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Forecast-Based Decision Framework for Replacement of Ros and Onboard Components in Autonomous Loaders: A Case Study at GBC Mine PT Freeport Indonesia

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ABSTRACT
The mining industry plays a critical role in global economic activities, particularly in supporting the supply of essential raw materials. In Indonesia, PT Freeport Indonesia operates the Grasberg Block Cave (GBC) underground mine, which utilizes autonomous loaders integrated with the Remote Operating System (ROS). The reliability of ROS and its onboard components is essential to ensure continuous production and operational efficiency in a complex underground environment. This study aims to develop a forecast-based decision framework to determine the optimal timing for component replacement in autonomous loaders. A quantitative approach was employed using time-series forecasting based on historical downtime and component replacement data from 2023 to 2025. The Autoregressive Integrated Moving Average (ARIMA) model was applied to identify failure patterns and predict future degradation trends. The results indicate that component failures, particularly in joystick and other critical onboard systems, follow a non-random and progressive degradation pattern influenced by environmental and operational factors such as vibration, dust, humidity, and intensive usage. The ARIMA (1,0,1) model demonstrates adequate performance in capturing temporal failure behavior and supporting maintenance planning. The proposed decision framework integrates forecasting outputs, degradation trends, and operational risk considerations to support proactive maintenance strategies. The implementation of this framework is estimated to reduce downtime-related production loss by approximately 62.5%, equivalent to around 5,750 tons per month. These findings highlight the practical value of integrating forecasting models into maintenance decision-making processes. This study contributes to predictive maintenance practices by bridging the gap between failure prediction and operational decision-making in autonomous mining systems.

INTRODUCTION

Operational forecasting is a crucial foundation for planning future needs across various sectors, particularly in fast-paced, complex, and interconnected work environments (Ampaw-Asiedu et al., 2024; Owen, 2024; Ozpinar & Soofastaei, 2025). Industries, research institutions, and operational institutions utilize operational forecasting to project production needs, estimate potential component failures, manage resource allocation, and optimize system performance for stability and sustainability (Adelakun, 2023). In the mining industry especially in underground mining operational forecasting plays an even more critical role due to the high-risk, capital-intensive, and geologically uncertain nature of subsurface operations. Underground mining requires precise forecasting to predict ore grade variability, ventilation and energy needs, equipment utilization, potential geotechnical hazards, and maintenance schedules for critical machinery operating in confined environments. Effective operational forecasting enables mining companies to anticipate production fluctuations, prevent unplanned downtime, and maintain workforce safety by identifying early signs of ground instability, equipment fatigue, or environmental changes such as temperature, humidity, and gas concentration. As a result, underground mining operations can achieve higher efficiency, operational continuity, and compliance with strict safety regulations while optimizing cost structures and sustaining long-term productivity (Vudugula, 2023).

The reliability of forecasts as a tool for interpreting future conditions requires a framework capable of translating them into informed decisions (Bouazizi & Ltifi, 2024; Hossain & Mita, 2024; Rahman & Hye, 2022; Souza, 2026). A decision framework then serves as a systematic structure that guides how forecast information is processed, evaluated, and used as a basis for determining the most rational and efficient course of action (Chen, 2023). This approach ensures that every decision relies not solely on intuition but is based on measured analysis that considers risks, benefits, and operational consequences. A decision framework serves as a crucial bridge between the ability to predict the future and the ability to act strategically in an environment full of uncertainty (Cristofaro, 2025).

The use of decision frameworks becomes increasingly important when applied to systems that rely on complex technologies such as the Remote Operating Station (ROS). ROS serves as the primary control center coordinating sensors, actuators, and monitoring and navigation systems on autonomous loaders, so the quality of maintenance decisions is heavily influenced by the ability to understand the performance patterns and potential failures of the components connected to it. (Urrea, 2025). When forecasting results indicate a trend of declining functionality or an increased risk of failure in a particular module, the decision framework plays a role in determining the most appropriate replacement time to prevent disruption to the overall ROS performance. The integration of forecasting, the decision framework, and ROS creates a logical flow that enables the management of critical components to be carried out in a more measured, timely manner, and aligned with operational needs (Benhaifia, 2025).

