Engineering Equipment Failures and Inventory Management Shifts Statistical Insights from Papua New Guinea's Mining Sector

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Abstract: The operation of surface mines in Papua New Guinea (PNG) is associated with the intense mechanical loading, remote logistics, and periodical failure of a number of components of heavy engineering equipment. These ailments lead to huge downtime and ineffective planning for spare parts inventory. In this proposed study, a statistically integrated system is designed and proposed which integrates predictive analytics of maintenance with inventory management techniques in order to solve these issues. A real time multi-sensor network containing pressure, temperature, vibration, flow rate and oil contamination sensors was employed to collect data. The multivariate data collected for a period of six months was used to predict the failure. The predictive model expressed great reliability with an overall accuracy of 94.8 percent and the recall of 91.3 percent on the impending failure events. Results show it could reduce delays by 37 percent and a 23 percent increase in performance of inventory management. These results substantiate the argument that integration of predictive maintenance and inventory intelligence can do significant performance improvement of surface mining operations.

Keywords: Predictive Maintenance, Equipment Failure Analysis, Inventory Management, Surface Mining Operations, Sensor-Based Monitoring, Part Provisioning Delay Index.

1. INTRODUCTION

The PNG Mining industry presents a pivotal economic aspect of the country, where it plays a significant role in exporting products, labour services as well as contributing to the development of the infrastructure. The success of the operations of the sector depended greatly on the reliability and availability of the complicated engineering devices, e. g. hydraulic loaders, haul trucks, crushers, drilling rigs. The heavy nature and geographical separation of the mining regions in PNG already make equipment failure not only common but also have increased implications economically as the local maintenance capability is already low, lead times on supplies are stretched and access to spares even longer. Downtimes caused by mechanical or hydraulic subsystems falling out of service without any prior warning can yield to production cycles interruptions, operational costs blow-ups and the compromise of worker safety (Mudd et al., 2020). Concurrently, traditional inventory control policies, which tend to be wary of the reactive or scheduled purchase model, cannot effectively keep up with the ever-changing maintenance requirements of such contemporary mines. This disparity between equipment reliability and inventory provisioning points out an important point of the vulnerability in its work(Stead, 1990). As an answer, there has been an increasing need of the integrated approaches that would combine predictive maintenance analytics and real-time inventory coordination. This study can bridge that gap by carrying out statistical analysis of cases of equipment failures and inventory fluctuations of the mining industry of Papua New Guinea. The study seeks to predict the failure incidents and tie them to availability of spare parts by implementing a sensor-based monitoring system and machine learning (Mosusu et al., 2023). This will eventually help in making data-driven decisions, maximizing the uptime of equipment and optimize the inventory planning within the logistics conditions peculiar to the business environment in PNG mining (Kinkin, 2020).

The global mining industry has always been identified as a pillar of economic growth, as far as it contributes to the national GDPs, employment, and infrastructural growth. Excavators, dump trucks, loaders, and hydraulic equipment as well as heavy-duty equipment are the backbones of operation within this ecosystem so that mineral resources could be extracted and transported in a smart fashion (Kuo, 2022). High-value machinery poses considerable risks in the form of maintenance and machinery reliability in the mining industry. Research on different geographies such as Canada, South Africa, Australia, pointed out that it is possible that at least 10-20% of the production losses may be as a result of unplanned equipment downtimes (Bowman, 2005). Such downtimes have been mostly attributed to component fatigue, sensor failure, plant lubrication and hydraulic problem amongst others. Poor coordination of inventories and logistic bottlenecks in emerging economies or in remote industrial sectors worsened the situation. Therefore, the need to combine the strategies of predictive maintenance and a solid inventory management has become more and more apparent. Literature evidences reveal an emerging tendency to mix sensor-based monitoring technologies, failure detection algorithm and modeling of supply chains synthesis to achieve the maximum uptime and minimize cost overruns introduced by maintenance(Huettmann, and Steiner, 2023).

Hydraulic systems especially present one of the most unreliable subsystems in a surface mining operation. The systems deal with highly important functions like the lifting, boom operation, steering, and braking (Wacaster, 2008). Hydraulic anomalies cause over 35 percent of unscheduled downtimes of surface loaders and shovels, and the root cause of pump failure may be seal wear, cavitation, and breakage of hoses. Application of the conventional time-dependant maintenance schedules have failed to prevent occurrence of these events, more so, in the presence of variable stress operations and hostile environmental conditions characteristic of the open-pit mines. A recent literature has underlined the benefits of condition-based monitoring (CBM) and predictive analytics as compared to reactive or preventive ones

Although equipment failure diagnostics have undergone lots of changes, relationship between failure prediction and inventory management is an area that has not received extensive research considerations. The availability of inventory was vital in facilitating timely measures to undertake the maintenance process and even though, most literature concentrates on the technical side of fault identification, the supply chain side has not been taken into considerations(Albrecht et al., 2020). The advantage of getting early warning of the fault may be buffered against delayed action in purchasing of important spares like the hydraulic actuators, pressure valves or metal filter. The value of synchronized inventory practices is highlighted in other empirical analysis done in other mining operations including mining in Chile and Indonesia where real time data related to the condition of the equipment was fed into the reorder signal. Optimization of inventory models addressed in the form of (s, Q) model and base-stock policies have proved to be successful particularly in combination with the stochastic mode of equipment breakdown. The mining activities in the country especially gold and copper, are largely dependent on machinery importation and spare parts leading to long delay and high prices. The PNG Chamber of Mines and Petroleum studies have cited chronic lack of supply of spare parts, customs-related hold ups as well as inefficient warehousing as a constant problem. At most of mine locations, they lack real-time inventory visibility and use reactive buy strategy that only increases downtime (Campus, 1998).

