Prescriptive Maintenance Approach to Online Condition Monitoring Using Sendor Data and Artificial Neural Network (ANN) Models for Processing Plant Equipment: Case for Platinum Processing Plant

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Sub-theme:

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Abstract

Improving the reliability and efficiency of milling circuits is key to platinum processing plants. Thus, in line with this platinum processing plants are currently using two main maintenance strategies namely: condition-based and preventive maintenance. However, the wide variety of fault signatures and failure modes makes it difficult to derive cost-effective, useful, and accurate models to enable early detection of faults. Thus, the researchers proposed implementing a prescriptive maintenance approach using the acquired condition monitoring sensor data in a platinum processing plant. Related literature on the applications of conditional monitoring in processing plants was done to get a deeper understanding of the topic. Accelerometers and temperature sensors were installed on pinion bearings for the Semi-Autogenous (SAG) mill with embedded sensing, analysis, and communication capabilities. Using sensor data collected from critical components of the mill, the condition monitoring system was developed in MATLAB, to detect any abnormal operational conditions that are triggered from fault conditions. First, an automated online adaptation of the signal model was developed in MATLAB, using a support-vector-machine (SVM) approach utilizing vibrational data from sensors. Decision-making tactics were then implemented to determine the initiation point of a developing fault. Artificial Neural Network (ANN) tools in MATLAB were also used similarly. From, the findings, the classification accuracy for multi support-vector machine classifier was 96.7%. Also, findings showed that the developed models were able to detect faults, predict equipment failure for maintenance support strategy, compare healthy and faulty data signals, predict residual life for pinion bearings and the time to the initiation point of the second phase, which is the failure postponement period where a fault or hidden defect may have been initiated. Overall, using the proposed prescriptive maintenance approach in a mineral processing plant can prevent breakdowns and reduce costs associated with unplanned equipment failure.

Key Words: Artificial Neural Networks, Condition monitoring, Failure Mode, Life of Asset, Platinum processing, Prescriptive maintenance, Support Vector Machines

1. Introduction

Platinum processing plants have a high capital expenditure and their return on investment (ROI) depends on optimum maintenance and operational costs. To adhere to these cost-effective necessities, machine condition monitoring has become the dominant maintenance asset care strategy in platinum mining and processing plants [1]. Condition monitoring approaches have borne fruits on operational cost savings by avoiding unanticipated breakdowns, improving plant reliability, and enhancing safety in operations [2]. To achieve high plant productivity, availability, and low energy expenditure it is essential to deploy and implement effective maintenance management strategies [3]. Advanced technologies have emerged in machine condition monitoring to improve equipment performance over the past 100 years and the most common maintenance strategies being employed in industries include reactive and proactive maintenance strategies. Reactive relates to breakdown maintenance while proactive is attributed to preventive and predictive maintenance. Prescriptive maintenance is becoming prevalent with the deployment of advanced web-based technologies in online condition monitoring, transmission & data analysis using advanced proprietary systems [2]. Cloud computing can be used remotely to handle large amounts of data with distinct electrical and mechanical faulty conditions under different environments [4]. Industry 4.0 standards are emerging globally with a significant decrease in the glitches of inadequate computational power and available memory. Hence, mathematical models of plant processing equipment can be utilized for the training of AI algorithms for continuous plant monitoring.

Online condition-based monitoring is a predictive maintenance approach that continuously monitors the real-time condition of the machine using various types of sensors to determine the overall health state of the machine, and if there are any significant changes in the monitored parameters. The data collected is analyzed using proprietary software and expertise to predict failure, obtain trends, and calculate the remaining useful life of an asset (LOA). Current maintenance strategies in use on platinum processing plants are periodic, breakdown, and preventive maintenance, but considering the age of the plant and technological advancement, the local maintenance personnel are failing to cope with the increase in the frequency of breakdowns. A localized condition monitoring maintenance strategy must be adopted such that the condition of the equipment has to be monitored with time to detect a developing fault before any catastrophic failure. Nevertheless, this requires special skill and appropriate tools for data acquisition and analysis so that they achieve their set targets of 97.4% on milling plant availability. Platinum processing plants have various plant instrumentation already installed, but this is mainly used for plant monitoring, however, the same data that these instrumentations provide can be used for condition monitoring of the plant, which is a more efficient method to carry out the externalized condition monitoring maintenance of the plant. This maintenance strategy keeps plant assets up and running longer, reduces long-term repair costs due to the reduced likelihood of catastrophic failure.

2. Problem statement and justification

It has been practically noted that the life of an asset or machine can be split into two distinct phases. The initial phase is the normal operating phase with no significant deviation from the expected operating state. The second or final phase is the failure postponement period where a fault or hidden defect may have been initiated, and gradually developing into an actual catastrophe. At this last phase, the asset/machine may be defective but still performing its required function. Existing hidden defects in a machine can be detected using traditional routine condition monitoring techniques, but the prediction of the residual life remaining and the initiation of the second phase is crucial. The process is shown in Figure 1 below.

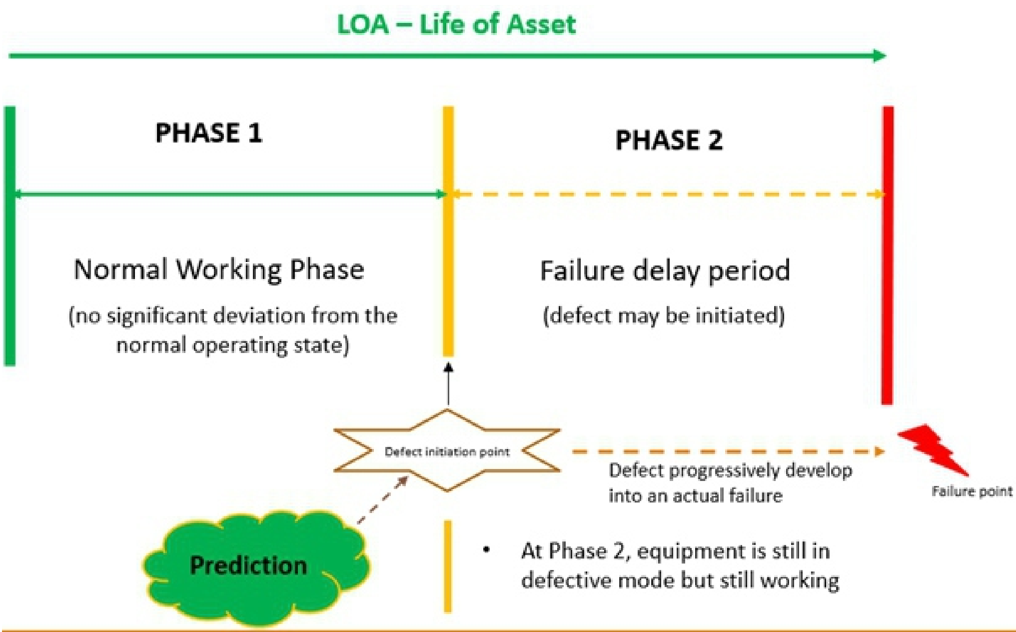


Figure1: Life of Asset, defect detection, and useful time remaining

Current maintenance strategies in use on platinum processing plants are based condition-based and preventive maintenance. Since artisans are failing to cope with the increase in the frequency of breakdowns, it is crucial to develop and implement a probability model to predict residual asset life after the initiation point of the second phase has been detected based on acquired condition monitoring sensor data. This will prevent breakdowns and reduce costs associated with unplanned equipment failure.

