equipment and processed/manufactured product. Examples of high energy consumption, includes wasted energy from heating, cooling and lighting during production downtime for maintenance delay (Raouf, 2009).

Figure 1 shows an illustration of component or engineering system failure rate over time. This is commonly known as the bathtub curve. The first stage of the curve in the time domain is the primary stage or infant mortality stage of the bathtub curve. This is characterized by high failure rate followed by a period of decreasing failure rate. These failure rates can be associated with poor design, poor installation, or misapplication or parts burn in period. The infant mortality stage is then followed by a secondary stage or useful life stage where the failure rate will be approximately constant throughout this stage. The tertiary and final stage is typically the wear out period, when the unit/equipment is worn out, tears or gives in. The failure rate in this stage increases exponentially.

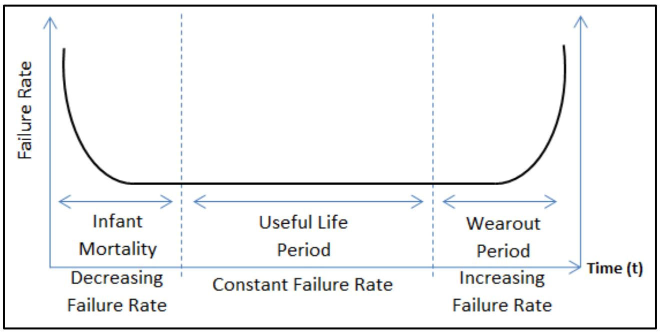

Fig. 1. Bathtub curve illustrating component failure rate over time

This classical wear evolution regime occurs for systems that are operating under optimum conditions. For abusive or other conditions the stages may be modified or difficult to distinguish.

In order to plan and set up a preventative maintenance plan, such data as used to construct the bathtub curve, will be required by the maintenance planner. This data could be crude as given by the asset supplier or it could be augmented and refined based on practical considerations, previous experience, historical data and also common sense, modelling or other approaches (Lin, 1995).

There is increasing need and use of data driven approaches to predict and plan machine maintenance. Gutschi et al., 2019, used data mining, feature extraction and machine learning on real data sets from machine logs, event logs and operational information to define machine failure. Hiruta et al., 2019 highlighted the need for both data analytics and domain knowledge. They developed a framework for data scientists to propose hypotheses for condition based maintenance to domain engineers allowing data scientists to update their process on the basis of feedback from domain engineers. Thus the development of maintenance systems based on data and sensors also requires the strong input from experts in order to improve and de-risk the solutions. Makinde et al., 2016 investigated the best maintenance system for reconfigurable vibrating screen machine used for sorting, sizing and screening mineral aggregates in South Africa. Weighted decision matrix and analytical hierarchy process were used to establish the best maintenance practice. They also provided a good review of different maintenance approaches. In this case, of fans, Velarde-Suárez et al., 2006 used the spectra of acoustic pressure and acceleration signals (vibration signals) to detect failures in a selected fan.

1.1. Failure based Maintenance

In failure based maintenance or corrective maintenance a failure must happen before the maintenance team can attend to a problem. This is a simple but reactive and unplanned way of maintenance. It can lead to high levels of plant stoppages and production down-time and increased maintenance costs (Ahmad and Kamaruddin, 2012) and opportunity costs. The technique negatively affects plant availability, due to unforeseen or unplanned plant stoppages and increases the number of injuries to operators (Lin, 1995).

1.2. Predictive Maintenance

The common basis for predictive maintenance is to apply regular monitoring of the actual condition of assets. Operating efficiency and other indicators of the operating condition of machines and process systems will provide the data required to ensure the maximum interval between repairs and minimize the number and cost of unscheduled outages created by machine failures (Lin, 1995). The process involves monitoring the condition of machines, advance or early detection of possible faults/breakdowns and acting upon such information to restore the condition of the asset. Figure 2 illustrates the bathtub curve of predictive maintenance. Taking corrective action in response to the warning signal delays the breakdown and extends asset availability.