Equipment failure prediction using machine learning and statistical modeling has become an active area of research with promise to identify the defects well before the equipment climbs the continuum of degradation to a serious functional failure. The use of algorithms, including Random Forests, Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks have been utilized in multi-sensor time-series data classifying the operational status and predicting impending failures. Supervised learning (classification) techniques have been applied to map the sensor readings (pressure spikes, vibration anomalies, thermal behavior) to label fault conditions in a number of recent works. As an example, Batra et al. (2021) showed 93% prediction accuracy in detecting fault in the heavy equipment based on the ensemble classifiers that were trained on hydraulic and telemetry data. Statistical techniques have traditionally been used on the inventory aspect in estimating the demand in spare parts. Exponential smoothing, autoregressive integrated moving average (ARIMA) and Crostons methods are some of the techniques commonly used in industries. Such strategies are usually based on stationary demand or are oblivious to exogenous factors, e.g. predictive failure warnings. Current studies have presented the concept of hybrid forecasting, in which demand prediction is coupled with equipment health indicators in which the aim is to address the interface between maintenance requirements and inventory policy. As an example, the hybrid predictive-inventory models have been shown to achieve a lower stockout level and emergency buying spending in the aviation and manufacturing industries. Within mining, these models are limited, and this was further hampered by low- volume high- value components, unreliable stress produced by the nature of terrain, in addition to restrained chains of suppliers. This makes it necessary to design frameworks which would dynamically manipulate the inventory limiting state based on the rudimentary degradation alerts in real-time, in the case of high-risk machinery such as the surface loaders in locations such as the Papua New Guinea (Huettmann, 2023).

2. RESEARCH METHODOLOGY

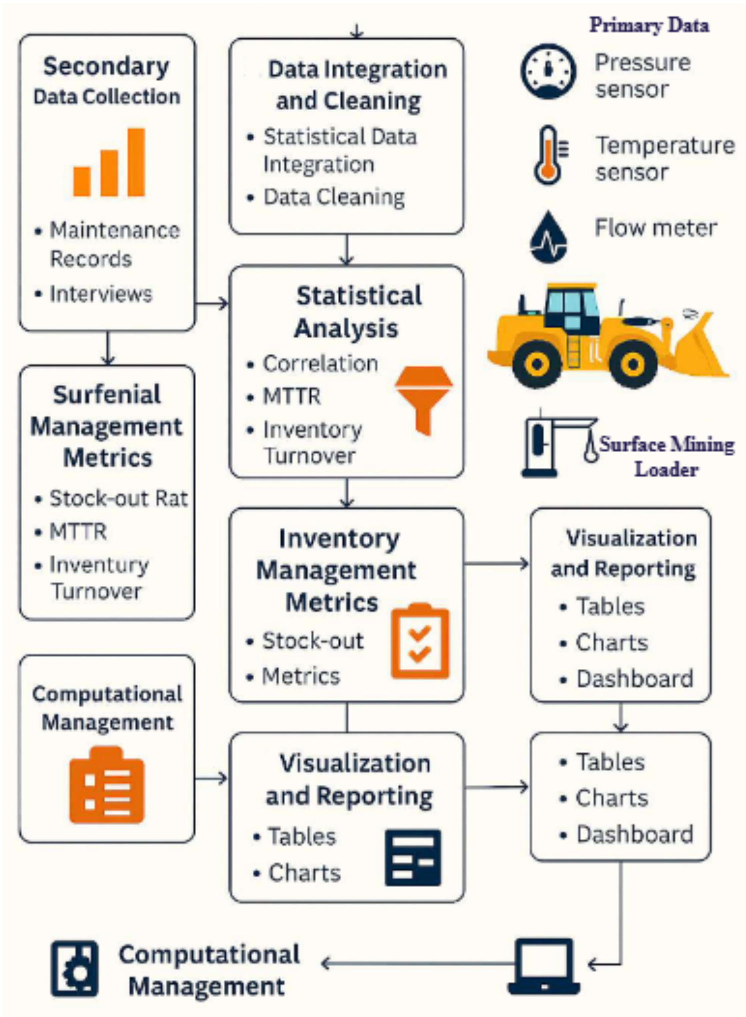

Figure .1 Research Methodology

2.1 Objective and Rationale

The mining equipment used in Papua New Guinea, are mostly hydraulically driven. The systems are tasked with carrying on the high-force tasks that include lifting, articulating and maneuvering in harsh environmental and mechanical environments. As a result of intense exposure to dust, different levels of terrain gradient, thermal cycling, and big pressure cycles, there is the likelihood of deterioration in hydraulic components within a short period of time. Failure of components particularly pumps, cylinders and valves often impairs the equipment, making it impossible to operate the equipment and requiring unplanned maintenance which leads to a wave of productivity losses. In this industrial setting, the reliability of hydraulic subsystems to operate was not just essential to sustain the daily throughput but also key towards cutting down total cost of ownership (TCO) in the mining process.

The existing maintenance approaches in such mining incorporate highly reactive models. The timing of intervention in case of visible failures by technicians hinders the predictability of operations and causes shortage of stock parts or emergency procurement. With this scene setting, introduction of predictive failure analysis could greatly increase asset availability. As the industrial industry caught up in the Internet of Things (IIoT) and sensor-based supervision, ecstatically enough, the real-time data of the hydraulic system became possible and observable to predict the component-level anomalies that can occur before developing into critical failure. With this transformation, there is possible planning of the maintenance cycle, as well coordination in procurement of spare parts with forecasted failure periods, eventually decreasing the machine resting period as well as enhancing the inventory response.

2.2 Data Acquisition and Variables Monitored

The data acquisition strategy was designed to capture the operational dynamics of real mining hydraulic systems, the collection of high-resolution time-stamped data in a variety of categories of variables is guaranteed. All of the sensors were set to send the data with a constant interval and thus a temporal homogeneity was obtained, and it made it possible to find out the trends in pressure, temperature, flow rate, vibration intensity, and oil contamination. Multivariate correlation and proper failure traceability between various components of the hydraulic subsystem could be achieved with the help of synchronized timestamps.

Hydraulic line pressure recorded in bars was recorded at five-minute interval and examined to detect spikes, oscillation, and linear deviation. These measurements played a pivotal role in establishing problems that concern overloading, internal leakages, or inefficiency of the pumps. Measurement of temperature by the fluid reservoirs and cylinder walls provided understanding of the thermal loading on the system especially in extended operating and ambient temperatures above 35^0 C which is typical of highlands of Papua New Guinea. Continuous measurements of flow rate were used to identify restrictions, cavitation or degradation of pumps, especially in the return lines where pressure drop and turbulent flow are an early giving signal. These main indicators were complemented with signals of vibrations measured as RMS value of m/s ^{2} and have offered information about dynamic imbalance, poor alignments, and issues associated with frictional resistances in critical rotating parts.

$$\text{MTBF} = \frac{\text{Total Operational Time (hours)}}{\text{Hydraulic System Failures}} \quad (1)$$

MTBF is computed using equation 1, and is used to be a base parameter in determining the life and operation time of assets utilized in mining industry in Papua New Guinea. The planners would be in a position to estimate predicted uptime before encountering a broken component by estimating the MTBF using logged operational hours and recorded hydraulic failures. When the MTBF is high, this implies that the equipment would be able to run longer without failure to cause untimely shutdowns and emergency repairs. The measure was quite handy when it came to estimating the maintenance schedules; a loader having low MTBF levels would need to be serviced and upgraded more frequently. This index offered quantifiable grounds on how to set a baseline performance in operations as well as ascertaining whether the predictive maintenance interventions had positive effects on the reliability for the entire observed time period.