3. Aim

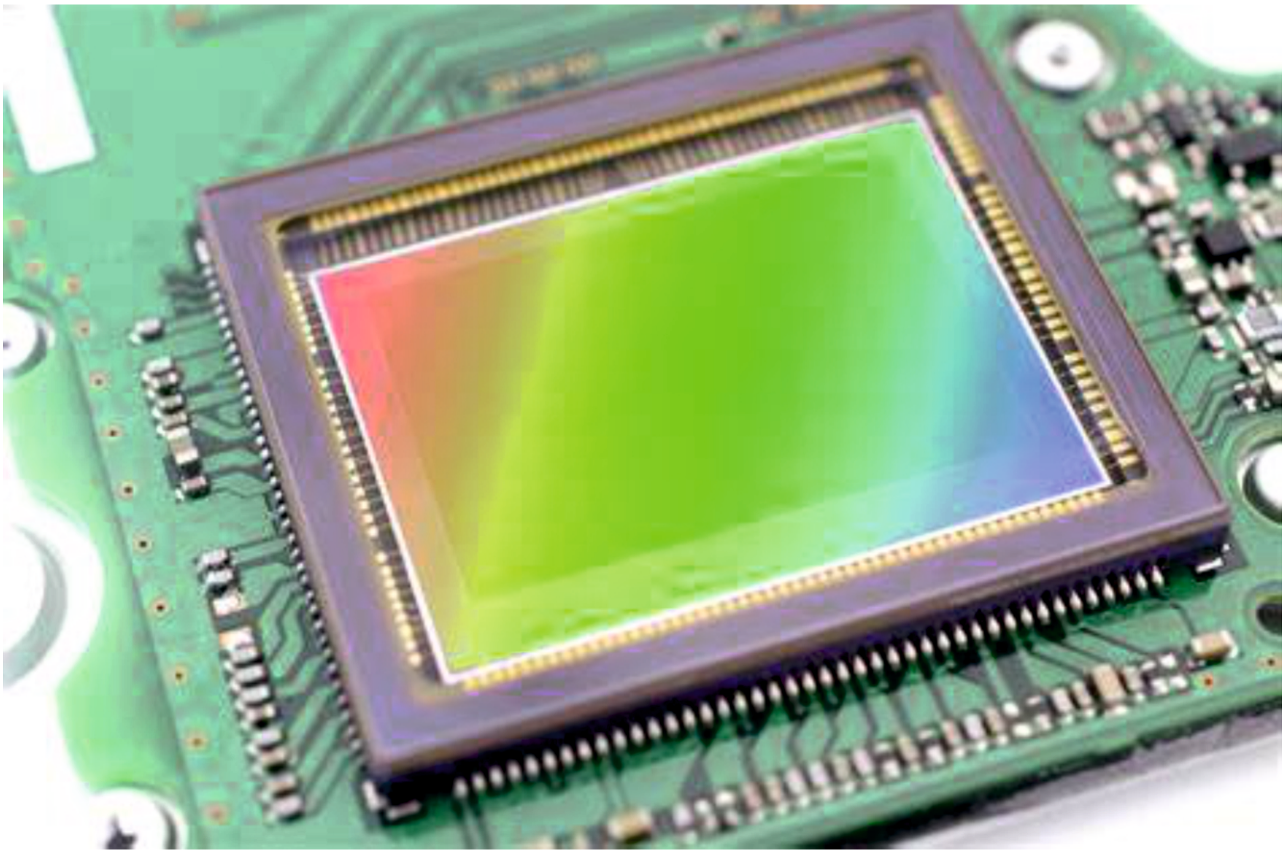
To develop a faulty detection and equipment failure probability model for operation and maintenance support strategy using artificial neural network (ANN) and online sensor data to predict the commencement point of the final phase and the residual asset life

4. Objectives

i. Explore the application of the prescriptive maintenance strategy at platinum processing plants using advanced condition monitoring instruments and online sensor data

ii. Explore how equipment faulty detection, failure probability, and predictability may be improved using condition monitoring proprietary instruments, software, and online sensor data

iii. To develop a faulty detection probability model using online sensor data & faults history for the milling plant on platinum processing plants



2. Literature Review

2.1. Condition Monitoring

Condition-based monitoring is a predictive upkeep/maintenance approach that continuously monitors the real-time condition and health status of the machine using various types of sensors to determine the overall health state of the machine, and if there are any significant changes in the monitored parameters. System data is acquired through sensor devices and then processed into meaningful statistics which allow making decision-making tactics to be implemented to effectively schedule planned maintenance [5].

Fault detection and diagnosis are the fundamental techniques utilized in condition monitoring to detect and identify fault conditions. Condition monitoring is now predominant in the platinum processing industry and has been widely implemented in automation, predictive maintenance, and quality control [6]. Condition Monitoring systems have been developed for motors [7], distinct bearing components [8] and numerous plant equipment [9]. Condition Monitoring system statistics can be extracted from various categories of acquired data in the form of electrical signals, vibration, thermal, environmental, results from oil analysis, etc. [10]. Asset or equipment health monitoring can detect faults and alarm users before catastrophic failure, optimizing maintenance activities during impromptu outages and planned stoppages [6]. Signal-based fault diagnoses is depended on signal processing of reliable data acquisition and its evaluation against acceptable baseline values [11]. The basic relationships of signal transformation from time domain signal to frequency domain signal and vice versa are described by the equations below [12].

$$S_x(t) = \int_{-\infty}^{\infty} x(t)e^{-i2\pi ft}dt \qquad (1)$$

$$X_x(t) = \int_{-\infty}^{\infty} S_x(f)e^{-i2\pi ft}df \qquad (2)$$

Where:

$x(t)$ is time history

$S_x(f)$ is the Fourier transformation of x

Discrete Fourier transform (DFT) pair equivalent to equations (1) and (2):

$$S_x(m\Delta f) = \Delta t \sum_{i=0}^{n-1} x(n\Delta t)e^{-i2\prod m\nabla fn\Delta t} \qquad (3)$$

To enable the investigation of temporary features (faults or impacts), time-frequency analysis can be implemented [10] which becomes the most widely used method for non-stationary signals [13]. The short time Fourier transform (STFT) is an efficient method used when the waveform is split into short-time sectors then FFT is implemented to respective windows of the segments [10], however, it offers relentless resolution for all frequencies within the window [6] making it problematic to study and evaluate high and low frequency contents at high resolution. To overcome this resolution limitation, Wigner Ville distribution (WVD) can be used. Cone-shaped and Choi-Willams distribution transforms have been established to advance the analysis of time-frequency waveforms [13].

2.2. Artificial Neural Networks

Artificial neural networks are scientific and accurate models with multiple inputs and outputs that are utilized for the diagnostic of faults for matching and classification of signal patterns [14]. ANNs can train complex modeled systems by continuously monitoring the input and outputs and regulating weights of the internal modeled system. This exercise can be attained via unsupervised or supervised machine learning. The latter entails priority data of the system inputs or its outputs while unsupervised learning attempts to recognize patterns for classification purposes [10]. ANN was utilized in previous research to learn from fault signals and classify succeeding faults, however, typical physical modeling and the existing knowledge base was not adequate [15]. Another research was done to expand artificial neural networks through assimilation with qualitative tactical methodology from fuzzy logic which has been implemented in medical, engineering, and chemical fields [9].

2.5. Vibration Monitoring System (VMS)

VMS is a full condition monitoring system with sensors, processing hardware, and proprietary fault diagnosis software. The steps involved in designing a VMS are shown in Figure 2 below.