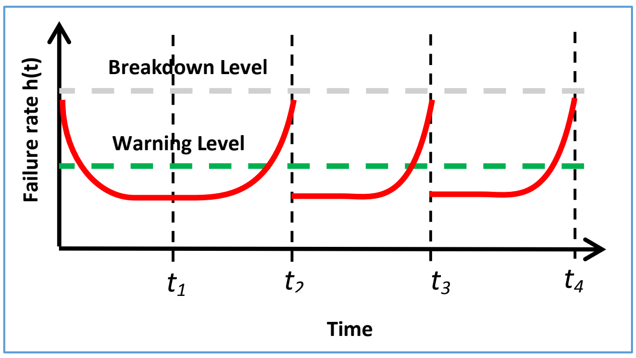

Fig. 2. Bathtub curve illustration for component failure rate over time in predictive maintenance

The key question to consider is what type of condition monitoring is required for assets. This is predominantly determined by the failure mode of the equipment alongside with cost, accessibility and other factors. For motors and fans sensors can be employed to pick up changes in vibration. There are a number of factors to consider when applying sensors for vibration based condition monitoring. These include type of sensor to be used (and its sensitivity), number of sensors to be installed and where to install to pick up the vibration (Rastegari and Archenti, 2017). Condition monitoring can be provided by installing a vibration sensor near the bearing or coupling.

There are also several techniques and sensors that are applicable to condition monitoring. Several studies have suggested that industry is far from utilizing production equipment to its full potential. Many failures are not age related and give early warning in the process of failing. Figure 3 shows the potential failure curve for a ball bearing as illustrated by Fan (Fan and Zhan, 2016). According to Figure 3 and Fan and Zhan, 2016, vibration characteristic could be used as an early detection system for ball bearing condition. Particle analysis is oil, audible noise and heat are candidates for detection of ball bearing condition in advanced wear state. To make use of vibration analysis there is need to characterize the vibration according to machine condition. For industrial practice guidance such as Table 1 and 2 on Hydraulic Institute Standard ANSI/HI 9.6.4, 2000 and ISO General Standard machine vibration are relevant.

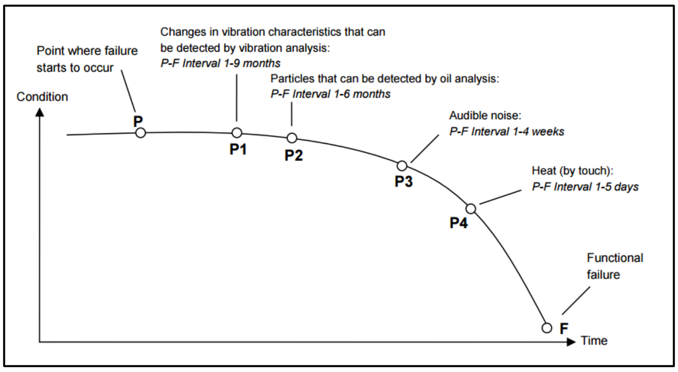

Fig. 3. The potential failure to failure curve of a ball bearing (after Fan, 2016)

Table 1. Hydraulic Institute Standard ANSI/HI 9.6.4, 2000

RMS Vibration Velocity	Class 1	Class 2	Class 3	Class 4
0.28	A	A	A	A
0.45	A	A	A	A
0.71	A	A	A	A
1.12	B	A	A	A
1.80	B	B	A	A
2.80	C	B	B	A
4.50	C	C	B	B
7.10	D	C	C	B
11.20	D	D	C	C
18.00	D	D	D	C
28.00	D	D	D	D
45.00	D	D	D	D

Table 2. ISO General Standard machine vibration

Zone A: Newly commissioned machined
Zone B: Good. Acceptable for unrestricted, long operation
Zone C: Unsatisfactory for long term, continuous operation
Zone D: Bad. Sufficient severity to cause long term damage to machine (alarm level)
Class 1: Very small machinery or part of machinery (20HP or below)
Class 2: Small machinery (20 - 100HP) on rigid foundation
Class 3: Large machinery mounted on rigid and heavy foundations
Class 4: Large machinery mounted on relatively soft foundations

1.3. Research Motivation

The motivation for this work was to investigate alternatives to corrective or run-to-failure maintenance which was leading to a huge inventory of critical spares and escalating maintenance costs. High inventory levels present challenges for cash flow. The scientific research was to develop the capability for predictive maintenance. Sensors were put in place to monitor mechanical vibrations and thermal expansion in real time. The objective was to develop systems for tracking a motor’s vibration to spot abnormal trends. According to (Bloch and Geitner, 1983), 99% of failures can be predicted by trend from relevant indicators of equipment condition. Action can then be taken to minimize further damage on the equipment for example by stopping the pump or fans.