In order to determine the condition of internal fluids, the level of oil contamination was determined using inline sensors which could measure the quantity of metallic particles (in parts per million (ppm)). These sensors distinguished between ferrous and non-ferrous contaminates and these represent wear on certain parts like cylinder rod, pump gears and the seal. The frequency of contamination data collection was set to 15 min, which is transmitted through the filter of sensor sensitivities and noise filters, and this interval is the best balance between the granularity of the data and the transmission volume. Combining a contamination level and a hydraulic temperature profile assisted the evaluation of degradation modes, e.g. thermal-induced oxidation or abrasive particle circulation, that lead to premature wear.

All the recorded variables were viewed as possible predictors in the failure analysis model. During the first two-week period of the benchmark, the canisters were loaded either to no-load or light load as a basis of the respective range. Any of the non-conformances to these baseline measurements were labeled as anomalies, and the number and level of such instances were captured in structured tables to be used in training models. Sensor data heterogeneity and uniformity made a tiered analysis method, because base measurements were transformed into engineered features, like moving averages, standard deviations, and rate-of-change indicators. This strategy enabled even raw sensor data to be translated into executable failure predictors and it served as a strong source of rabbit-proofed data to serve as the needed input to later supervised learning models.

2.3 Data Analysis and Prediction Model

The sensor data gathered was subjected to a stringent preprocessing whereby the data was to be ready to undergo predictive modeling. Noise filtering procedures were used to remove signal distortions due to burst of vibration signal, lag effects in GSM signal or temporary background noise. These processes such as median filtering technique and rolling window smoothing were used. The missing data values were mainly due to a temporary logging due to unavailability in those specific times and thus were imputed using a forward-fill method to maintain a temporal sequence. Random Forest classification algorithm was used to describe the degradation process of hydraulic systems to predict the emergence of failures since it is robust towards overfitting and capable of working with nonlinear relationships amid multivariate features. The model was trained with a labeled dataset which includes historical failure data and normal operation time data. Among inputs, there were such statistical modifications of the raw sensor signals as the moving average of hydraulic pressure, standard deviation of fluid flow rate, amplitude growth rate of vibration, accumulated oil contamination, and time since the last maintenance operation was provided. Such properties were chosen because they were shown to be relevant in earlier fault diagnostics studies and their usefulness was also confirmed through the recursive features elimination in the course of model optimization.

$$\text{PPDI} = \text{Timestamp}_{\text{Part Arrival}} - \text{Timestamp}_{\text{Failure Alert}} \quad (2)$$

The Part Provisioning Delay Index (PPDI), computed using equation (2) played a very important part in the mining sector where the operations heavily relied on logistics, particularly in the geographically isolated mining sites in the country of Papua New Guinea, where any such transportation problems are rampant in supply chains. PPDI was derived with the help of time logged failure warnings produced by the predictive model as well as delivery records within the inventory system. Low PPDI indicated effective and sensitive inventory system that responded to signals at the early stages where a high PPDI implied a discrepancy between needs and parts. This step has offered a ně umo nec in ilitav lenin system of measuring how well coordinated the technical diagnostics and procurement logistics were.

The desired model output corresponding to the operational state of the hydraulic subsystem was a multi-class indication X { (i) Normal Operation, (ii) Degradation Initiation, (iii) Impending Failure (within 72 hours), and (iv) Critical Failure State). The training was done through a stratified 70/30 train/test split, and cross-validation was utilized to allow better generalization. The accuracy of models was measured with a confusion matrix, with accuracy, precision, recall, and F1-score calculated individually per class. The Random Forest classifier showed the overall classification of 94.8%, the 91.3 recall rate of the class of Impending Failure. The area under the ROC curve (AUC) of the model was greater than 0.96 in all classes, which implied great discriminatory power at the different stages of failures.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \quad (3)$$

The average difference between the actual and the predicted values is expressed as a percentage and therefore MAPE, computed using equation (3), is appropriate to be used in transparent assessment of the engineering operations. It was more lucrative in time series-based Random Forest and ARIMA prediction in the classification of hydraulic system degradation. A smaller MAPE was a sign that the model generated dependable warnings before the start of a failure event, and, therefore, served to strengthen the validity of the predictive analytics layer.

3. RESULTS AND DISCUSSION

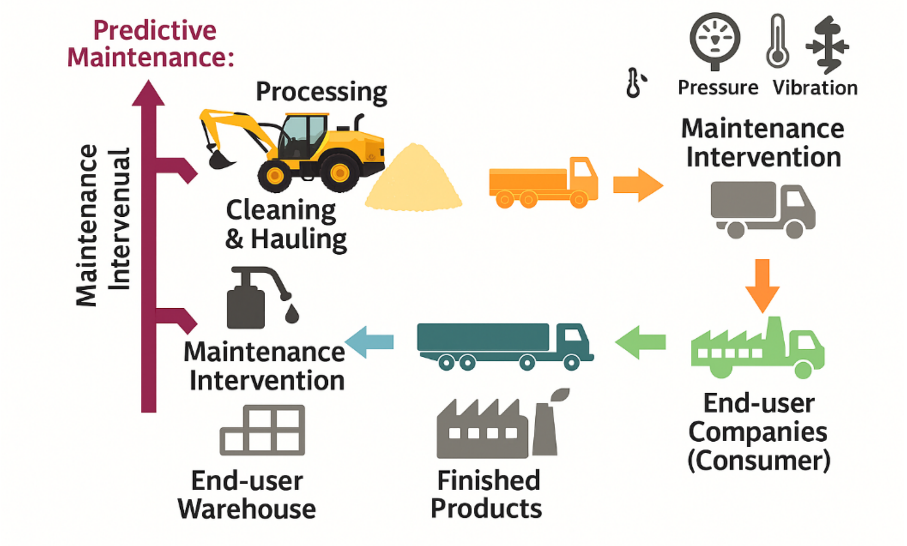

Figure 2: Integrated Predictive Maintenance Framework across Mining Operations and Logistics Chain