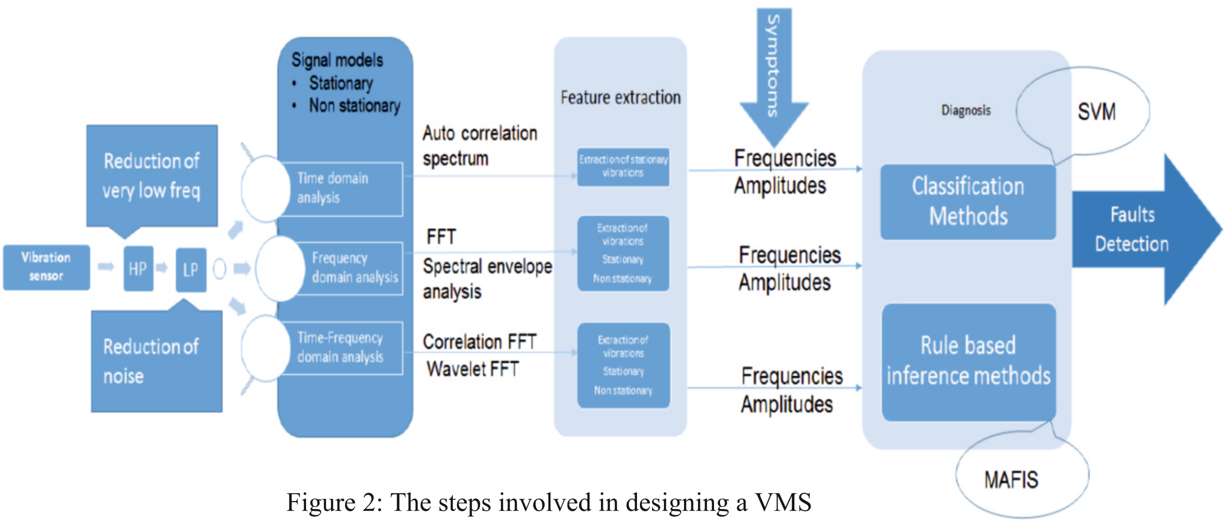


Figure 2: The steps involved in designing a VMS

2.6. Support Vector Machine (SVM) in Condition Monitoring

Computer technology advancements through the use of artificial intelligence (AI) techniques have supported the development of conditioned-based maintenance strategy on both software and hardware. A practical intelligent maintenance system is crucial to enhancing maximum machine reliability and effectiveness of the maintenance management system. Intelligent condition monitoring systems are utilized by the maintenance management scheme to religiously execute equipment upkeep routines. This can be achieved by using a tool called expert system in plant maintenance which can transfer specific prescribed monitoring data from engineers to a computer where the data is kept, and users reference it when needed. Computers have the capability of automatically making inferences without human intervention and also can advise with explanation of the logic behind the advice.

SVM's roots are founded on Vapnik Chervonenkis' (VC) concept that combines self-consistent mathematical theory, fundamental principles, and concepts related to machine learning which can be used for various machine learning methods developed in fuzzy systems and neural networks [16]. The following algorithms are widely being used for fault classification:

- SVM, see Figure 3 below.
- Discriminant analysis,
- Artificial Neural Networks and
- Bayesian classifier

SVM has been applied to multiple classification problems [17], some of these include:

- text classification,
- image categorization/organization,
- Bioinformatics and
- character recognition for written handwritten

SVM classification has been widely used to study the features of signals (for example, vibration) for distinct damage category categories/classes in the acquired data and prediction of the category for the unknown signal [18].

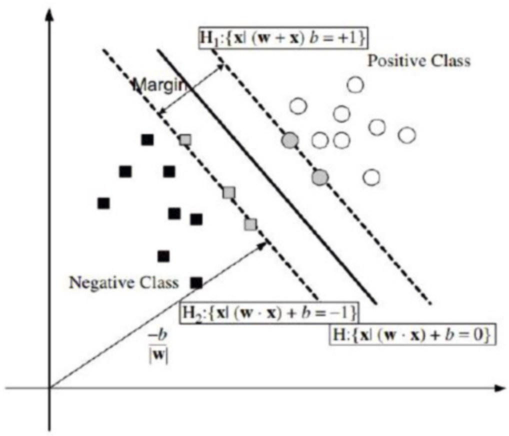


Figure 3: Libsvm for linear classification

3. Methodology

3.1. Approach for a conceptual model to enable prescriptive maintenance

Procedural Approach for the Development and Implementation of Data-Driven Maintenance.

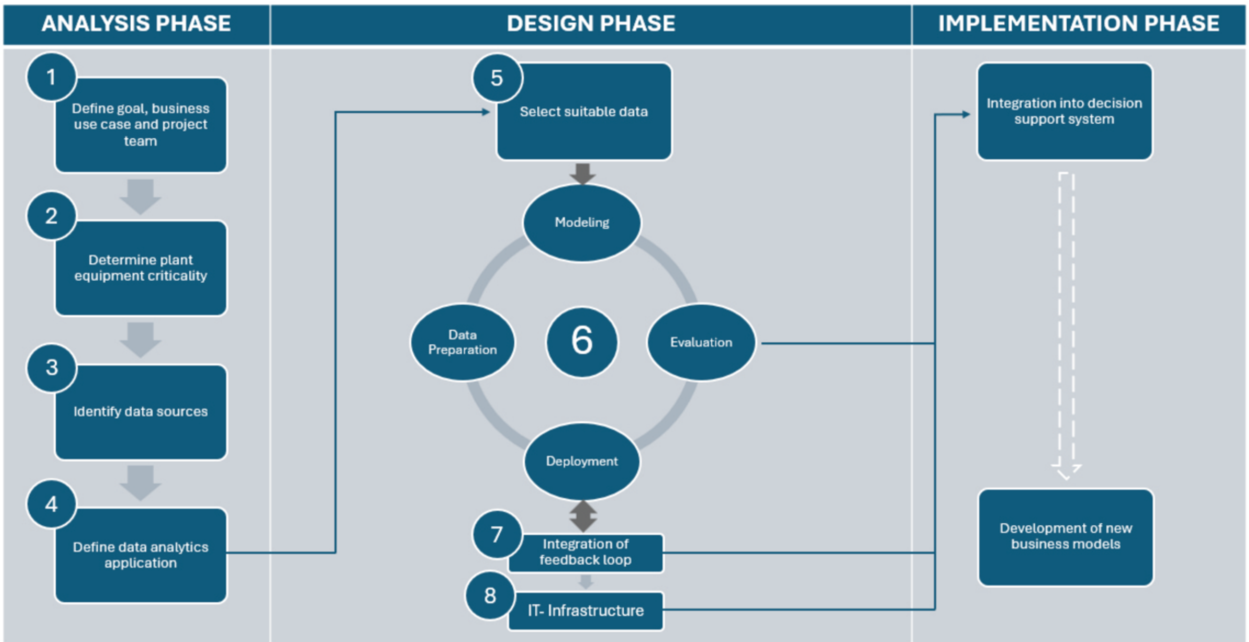


Figure 4: Approach to the Development and Implementation of Data-Driven Maintenance

The approach towards a prescriptive maintenance model for equipment in processing plant shall be carried out in five main steps, see Figure 5 below:

1. Equipment criticality assessment
2. Data cleaning and preparation
3. Model building for prescriptive maintenance
4. Development of a fault diagnosis model
5. Deriving decision support

3.1.1. Equipment criticality assessment

Machinery criticality is crucial in the production maintenance planning process. It allows the identification of failures with utmost probable influence on the business's corporate goals. This can be implemented to define asset maintenance policies, development plans, and maintenance strategies, assisting the platinum processing plants in prioritizing apportionments of monetary funds to equipment on condition monitoring plans and machines that are critical within the business scope and criteria, in terms of risk, performance and cost.