Developing cumulative and big data sets from plant monitoring is also very useful. Big data sets can help to evolve and improve the maintenance practice and improve plant availability and lay the foundations for the fourth industrial revolution, Industry 4.0.

2. Research Approach and Design

The research was based on (1) examining records for failures, and maintenance methods, (2) installation of vibrations sensors, data collection and developing methods of processing the data into useful information to drive condition based maintenance.

Figure 4 shows the centrifugal pumps that were the assets of focus. The pump is installed horizontally and there is a shaft coupling between the motor and pump. Figure 5 shows another asset of interest and focus for the study which was a centrifugal fan installed horizontally.

Fig. 4. Centrifugal pump set-up

Fig. 5. Extraction fan set-up

2.1 Sensors

Vibration sensors are installed vertical to the horizontal and drive axis on both front and rear bearings housing as shown in Figure 6. A frequency is generated during motor rotation. As the resistance or conditions changes the sensor picks up normal and ab-normal vibrations by modulation and demodulation principle. The aim was to monitor vibration magnitude and displacement on the input or the load side.

Fig. 6. Vibration sensor mounted on the motor

Under normal conditions the machines will operate uniquely and have its normal profile, this profile will change due to different events causing unique vibration signature. It is important to understand the signatures. The vibration picked up is a combined vibration signal that could arise from unbalance, looseness, misalignment (Rastegari and Archenti, 2017) and other factors. Frequency domain analysis such as Fast Fourier Transformation could be used to illustrate different contributions or signal make up. The positive identification of each frequency domain significant contributor could be facilitated by mode modelling or controlled experiments.

2.2 Context Data Collection

To support the study two separate systems were used for collecting data, namely the System Application Products (SAP) and the Wonder-ware Historian (database). The System Application Products (SAP) is a system which provides users with a soft real-time business application. Plants functional locations, equipment and components are structurally built onto the system. These hierarchies are constantly updated on the system whenever new instruments are added on the functional location. The system track costs and faults associated with a specific instrument. End users cannot change the hierarchy structure of a particular plant functional location, that's how data is secured. The system allows access to be controlled for example for certain functions or as per job description. This allows engineering and sales personnel to have different access.

Wonderware Historian database captures real time profile data from measuring instruments in the field and stores data in a database. A report can be drawn from a particular instrument in graphic and data points. It can be exported to a spreadsheet.

2.3 Turning data into information

Minitab 17 software was used to process historical data from recorded machine failures. Process Capability Cp and Cpk where applied to test if the process is operating within limits according to the relevant condition monitoring signals and is hence under control. These assess process capability by considering that the process mean may and may not respectively be cantered between the specification limits.

From the history of failures, Pareto charts were used to evaluate the dominant parameters. By ordering the bars from largest to smallest, a Pareto chart can help you determine which of the machine failures comprise the "vital few" and which are the "trivial many." A cumulative percentage line helps to judge the added contribution of each category. Pareto charts can help to focus improvement efforts on areas where the largest gains can be made. Under the 80/20 rule it is assumed that 80% of the problem or challenge can be attributed to a small subset of the dominant factors.

3. Results

The first part of the study was to understand the main elements that were dominating the maintenance challenge for the company. Pareto analysis was used to determine which faults are dominating pump systems. Categories of reported faults over a two year period were analysed based on the data captured from company historical database. The results are shown in Figure 7.

The analysis based on the two years of data collected on the fault logger indicates that pump systems are failing mostly on overload, followed by faulty pump internals and third on the list is the collapsing of bearings. This constituted 80% of the reported failures. Applying an early detection on vacuum systems as part of prediction maintenance, can cut or reduce failures that are associated with bearing collapses and overload failures. For confidentiality this paper does not discuss the Pareto in relation to cost of maintenance. However, this is an area that could be explored using the techniques of analysis.