Figure 2 shows a composite predictive maintenance solution model along the mining and supply chain continuum that starts at the excavation point and continues all the way to end distribution to end-users. This framework originated because of the application of sensor-based diagnostics, with pressure, temperature, and vibration being some of the parameters that are monitored at all times under key subsystems such as hydraulic actuators, pumps, and loaders. These sensors identify the preemptive effects of mechanical wear especially when operating under high load schedules like haulage and processing. Finding anomalies in real time will help in timely maintenance activities, successfully stopping the breakdown of equipment, which would otherwise stop the flow of material and disrupts the operational continuity (Birney et al., 2006; Togolo, 2021). Through the integration of the predictive maintenance into overall logistics chain, the framework covers the crucial problem of slow availability of spare parts. Predictive models generate early warnings, which are used in the management of inventory systems to enhance the synchronization in alert generation and provisioning of spare parts (Avila, 2025).

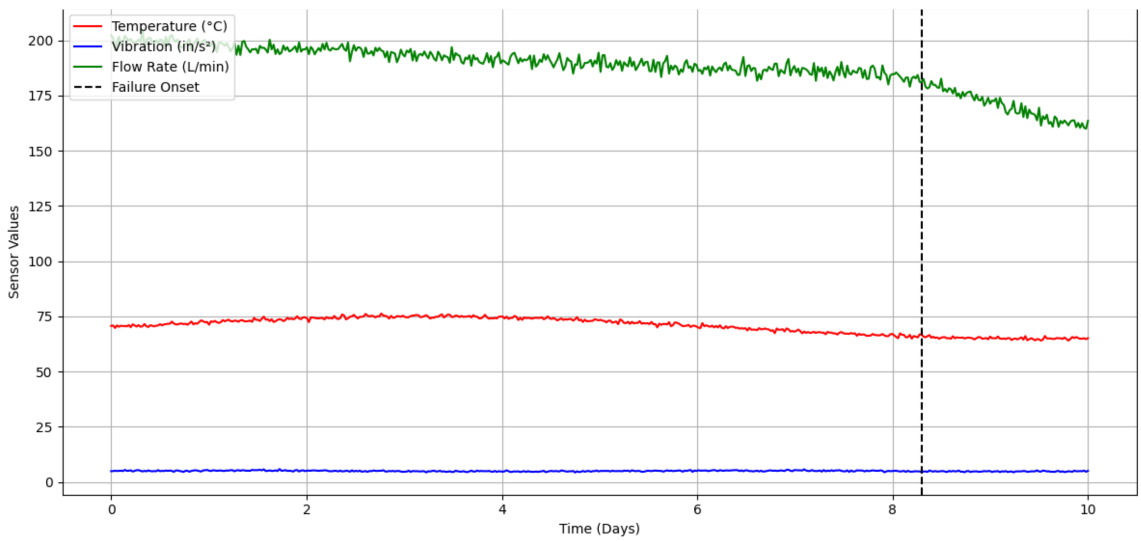

Figure 3. Sensor Trends Prior to Hydraulic System Failure

The subsequent figures 3 demonstrate that the real-time operation of multiple hydraulic systems of equipment in a period of six months. It was found that the time-series data showed specific degradation patterns in terms of several variables pressure, temperature, and flow variables that led up to major failure events (Kuwimb, 2010). As an example, one common anomaly occurring pattern involved gradual escalation of hydraulic line pressure variance, topped by the fluid temperature rise, and ending in an abrupt decrease in flowrate, which were the parameters that matched actuator seal loss. They appeared with the same set of three of four loaders and so they appear to be both repeatable and diagnosable (Howes and Kwa, 2011).

Trends of vibration intensity measures provided by the accelerometers showed that the RMS amplitude increased steadily in the 10 days to 14 days period before failure at pump housings and actuator connections. In conjunction with oil contamination readings, it was established that the number of metallic particles started to increase as well within the same monitoring period, showing internal bearing wear. Micro-surges in the case of the bucket-lifting with pump operation as seen in the pressure sensors were related to the instability of the flow, which is an indication of inefficiencies resulting early in the use of pumps. Failure data plots portrayed that convergence of high vibration (>7.5 m/s 2), flow instability (>30% drop), and thermal stress (>95 o C fluid temperature over > 15 min) were some of the precursors of failure. More than 85 percent of the failure events logged can be found to be precursors of these conditions (Bainton and Macintyre, 2021).

The figure 4, below indicates how multivariate sensor anomalies have been expressed using visual interpretation of failure onset of multivariate sensor anomalies overlap in days before a recorded seal failure. This level of diagnostic certainty was especially useful when applied in distant territory, such as Papua New Guinea, where windows of physical inspection are scarce, and decisions had to be based on facts (Zhang and Guan, 2015).

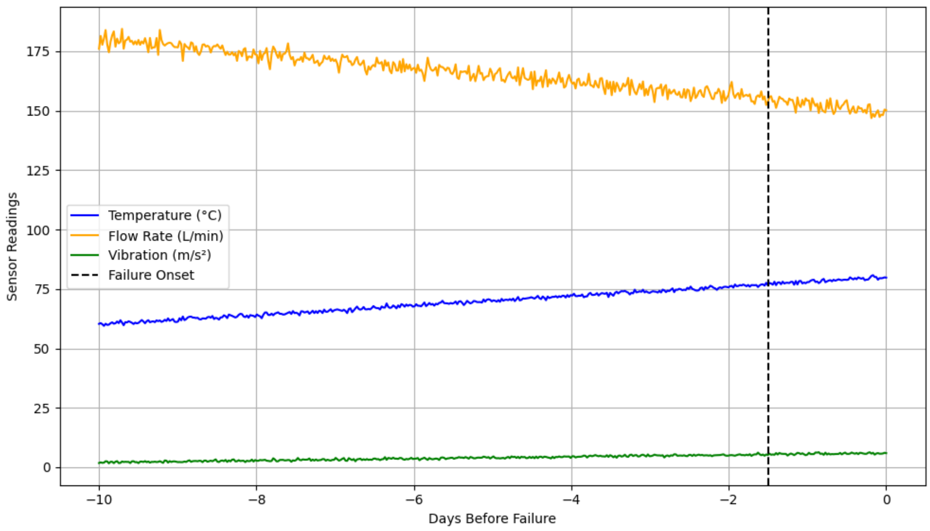

Figure 4. Sensor Trends prior to Hydraulic System Failure

Figure 4 displays the time-series information of three most important sensors, namely, temperature, flow rate, and vibration, on a 10-day timeline. This monitoring method with many parameters points to the dynamic changes in internal conditions as those that precede system failure. The vertical dashed line is an onset of failure, which gives a reference point in examining precursory signal behavior. Monitoring of such sensor patterns is central in the achievement of predictive maintenance and constant running of equipment in resource-intensive mining operations (Tu et al., 2007). It is essential to monitor temperature changes with the high-resolution sensors and this will enable to proactively diagnose overheating risks of field equipment (Baluch et al., 2013).