The equipment criticality assessment focuses on the maintenance of physical asset reliability and those parts of the asset that are critical in terms of safety, environment, process/operation, or legal class restrictions. The process involves two main stages:

1. Building equipment register with all equipment under study

   Elaboration of the Milling section/PLANT containing all physical equipment systems. The items will be numbered with unique IDs derived from platinum processing plant's Computerised Maintenance Management System (CMMS) in use
2. Assess the degree of criticality by using proven methods taking into consideration the following factors:
   - Consequence of safety
   - Consequence on environment
   - Risk failure starting up
   - Risk failure in operation
   - Level emergency stop
   - Effect on production
   - Complexity
   - Replacement repair/replacement costs

3.1.2 Data cleaning and preparation

This step aims on concatenating different data sources and conduction of pre-processing (e.g. linearization) tasks to get a ground truth data set, which can be used to apply machine learning algorithms

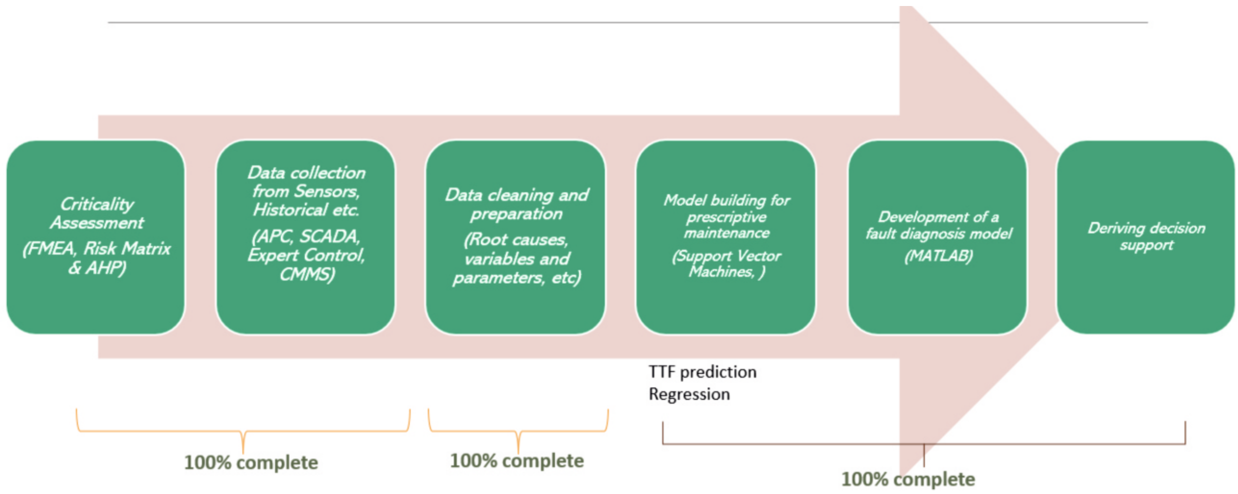


Figure 5: General System Operation

At the platinum processing plants, different data sources are available e.g.:

i. Process data
ii. Alert/Alarm log data from SCADA (supervisory control and data acquisition)/ Historian database
iii. quality data from proprietary sensors
iv. periphery data
v. documentation of errors
vi. data extract/ implicit know-how from experienced employees

3.1.3 Creation of the ground truth data set

To be able to create a ground truth dataset, it is necessary to pre-process existing datasets. Use-case datasets from five different sources shall be collected, cleaned, and processed.

i. SCADA Data (Supervisory control and data acquisition)/ Historian Database

This dataset contains information about sensor data from the platinum processing plant's process control system which includes linked parameters like pressure, temperature, vibration, water flow, current, applied voltages, and process parameters

ii. Automated Process Control (APC) Alarms/Alerts - Historian

Alarms defined by original equipment manufacturers shall be split into four categories:

- critical,
- errors,
- information and
- safety interlocks.

iii. Expert Control System – Limit controls

Domain experts of the manufacturer defined specific thresholds for process control parameters. If set points are exceeded and fall below the defined limits, predefined actions are triggered.

iv. Real-time clock system (SCADA)

This system records the current state of the processing plant's Milling section/PLANT

v. Computerized Maintenance Management System (CMMS)/ SAP System

The PM module within the SAP system serves as a documentation tool for the maintenance crew. It includes inter alia information about the equipment, moment of failure, event type, and conducted maintenance measures

3.2. Model building for prescriptive maintenance

3.2.1. Time to failure (TTF) prediction

To predict and develop the chamber-based TTF, three different tasks shall be used in MATLAB. Vibration data is downloaded from the historian and time domain waveform and frequency domain waveforms are plotted and analyzed in MATLAB:

1. Modelling the TTF prediction as a regression task.
2. Transferring task 1 (above) into a more effective health state prediction by converting the TTF values into a range between 0 and 1.
    - 0 indicates a breakdown and
    - 1 indicates the state of the machine when it is healthy.
3. Modelling TTF prediction as a classification task to predict whether a breakdown occurs within a defined interval

The TTF shall be defined by joining the machine's state from historic and real-time data with process durations, extracted from the SCADA system. Pre-processed data and engineered features (Alarms, Alerts, and Interlock Limits) shall be fed into distinct machine learning models such as SVM - Support Vector Machines and ANN-Artificial Neural Networks. To ensure the reliability of data evaluation, a 4-fold cross-validation shall be applied to the Dataset where three parts of the data shall be used in the training phase and one part of the data for the evaluation phase.

3.2.2. Prescriptive Model's Performance Evaluation

Three different benchmarks were adopted to evaluate the prescriptive model's performance, resembling human decisions as defined below:

1. A naïve benchmark, which assumes a constant TTF by calculating the mean TTF over all the production runs.
2. A visionary benchmark, which considers an adjusted mean TTF for each productive segment. This benchmark is unrealistic as it requires knowledge of the upcoming breakdown.
3. A realistic benchmark that assumes the breakdown occurs in X productive hours, where X is the mean TTF of historical data.

3.2.3. Faulty Diagnostics & Prediction

After building up prediction models for each of the defined modules, the fault diagnosis model is developed using a three-layer network called Bayesian network where;

- 1st layer – top layer consisting of root causes and possible fault modes for the components in the second layer. This data is driven by FMEA and defect elimination processes as well
- 2nd layer – the second layer is the component layer, which influences the state of the module
- 3rd layer - The third layer is the module layer which consists of only one node.

After the identification of important parameters and the definition of the Bayesian network structure, the probability tables for each node shall be calculated respectively and defined.
SVM classification in MATLAB is used to learn the features of signals for different damage classes in raw acquired data and to foresee faults related to the unknown vibration signals on the mills. System modeling and training of the SVM were conducted offline and a precise model for classification was carefully chosen because of cross-validation. SVM was utilized to recognize distinct patterns from acquired signal data, and the patterns were classified according to the fault existence/ manifestation in the machine. Feature representation technique was adopted to define the features of the acquired data. The overall Condition Monitoring System block diagram is shown in figure 6 below.