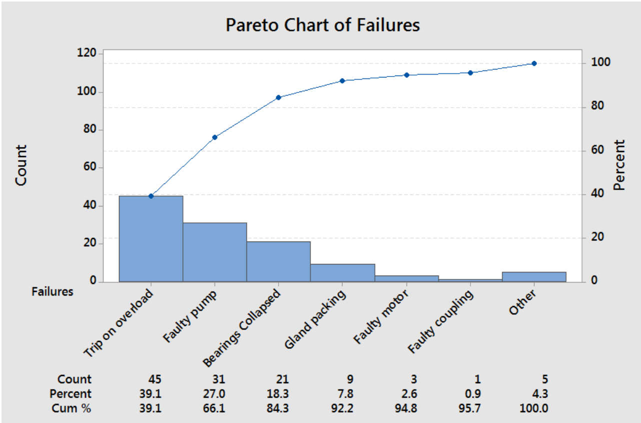

Fig. 7. Vibration sensor mounted on the motor

To evaluate the condition of the fans and motors based on the vibration signals, a process capability index was used as a rolling measure to benchmark the vibration in relation to the appropriate thresholds as shown in Table 1 and 2.

Figure 8 and 9 shows process capability report of vibration detected on the motor side and fan side bearings respectively. From the Figure 8, the Cpk of -0.656 is evaluated for the motor side while from Figure 9 it is -1.127 on the fan side. The LSL set to 0.1 and USL set to 2 (Class 2, zone B, adjusted for industrial case). Both results show that the vibration is out of specification since the value is less than 1. Additionally this shows that fan side of the assembly is the most critical in terms of vibration and possibility of advance failure.

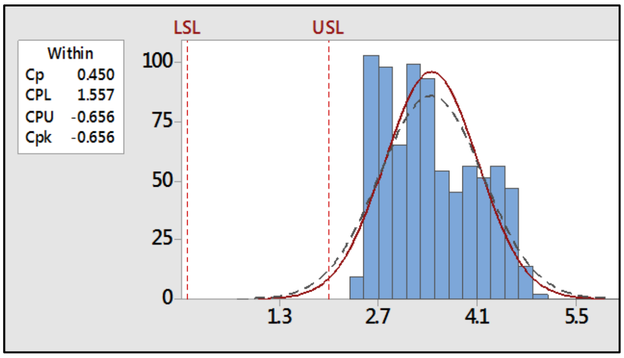

Fig. 8. Process capability index Cpk report for motor side bearings on assembly (Y-axis is number of hits and X-axis the root mean square (rms) of the vibration in mm/s)

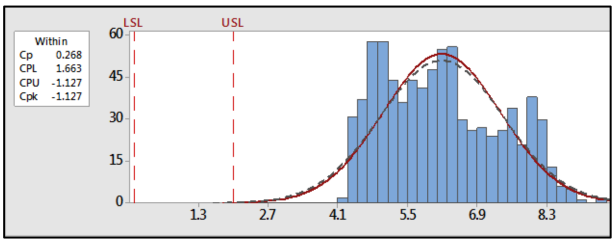

Fig. 9. Process capability index Cpk report for fan side bearing on assembly (Y-axis is number of hits and X-axis the root mean square (rms) of the vibration in mm/s)

Figure 10 shows the pump condition running within the set parameters both vibrations averaging 1.5mm/s.