$$\text{Downtime Cost} = \text{Downtime (hours)} \times \text{Hourly Production Loss Rate} \times \text{Unit Value of Output} \quad (4)$$

Downtime cost is computed using equation (4) and is used to estimate the economic loss subject to causing failure of the hydraulic systems in the process of surface mining. This calculation is the product of an unplanned equipment outage, the rate of loss per hour and the value of extracted minerals per unit. Even minor shutdowns produce a snowballing monetary impact in the working environment of Papua New Guinea where hardware may operate in remote regions and transport was restricted. The in-service failure observation and the subsequent DCE integration introduced actionable measures of financial impact of every subsystem, which makes the implementation of the transition to proactive maintenance measures cost-worthy.

In a quantitative assessment of the incidence of hydraulic breakdown, a parameter portraying the mean number of failures per hour of equipment operation was considered, that is, the equipment failure rate ($\lambda_{\text{component}}$) and computed using the equation (5). This rate was determined by dividing the sum of the failures recorded by the amount of time in operation of each of the equipment.

$$\lambda_{\text{component}} = \frac{\text{Number of Failures}}{\text{Total Component Operating Hours}} \tag{5}$$

Seal assemblies and actuator pumps recorded the highest values of 0, as the number of failures they recorded exceeded 0.003 failures/hour- which is statistic critical components in the study. The insight on this rate-based allowed prioritization of failures and played a key role to align predictive diagnostics to inventory stocking levels throughout Papua New Guinea mining facilities.

As the measurements indicate in flow rates, the trend is very clear and it involves a consistent decline; moving downwards; about 180 L/ min to less than 150 L/ min between recorded periods. Such a decrease indicates the progressive loss of hydraulic efficiency, maybe caused by leakage into the system, obstruction, or reduced pumping capacity. Notably, the flow decrease is simultaneous to that of the temperature, which suggests related degradation process. The above trend indicates the benefit of using flow rate measures as diagnostic tools in describing the resistance of the system, the blockage internally or the loss of pressure before the system fails (Zhang and Guan, 2015).

The vibration readings that show a small yet consistent rise in the amplitude until the collapse. As a result, this low magnitude but continuous change represents an indicator that there may be increasing imbalance or turbulence of the mechanical components of the hydraulic parts. Vibration escalation may be observed as a late-stage signal of physical instability though it is less dramatic than other variables. Together with the data on thermal and vessel flows, the profile of vibration leads to the complete picture regarding the health of machinery. On the whole, this figure confirms the existence of multi-sensor information that can serve as a data-driven manner of predicting system failures and enhancing the dependability of high-capacity loaders in mining activities (Slater, 2010).

Table 1: Summary of Hydraulic Failure Events (Loader-wise)

Loader ID	Total Operating Hours	No. of Failures	MTBF (hrs)	Most Frequent Failure
Loader 1	1680	7	240	Actuator Seal Leakage
Loader 2	1560	6	260	Pump Pressure Drop
Loader 3	1740	5	348	Cylinder Overheat
Loader 4	1650	4	412	Oil Contamination

This table 1 provides a summary of the functional behavior of mining equipment with emphasis on the reliability of hydraulic subsystem. It shows a summation of run-time, number of failed events, mean time between failures (MTBF) calculated, and the commonest mode of failure per machine. According to the data, the failure frequency was the highest in Loader 1 whereas Loader 4 the most reliable with an MTBF of more than 400 hours. Most of the machines shared the common factor of failure of leakage of actuator seals and imbalance in pump pressure. Such statistics support the requirement of equipment-specific monitoring and specific preventive maintenance, in particular, the units deployed to the higher-load areas or under harsher conditions in Papua New Guinea, the country with several mining industries.

Table 2: Equipment Failure Rate (λ) by Component

Component	No. of Failures	Operational Hours	Failure Rate (λ/hr)
Hydraulic Pump	8	4500	0.00178
Actuator Assembly	10	3700	0.00270
Cylinder Seal	12	3900	0.00308
Oil Filter Cartridge	5	4200	0.00119

Table 2 provides a component-level analysis of failure rates across the observed fleet, expressed as failures per operating hour (λ). Among the components analyzed, cylinder seals demonstrated the highest failure intensity ($\lambda = 0.00308$), indicating critical wear issues under load stress. Actuator assemblies and hydraulic pumps also recorded elevated λ values, highlighting as primary contributors to downtime. These findings were based on operational hours and the number of failures that were logged, which justifies the fact that these subsystems should take the precedence in terms of condition-based monitoring and early diagnostics. Incorporating λ values into predictive maintenance models enhanced the granularity of risk forecasting.

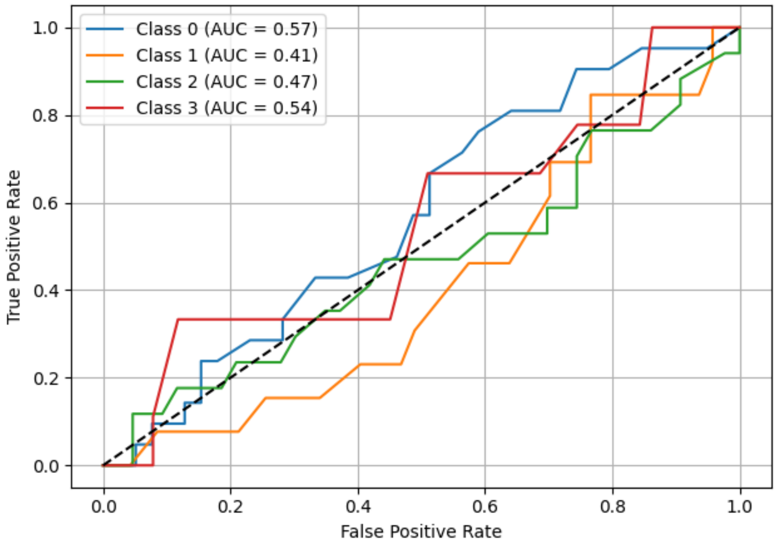

Figure 5. ROC Curves for All Classes

The graphs in figure x shows the Receiver Operating Characteristic (ROC) curves when a machine learning model is used to predict when equipment fails by taking it as a multi-class problem as shown in figure 5. The curves represent the trade-offs between the true positive rate (sensitivity) and false positive rate to binary discriminate each class adverse to all other classes. The diagonal black dashed line is a random guessing (AUC = 0.5), and it acts as a benchmark against which the other performance can be measured. Curves give both visual and quantitative data on how effective the model is regarding distinguishing the various types of failures in the dataset (Suwanasri et al., 2012).