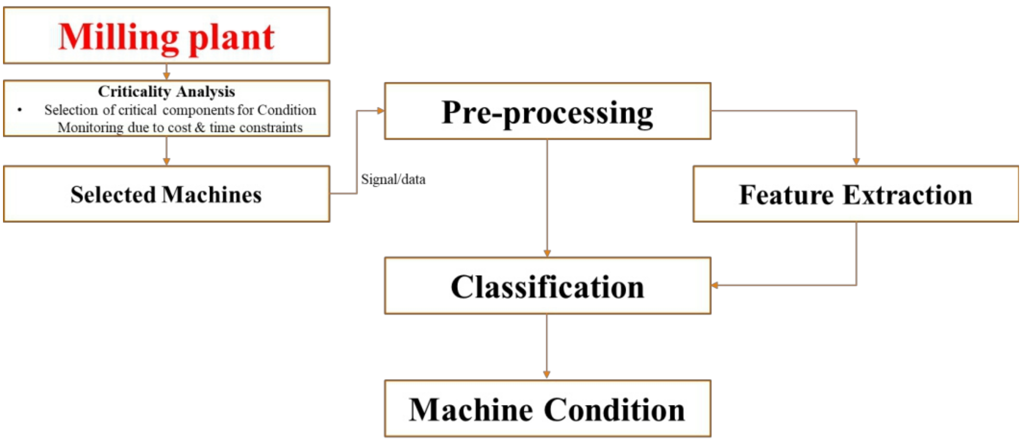


Figure 6: Condition Monitoring System Block Diagram

3.3. Model Development and Implementation for Fault Diagnosis Using Support Vector Machine

To classify multiple classes, the SVM method was adopted and the concept for the workflow is shown below.

3.3.1. Condition Monitoring System MSVM - MATLAB workflow

Figure 7 below shows the condition monitoring system MSVM-MATLAB workflow that will be used in the review.

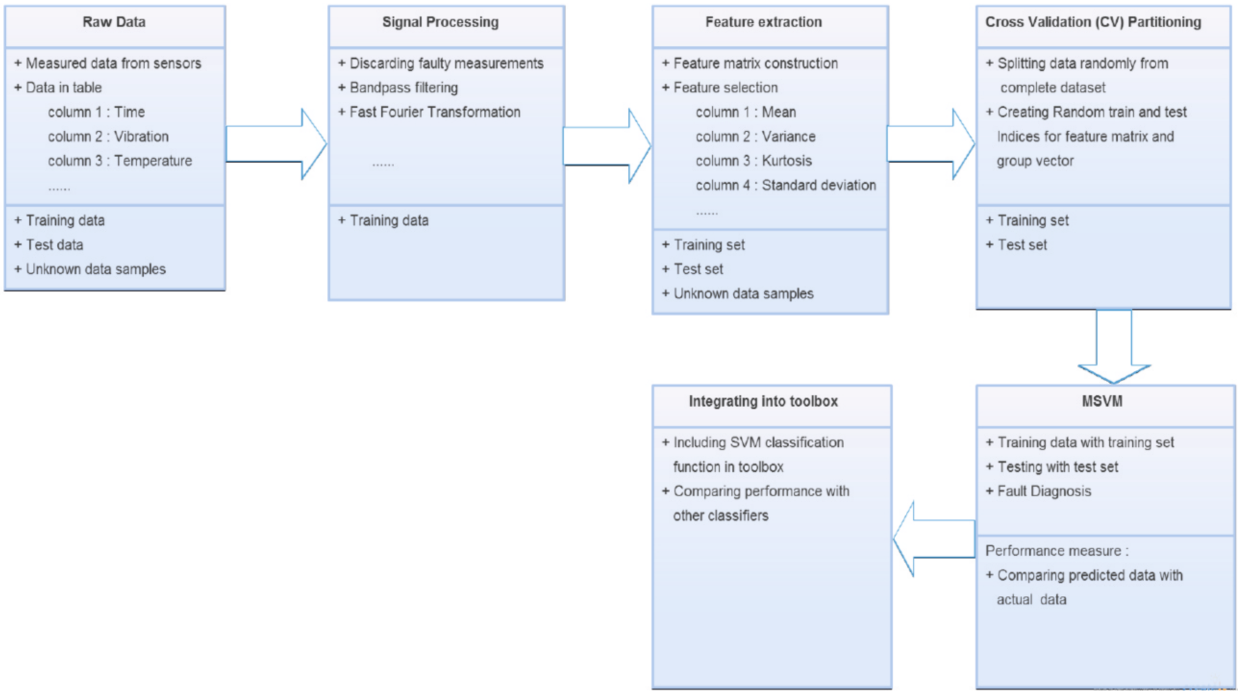


Figure 7: Condition Monitoring System Block Diagram, MVSM

3.3.2. Data acquisition – Vibration sensor installation setup at Platinum Processing Plant

Figure 8 below shows the vibration sensors installed on the SAG mill pinion bearings at one of the platinum processing plants in Zimbabwe, which is used for online data acquisition.

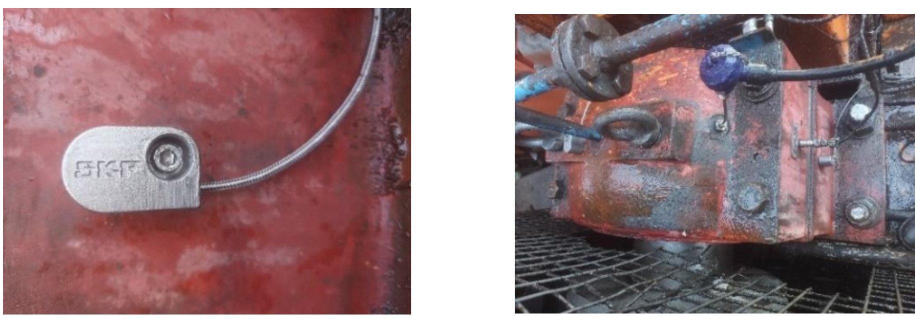


Figure 8: Vibration sensors mounted on opinion bearings

The system comprises SKF Multilog devices (IMx-16 plus) which provide a complete solution for the early detection of fault, see Figure 9 below.

Figure 9: Real-Time Based Monitoring (Platinum processing plant - Zimbabwe)

3.3.3 Vibration failure signals

Damages classes created from past breakdown history and FMEAs (discussed in the results and discussion section below), and are shown below for evaluation of vibration data:

- Signal_1: Small damage on the outer ring (Small_OR_damage)
- Signal_2: Heavy damage on the outer ring (Heavy_OR_damage)
- Signal _3: Small damage on the inner ring (Small_IR_damage)
- Signal_4: Rolling elements damage (RE_damage)
- Signal_5: Cage damage (C_damage)

3.3.4 MATLAB Condition Monitoring Solution Overview

The condition monitoring tool developed can analyze measured raw data as shown in Figure 10 below, with three main planes namely project creation, navigation, and visualization plane for user interface.