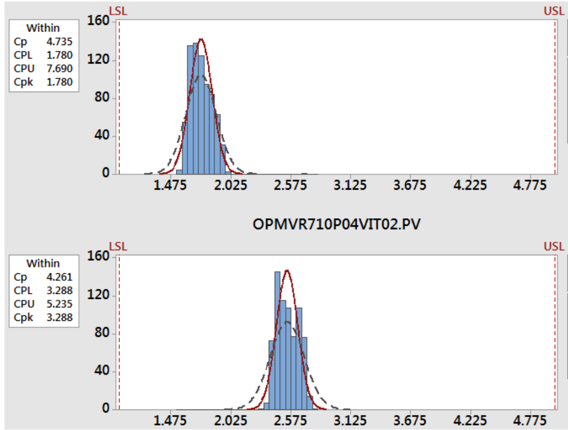

Fig. 10. Process capability index Cpk report for pump 4 for sensors 1 and 2 on bearings on assembly (Y-axis is number of hits and X-axis the root mean square (rms) of the vibration in mm/s)

Both bearings Cpk are showing normal condition, the machine is operating within the specified accepted ranges, meaning the alignment and vibration are with the tolerated values below 7.1 mm/s, that's according to Class 4, Zone B (good condition) in table 1 and 2. The vibrations on the motor side's Cpk = 1.78 and fan side Cpk = 3.288 both vibrations are within the industrial set limits (0.5 and 5 mm/s). The data is suggesting that there is slightly more vibration coming from the fan side. The probability plot was also used and it showed that the process was 95% within the set range. The two cases shows the ability to pick up the sides were vibration is more critical. The process capability index presents a simple tool for industry that can be used as green, amber and red lights.

4. Discussions

Motivation: Safety, plant availability and reducing costs is important in metal processing plants. Increasing maintenance cost were a typical challenge explored in this industrial case study.

Failure based maintenance: The traditional approach is to use failure based maintenance and run equipment to failure. Under this system failure is unpredictable. The maintenance team has to keep more spares ready, building up inventory and limiting cash flow as money is tied up in stock.

From time to condition based maintenance: Time based, or periodic scheduled maintenance is easy to plan and requires no investments in sensors or intelligent machines. This can be based on manufacturer hours, years or months that the machine should run until it is replaced. However, in real applications the estimated time to failure cannot be guaranteed, many factors can influence failure such as overload or variation in processed aggregate, this will reduce the life span of a motor. Harsh operating conditions also lead to deviations from manufacture recommended use patterns. This requires condition-based maintenance or other better approach. The study has shown that simple tools based on process capability index could be used to track deterioration of equipment and enable condition based maintenance.

Implications for design. In this study the plant in question had the vibration sensors installed long after the plant design, commissioning and initial operation. In an ideal situation the design of the plant and the installation of equipment should consider the essential sensors for condition monitoring taking into account the load on equipment, operating conditions and domain expert knowledge. The earlier sensors and signals are collected the more complete picture can be obtained regarding deterioration of the plant. Indeed the early deployment of sensors and monitoring the equipment in the initial burn-in period in Figure 1 would enable an assessment of issues to do with product design, assembly or plant commissioning. This is not common practice now in metal processing plants in South Africa. In the era of Industry 4.0 this may become the foundation for plant systems and learning from failure.

A key challenge facing any designer is to consider the possible failure mechanisms, failure loads and design equipment for extended life. Historical trend analysis and condition monitoring enables collection of vital information that can be used as feedback to design also enable comparison among different design variants and inform a basis for evolving designs. The utility of the work presented here is that simple tools to identify dominant challenge assets for maintenance can be used to priorities condition based maintenance on key assets in order to deliver the highest impact.

Conclusions

This research was inspired by the challenges of escalating maintenance costs being faced by a precious metal processing plant. Through this research the following contributions were made.

- Pareto analysis was used to define the critical assets that contribute 80% of the maintenance failures in the plant. These were defined as (i) tripping of pumps on the circuit breaker due to overload, (ii) pump mechanical failures, and (iii) collapsing of bearings. It follows therefore that plant load, pump condition and bearing vibration are critical areas of focus and condition monitoring in the metal processing plant.
- To monitor the condition of pumps and fans in metal processing, vibration sensors can be used to collect process signals at critical points and infer process condition based on defined application dependant limits.
- Process capability index Cpk and process probability tracking can be used as rolling statistics over time and be exploited to define when the process is going out of control and hence triggering maintenance repairs.
- The vibration monitoring and process controls techniques were applied on selected equipment and used to demonstrate effectively the capability of process control to predict and avoid equipment failure.
- Future research can exploit the growing database of vibration signals and plant processing context and use techniques such as machine learning to improve the predictive capability of the system.

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