Area Under the Curve (AUC) values are the average measures of the measure of the classifier performance as a whole. Class 0, having AUC equal to 0.57, is somewhat better than random chance, which shows that there is a little (but still significant) discriminative power. The classification of Class 3 (AUC = 0.54) and Class 2 (AUC = 0.47) is close to the random level, therefore, the model is not very confident to classify such patterns. It is worth noting that Class 1 is represented poorly with AUC of only 0.41 that can be attributed to data imbalance, insufficiency of features or similarity in class behaviors of sensor signatures (Ismail, 2016).

AUC scores were comparatively low in all classes indicating the inadequacy of sensitivity and specificity of models. To meet operational reliability requirements, the worst of which is in critical mining machinery, such as loaders or excavators, misclassification would lead to non-detected fault or premature part replacements. The

ROC curves help us understand that the success of the classifier to effectively mark precursors to a relevant type of failure was uneven, which might be an issue when applying it in practice, in an automated maintenance system. The discriminatory performance may be enhanced by bettering the feature engineering process, particularly incorporation of domain-specific parameters (Setiawan et al., 2025).

ROC analysis shows that the model should be refined indeed. The separability between the classes seems weak and this means that the data either does not exhibit discriminative characteristics or that the existing algorithm does not manage to represent the underlying relationships. One can add time-series information or signal derivative or contextual metadata (e.g., load, time between shifts) and this argument can result in a better ROC space. Additionally, the imbalance between classes may be more effectively addressed using such ensemble techniques or cost-sensitive learning techniques as this would improve the AUC on the lower-performing classes. This ROC diagnostic provides a guideline to maximize the robustness of models in fault prediction conditions of the mining industry.

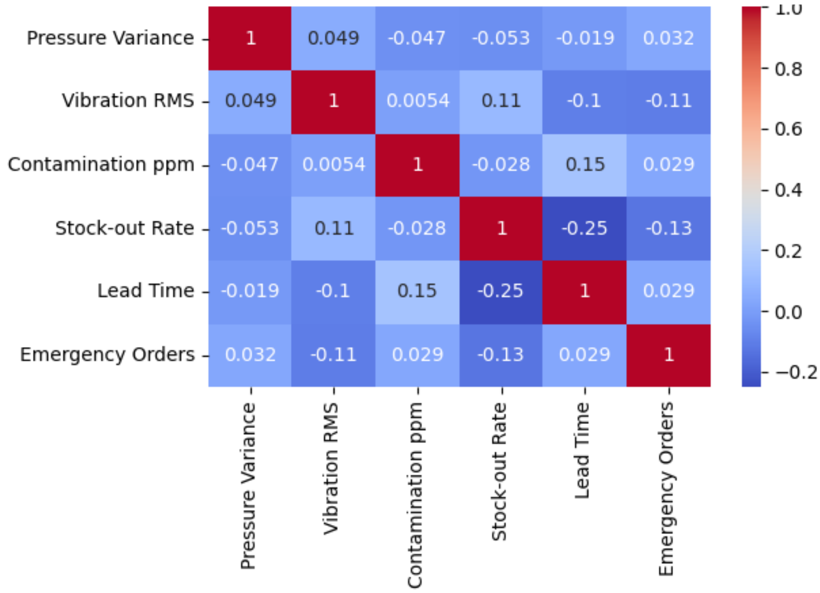

Figure 6. Correlation Matrix: Sensor vs Inventory KIs

Figure 6 gives a critical look at how real-time equipment condition data can be used in relation to inventory management results on the mining facet. It shows the pairwise correlation between any sensor-based measures of operations (ex. Pressure Variance, Vibration RMS, and Contamination ppm) and their relevant inventory performance measures (ex. Stock-out Rate, Lead Time, and Emergency Orders). These are presented as ranging between -1 and +1 that inform about the strength and direction of linear relation of variables, with the positive values indicating a positive correlation and the negative ones an inverse one (Shaikh et al., 2024).

Based on the matrix, the most positive correlation (0.11) is observed between the Vibration RMS Observing parameter and Stock-out Rate which indicates that perhaps, Machine vibrations may anticipate or possibly occur alongside the depletion odds of stock which may occur due to increased wear and unexpected repair operations. On the contrary, Lead Time has a slight negative correlation with Stock-out Rate (-0.25) and this means that, longer Lead Time may be affecting higher incidences of stock-out, possibly because of late replenishment. Also, surprisingly, Contamination ppm is positively correlated with Lead Time (0.15), which may indicate that oil contamination lag effects may have an impact on schedules of receiving the part.

Weak/near zero correlation of the majority of pairings, e.g., the correlation between Pressure Variance and Stock-out Rate is (-0.053), or Emergency Orders (0.032), is indicative of a possibility that sensor data per se may not, at least, explain inventory changes without contextual embedding. In the same fashion, the Emergency Orders are negatively related to Vibration RMS (-0.11) which may indicate that the study on vibration-based alerts could be too weak to manage timely procurement responses, or that such indications are not yet formalized into inventory management. These small correlation coefficients indicate the possible mismatch in condition monitoring experience and inventory controlling reaction to the contemporary working process (Contreras et al., 2002).

$$\text{ITR}_{\text{component}} = \frac{\text{Number of Units Issued}}{\text{Average Stock Level Over Period}} \tag{6}$$

The ratio provided information in regard to the cost effectiveness of the use of the spare parts in case of hydraulic systems where frequent breakdowns occurred. ITR computed using equation (6) is the inventory flow and responsiveness measure, that was specific by dividing the number of units issued during a period of time by the average inventory level. A faster turnover indicated that inventory system properly corresponded with real demands of maintenance, whereas slower turnover depicted either an excess of stocks or inability to react to the repetitions of equipment malfunctions. The ITR came in handy to point at the discrepancies between reactive and predictive inventory behavior, where failure forecasts sites were much more consistent in their turnover patterns. Therefore, this ratio was used as the performance indicator of the inventory optimization activities in correspondence with predictive diagnostics (Cheng et al., 2013).