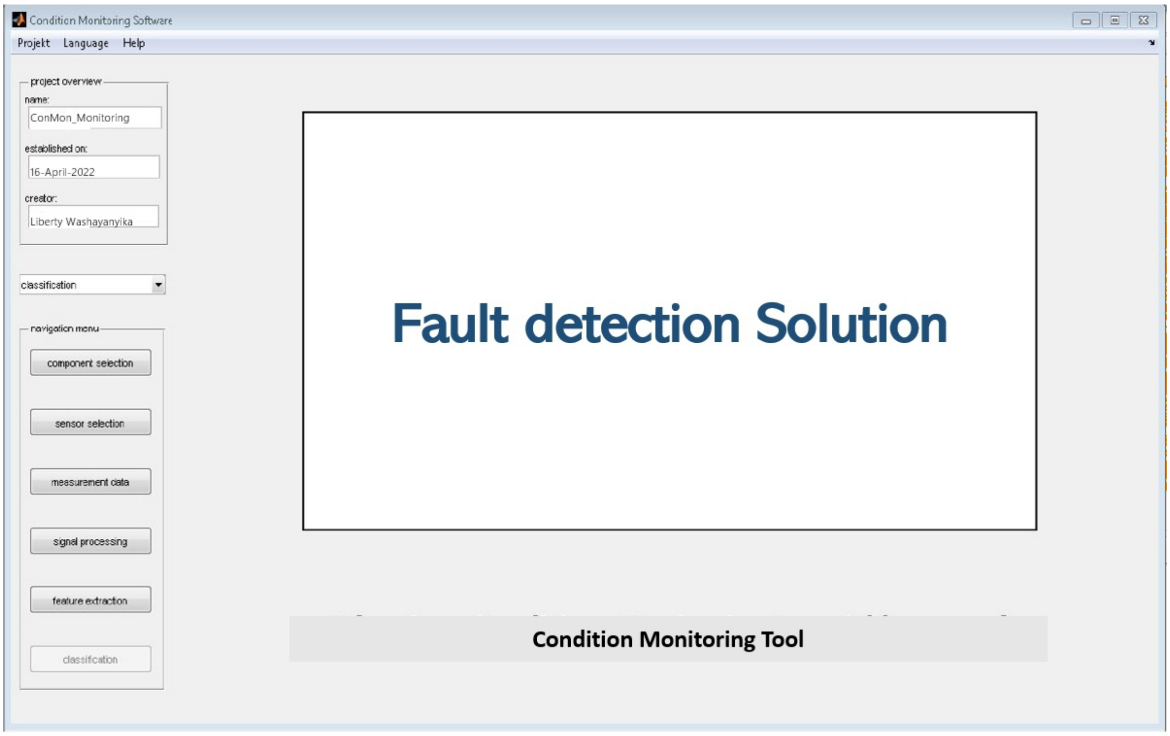


Figure 10: MATLAB Condition Mining Tool

4. Results and Discussions

4.1. Equipment Identification for Condition Monitoring

Equipment for Condition monitoring was obtained through surveys (seven mining processing plants) and process flow diagrams for platinum processing plants, see Figure 11 below.

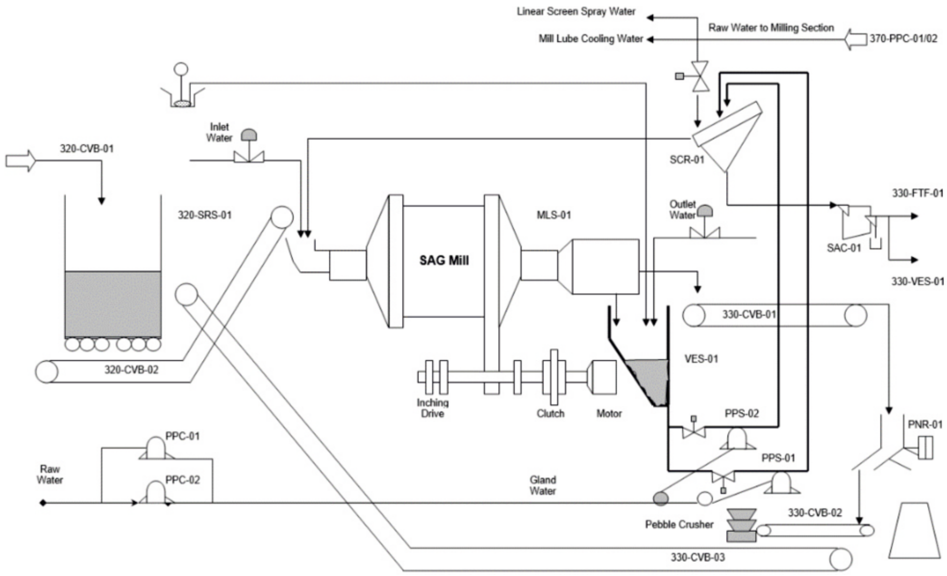


Figure 11: Platinum processing milling section circuit - PFD

Plant instrumentation diagrams (P&IDs), process flow diagrams (PFD), and OEM manuals were reviewed, which indicated some traditionally monitored parameters in industries, such as vibrations, current, temperature, flow, and pressure. The methods of condition assessments call for improvement with modern condition monitoring techniques.

4.2. Criticality Analysis

The following criticality analysis results have been obtained, and all Critical A equipment noted below were obtained and the suitability for condition monitoring tactic was concluded from the failure modes retrieved from the Failure Mode and Effect Analysis (FMEA) results, see Table 1 below. The failure modes obtained were used as inputs to the ANN model for fault prediction and diagnosis.

Table 1: Critical A Equipment from Criticality Analysis

Plant	Major Mill Components	Criticality		
		A	B	C
Milling Section	Mill shell	X		
	Trunnion bearings	X		
	Mill shell	X		
	Girth gear	X		
	Pinion bearings	X		
	Drive train	X		
	Motor	X		

It was noted that the majority of failures in a mill occur on the rotating components (bearing failures) of the mill. The failure modes experience survey that was done on seven mining companies in Zimbabwe for the year 2021, from January to December 2021.

4.3. Equipment Categorisation

The milling circuit for platinum processing plants comprises assets that have common component types such as mill shell, trunnion bearings, girth gear, pinion gear, mill motor, gearboxes, pinion bearings, slurry discharge pumps, clutch, and instrumentation devices, see Figure 12 below.

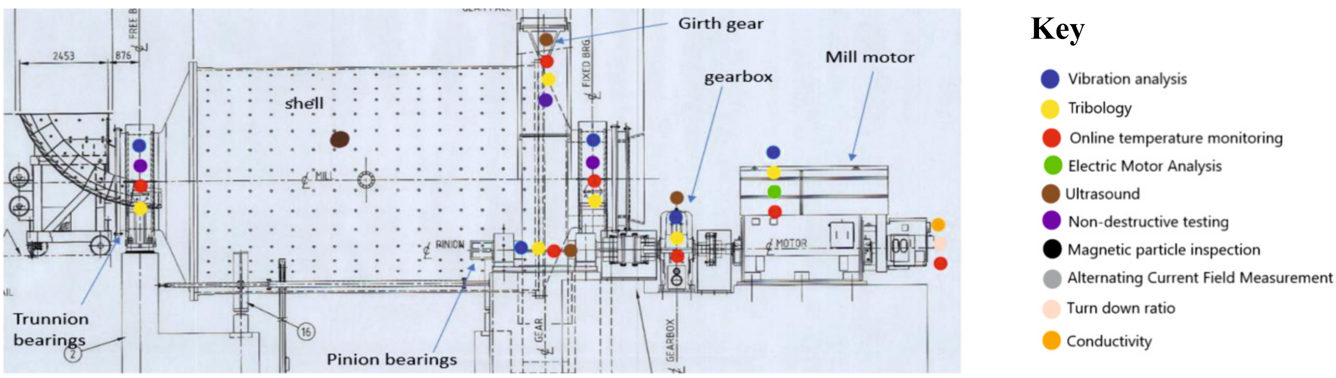


Figure 12: Condition monitoring techniques selected

4.4. Results from FMEA

Reviews of failure log reports from other similar mines, showed failures that could have been predicted by condition monitoring interventions, enabling scheduled maintenance and reduced downtime. The following are some of the repeated predictable failures experienced on major platinum processing plant's equipment:

- Motor failures
- Bearing collapse
- Idler failures
- Belt misalignment
- Coupling misalignment
- Belt failures
- Pump failures
- Compressor leaks
- Gearbox failures
- Fan failures
- Coupling failures
- Structural failures

Failures experienced in 2021 by seven (7) mineral processing plants in Zimbabwe are shown in figure 13 below. This data is referenced to the 2021 breakdown data survey that was done across seven mining companies in Zimbabwe.