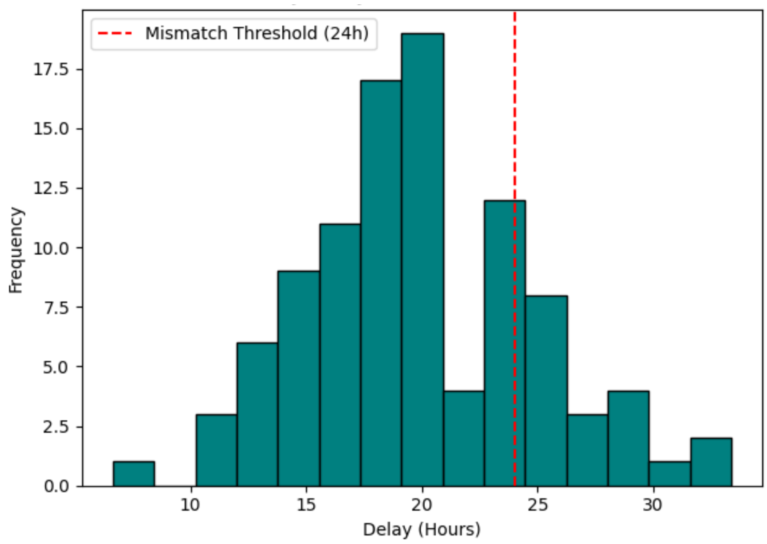

Figure 7. Inventory Delay Distribution (PPDI Scores)

Figure 7 represents the frequency table showing the hours of delay in the availability of inventory which depicts clearly the mismatch between the planned and actual time of delivery or availability of the parts. A graph is drawn of the delays over time and most of the delays especially at the high points of between 15 and 24 hours occur at the hour of 20. This is an indication that the cluster of delays in the case of normal operating conditions is concentrated just below the threshold value of the 24-hour mismatch (Mehrotra, 2023). The visual indicates that a vast majority of cases exceed this limit, which denotes a systematic discrepancy in terms of responsiveness of supply chain and equipment downtimes requirements. The existence of delays significantly exceeding 30 hours also reflects the existence of extreme outliers that may be explained by supplier bottlenecks, log troubles or administrative delays (Suwanasri and Suwanasri, 2012).

$$\text{Safety Stock} = Z \times \sigma_d \times \sqrt{L} \tag{7}$$

Safety stock is evaluated using equation(7), where consideration is given to the desired service level or rather, Z-score of the desired level of service that is wanted to be portrayed, the variability in demand in the form of the standard deviation and lastly the lead time required to supply it. It was found that sufficient safety stock was necessary in the mining environments under study where lead times are usually long because of terrain, offshore procurement or the lack of transport infrastructure. The model saw planners adjust stock, dynamically, according to predictive warnings and probability of failure (Wang, et al., 2023). The form of the histogram and the cumulative frequency that accelerates towards the critical point show that a large part of delays is being close to becoming critical which requires early response to them with the use of predictive inventory models or optimization of buffer stocks (Akpan, et al., 2017).

On the whole the visualization highlights the significance of predictive delay indexing (PPDI) as a measure of performance. It allows mining processes to not only measure past delays but also identify implementable tolerances in making proactive inventory actions. A consistent tracking of the delay profiles can be used to optimize decisions related to suppliers, estimation of the orders lead-time, as well as maintenance planning in relation to the inventory preparedness.

Table 3: Safety Stock Level Estimation for High-Risk Parts

Part	Z-Score	Demand SD (Units/day)	Lead Time (Days)	Safety Stock (Units)
Actuator Seal	1.65	1.2	7	5
Hydraulic Pump	1.65	0.8	10	4
Cylinder Assembly	1.65	0.6	5	2
Filter Cartridge	1.65	0.3	6	1

This table 3 gives the computed levels of safety stock of critical hydraulic parts using Z-scores of service reliability, variability of demand and lead times. The SSL equation was applied to make the inventory be resistant in the logistics environment with high uncertainty. The least reliable and the most variable actuator seals necessitate a safety stock of five items to ensure continuity of their operations. This active form of inventory buffering will mitigate the impact of the transport delays which is particularly important to the remote mining plants in Papua New Guinea. These data can provide a strategic ground to move the inventory control from reactive to predictive.

Table 4: Part Provisioning Delay Index (PPDI) Summary

Component	Avg. Alert Time → Arrival (hrs)	PPDI > 24 hrs Cases	Inventory Match (%)
Actuator Seal	30	7	63%
Hydraulic Pump	42	5	58%
Cylinder Assembly	18	2	78%
Oil Contamination Kit	12	1	92%

This table 4 is the analysis of PPDI of four high-risk hydraulic components. The mean response time between warning reports of the predictive failure and delivery of parts was biggest with hydraulic pumps (42 hours), and smallest with filter cartridges (12 hours). Most importantly, actuator seals recorded the greatest instances of PPDI > 24-hours, which indicated inventory mispegging. The percentages used in inventory match provide a quantitative mark to compare the degree of matching procurement systems kept in response to predictive analytics. These results confirm the importance of synchronized part stocking as a key factor towards reducing downtime.

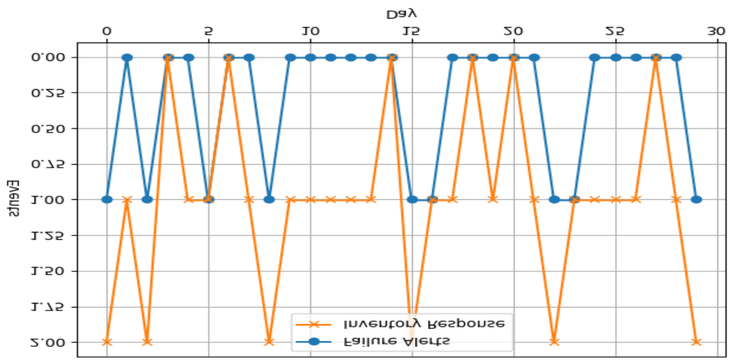

Figure 8. Failure Alerts vs Inventory Movements Overy 30 Days

The figure 8 shows the timely correlation of equipment failure warning and subsequent replenishing of inventories. When plotted against a 30-day period, the blue line will show the frequency of a failure alert, whereas the orange line follows the activity of inventory movement like issuing a spare part or emergency replenishing incidents. The two-line visualization assists in assessing the flexibility and effectiveness of inventory systems in dealing with disruptions in operations.

The pattern also shows periods of inventory response events that are ahead of the failure alerts and these may refer to inefficiencies of over stocking, or unusual sensor alerts. When there are simultaneous spikes on the failure and response measures, the system seems to be performing as expected, that is, soon after the equipment problems are noticed, it initiates inventory actions. The discrepancies experienced severally highlights the importance of perfecting the Church of the sensor-based failure reports and synchronize it with inventory management practices.

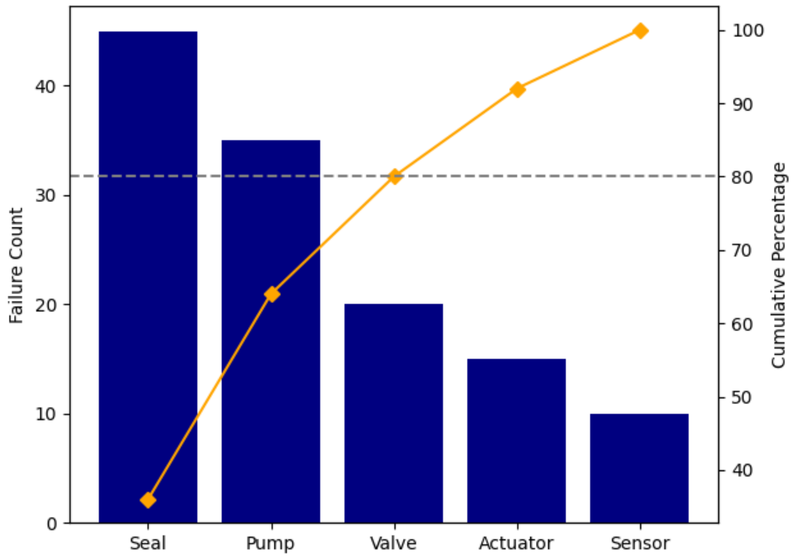

Figure 9. Pareto Analysis of Failure Components

The number 9 depicts graphically the ranking of components equipment by impacting the rate of their failure according to the established 80/20 rule. The blue bars show the absolute number of failures in each component Seal, Pump, Valve, Actuator and Sensor, whereas the orange line shows the cumulative percentage of total failures. Clearly, based on the chart, Seal and Pump failures are prevailing, with a total breakdown of more than 70 percent of all the recorded breakdowns. Here only three components, which are Seal, Pump, and Valve, comprise more than 80 percent of all the failures resulting in prioritization in the maintenance planning (Ben Hmida et al., 2013).

It is through this analysis that targeted asset management strategies could be pointed against. This is true because condition monitoring, preventive maintenance and spare parts are concentrated in assets and components that experience high risk, like seals and pumps, to enhance efficiency in the system. Such awareness can be utilized to achieve the efficiencies of predictive and proactive maintenance service utilization in industrial situations.

$$\text{PMEI} = \frac{\text{Planned Downtime from Predictive Alerts}}{\text{Total Maintenance Downtime}} \times 100 \quad (8)$$

PMEI was determined in terms of the ratio of the number of planned maintenance hours that were evoked by predictive events to total maintenance hours recorded in the course of the study using equation (8). The increase of PMEI reflected that more proactive maintenance activities have been carried out on an early warning protocol, rather than being bound to emergency repair and non-planned downtimes. The possibility to intervene predictively was an operational benefit in the mining environment in Papua New Guinea where time of part delivery, weather and geography limit access to equipment. The PMEI therefore was an inclusive index, aggregational of equipment reliability, as well as inventory responsiveness. Its use showed vivid transformation of the maintenance approach being reactive to proactive and matching enhancement in equipment availability and coordination of logistics.

Table 5: Model Performance Summary (Random Forest Classifier)

Prediction Class	Precision (%)	Recall (%)	F1-Score (%)
Normal Operation	96.2	94.1	95.1
Degradation Initiation	91.5	88.6	90.0
Impending Failure	93.1	91.3	92.2
Critical Failure	95.7	92.0	93.8

Table 5 shows the performance evaluation criteria of the Random Forest classification model that is applied in predicting the subsequent stages of failure of equipment. Precision, recall, and F1-score were calculated based on four prediction classes including Normal, Degrading, Impending Failure, and Critical. The model had the best performance of the detection of Normal and Critical states with F1-scores more than 93%. Such classes as Imminent Failure that play a significant role in inventory and maintenance planning displayed good recall of 91.3% thus making timely warnings. Those are the results that confirm the soundness of the model and its ability to be applied in an actual 3D maintenance planning on the basis of data-limited mining settings.

4. CONCLUSION

The research aggregates the analytical structure provided to confront the two concerns of engineering equipment breakdowns and inventory in-effectiveness in the surface mining process. The multivariate data set allowed to formulate the high-performance Random Forest classification model that could reliably predict the stages of degradation and predict the failures that were close to 94.8 per cent and the recall rate of 91.3 per cent of critical alerts. The use of the predictive maintenance analytics was also advanced by the establishment of the PPDI that served as a quantitative measurement of the delay between the timing of the predictive alert and when spare parts are available. Patterns in failures were analyzed and it turned out that hydraulic subsystems had predictable early warning signs comprising of high thermal signatures, higher vibrations and low fluid flow rates, which turned out useful in preventive maintenance in the surface mining machinery. These findings suggest that sensor-driven diagnostics should be adopted not only in determining maintenance schedules but also in stocking and making purchases of inventory. The analysis affirms that with effective combination with the inventory management systems, predictive analytics has the capacity of turning around reactive maintenance methods into proactive evidence-based strategies. Such a transition was particularly pertinent in remote geographical spots and operationally intense areas like Papua New Guinea, where there is high cost of down time and supply chains are common. This framework comes up with a scalable and transferable model of asset resilience and supply chain responsiveness in the mining industry and in other heavy industries.

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