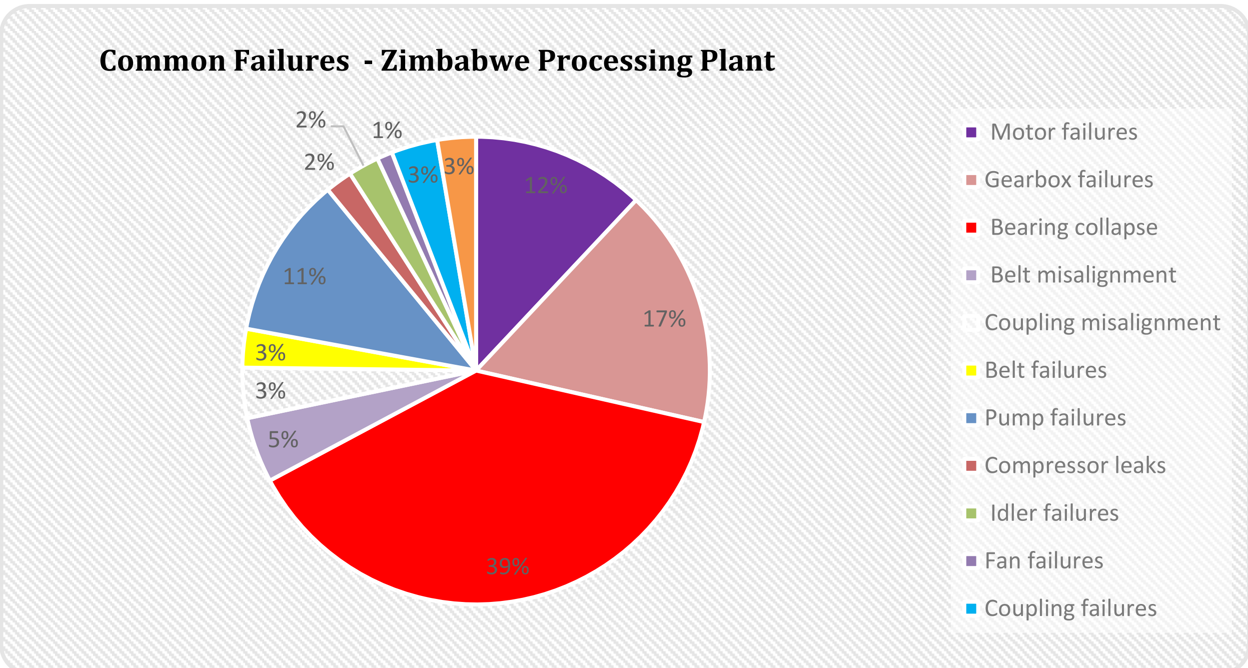


Figure 13: Common Failures - Zimbabwe Mineral Processing Plants

The following condition-monitoring interventions were deployed to avoid failure recurrence. As can be seen, these results are in line with criticality results in terms of the majority of failures on a mill occurring on the rotating components. Further, the same data was used for the ANN model for machine learning for fault detection, diagnosis, and prognosis.

7.5. Time and Frequency domain Curves for the signal damages

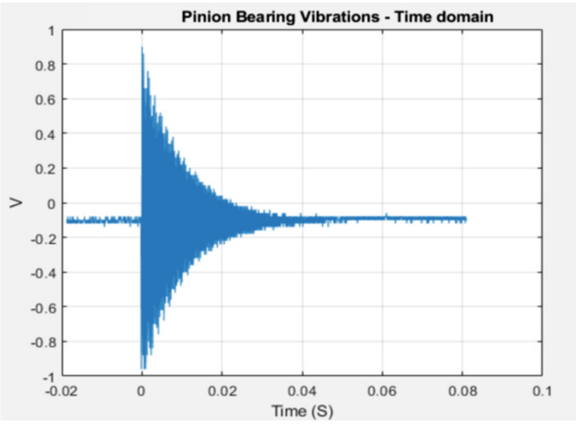


Figure 14 : Time Domain C_damage

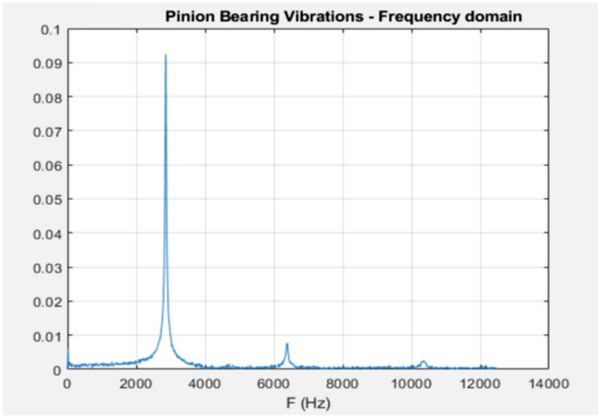


Figure 15 : Frequency Domain C_damage

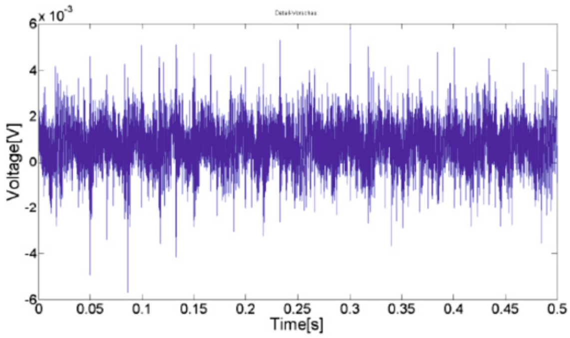


Figure 16: Time Domain Small_IR _Damage

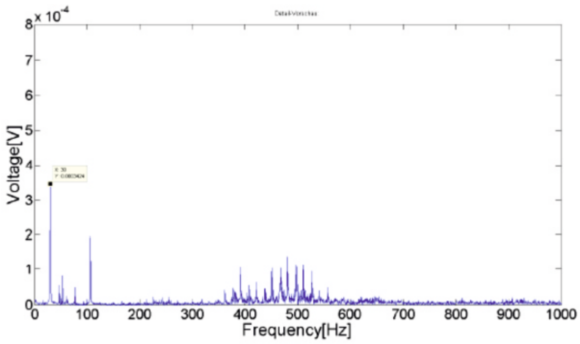


Figure 17: Frequency Domain Small_IR_Damage

The time domain and frequency domain curves for the signal damages are outlined in the following figures.

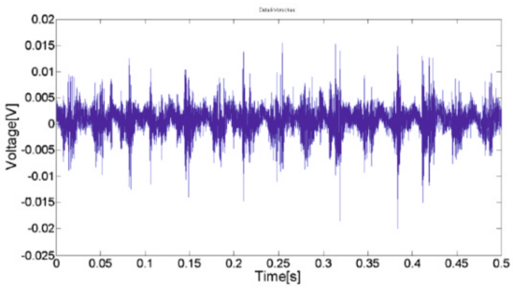


Figure 18 : Time Domain Small_OR_damage

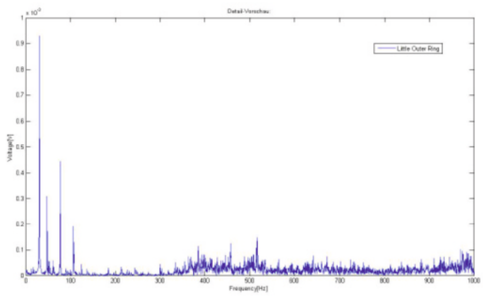


Figure 19: Frequency Domain Small_OR_damage

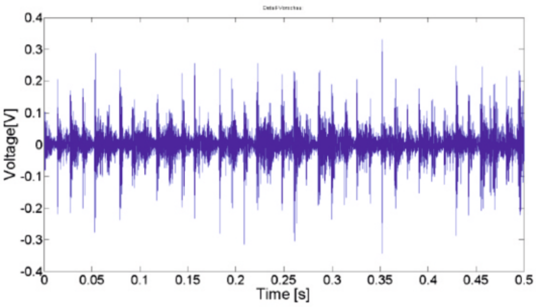


Figure 20 : Time Domain Heavy_OR_damage

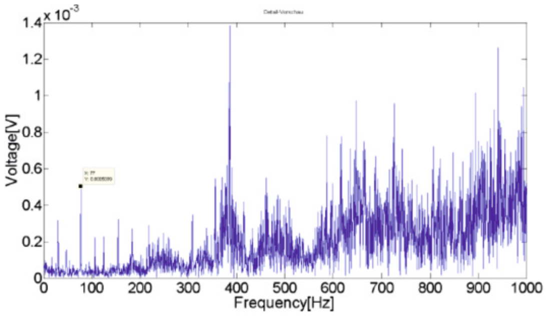


Figure 21 : Frequency Domain Heavy_OR_damage

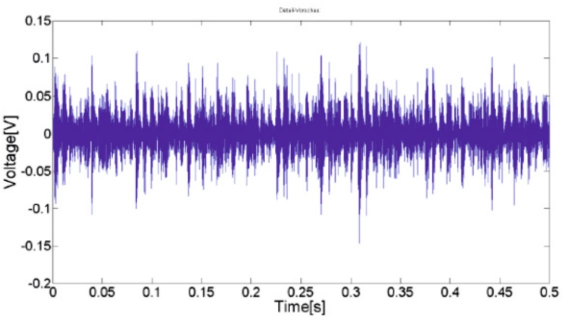


Figure 22 : Time Domain_ RE_damage

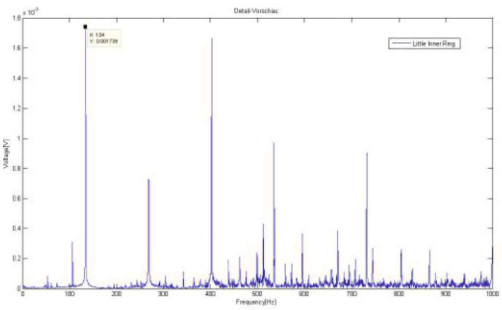
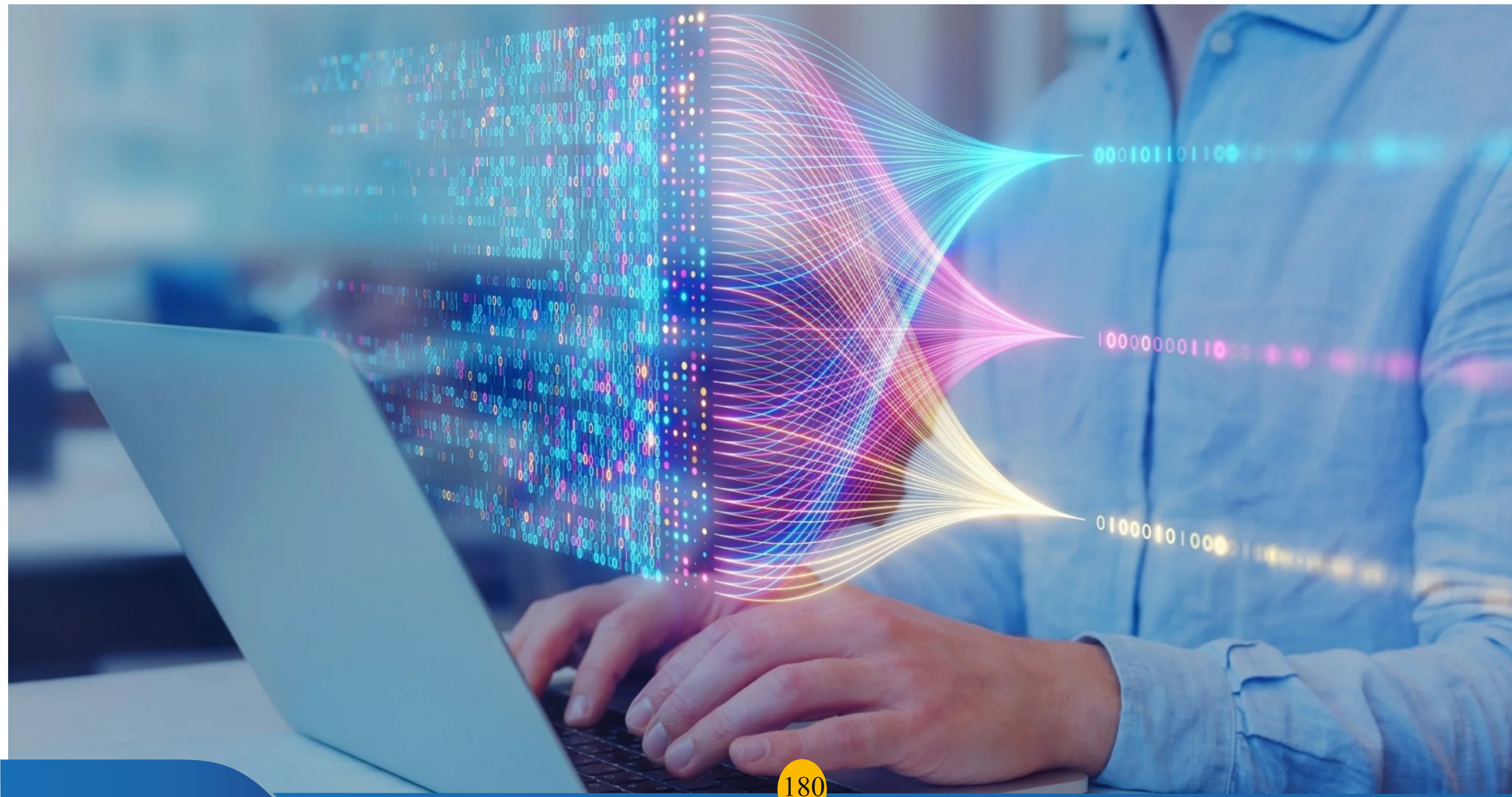


Figure 23: Frequency RE_damage

5. Recommendation and Conclusion

An analytical approach for early fault detection and diagnosis of asset components was investigated and implemented. The proof technique used a support vector machine (SVM) with strong fundamentals in statistical learning theory. The method employed uses vibrational data from pinion bearings on a mill at a platinum processing plant in Zimbabwe. The SVM learns directly from the training data acquired from the pinion-bearing vibration data for different class labels to determine the spread of feature space. The major advantage of the SVM approach used is that there is no need to model the system first since it can be easily integrated with any non-linear system. The developed fault prediction model was tested and integrated in MATLAB and performance analysis was carried out in the MATLAB tool using cross-validation (CV) and industrial benchmarking for the sample data used. This developed model was able to detect a faulty, predict equipment failure for maintenance support strategy, predict the initiation point of the second phase of a defect, and remaining useful life for pinion bearings. The SVM exhibited higher accuracy results with less computational costs.

It was recommended that future studies should consider installing numerous sensors for the condition monitoring tool on different key machine components for the processing plant and integrate the sensor nodes so that they can be integrated via wireless communication. The necessary components needed for fault diagnosis shall be assigned to each node permitting processing plants to operate efficiently and cost-effectively by implementing and enhancing intelligent maintenance management system.



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