Onboard components of an autonomous loader, such as LIDAR sensors, cameras, communication modules, actuator controls, and data processing units, play a critical role in ensuring the stability and accuracy of the Remote Operating Station (ROS) system. All of these devices are integrated into a single system that works simultaneously to provide real-time information on the loader's position, environmental conditions, and operational status. Due to the highly interconnected nature of these components, disruptions to a single onboard component can directly impact ROS performance, ranging from navigation inaccuracies to automatic malfunctions (Ficili, 2025). It is in this context that a forecast-based decision-making framework becomes crucial. When predictive data indicates a performance degradation in a component, the decision-making system can prioritize replacement before the disruption escalates and hampers the overall autonomous operation. The interconnection between ROS and onboard components makes a prediction-based approach a critical foundation for

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maintaining the reliability of autonomous loaders in demanding work environments (Loboichenko, 2025).

The novelty of this research lies in the use of forecasting methods as the primary basis for determining the optimal timing for replacement of ROS and onboard components on autonomous loaders in underground mining environments, an approach rarely discussed in previous research. Most previous studies have focused on conventional predictive maintenance, mechanical reliability analysis, or component lifespan estimation without integrating forecasting models capable of more precisely identifying degradation patterns of automated systems. This research fills this gap by modeling the forecasted performance of ROS and onboard components operating under extreme conditions, enabling early detection of functional degradation trends before failure occurs. The urgency of this approach is heightened given the mining industry's increasing reliance on autonomous systems that require accurate predictions to maintain operational stability. Without adequate forecasting, the risk of downtime, sudden failures, and inefficient maintenance costs increases. Therefore, this research makes a significant contribution by presenting a more proactive, timely, and sustainable forecasting-based maintenance strategy in the underground mining context.

PT Freeport Indonesia (PTFI) is a world-class mining company operating in Papua Province, Indonesia, and is recognized as one of the largest producers of copper and gold globally. Its operations span the full mining value chain, including exploration, extraction, concentrate processing, and international distribution. As reserves at the Grasberg Open Pit declined, PTFI transitioned from surface mining to large-scale underground mining operations, making the Grasberg Block Cave (GBC) Mine its primary production center. The GBC Mine is one of the world's largest and deepest underground block caving mines, located approximately 3,000 meters above sea level and supported by an extensive tunnel network and a 24-hour continuous production system. Over the years, PTFI's agreements with the Indonesian government have evolved significantly, beginning with the 1967 Contract of Work for the Ertsberg mine, followed by the discovery of Grasberg in 1988, subsequent contract renegotiations, regulatory changes in the 2000s, and the 2018 agreement that granted PTFI operational rights until 2041 while requiring a 51% divestment and domestic smelter development.

The GBC Mine represents a combination of large-scale operations and advanced mining technology, making it one of the most challenging and technologically demanding underground mines in the world. The operating environment is extremely harsh, characterized by high humidity, drastic temperature fluctuations, mineral dust, significant rock pressure, and continuous vibration from drilling and blasting activities. To maintain operational efficiency, PTFI has implemented advanced automation systems, including autonomous loaders integrated with Remote Operating Station (ROS) software and onboard components such as LIDAR sensors, cameras, communication modules, actuator control units, and real-time data processing systems. In this context, ensuring the reliability of these systems is critical, as any disruption can directly impact hauling operations, productivity, and maintenance costs. Therefore, research on predicting ROS and onboard component failures is highly relevant to support data-driven asset management and predictive maintenance strategies.

PT Freeport Indonesia currently faces significant operational challenges in managing autonomous loaders at the GBC Mine, particularly due to the increasing frequency of ROS and onboard component failures. The underground mining environment accelerates the degradation of critical components, especially joysticks, which serve as primary control devices. Historical replacement patterns indicate repeated failures within short intervals, suggesting progressive degradation rather than random breakdowns. These failures directly affect ROS stability, loader navigation, and the automated material hauling process, increasing downtime, disrupting production flow, and causing unplanned maintenance costs. In addition, major failure causes are concentrated in high-usage components such as the horn button, gear shift button, and cam switch, confirming the need for a more proactive and forecast-based maintenance strategy. Since one autonomous loader can transport approximately 230 tons per hour, downtime of 3–5 hours due to joystick replacement can result in production losses of 690–1,150 tons per incident, significantly affecting operational targets.

To address these challenges, this research focuses on analyzing component degradation patterns, identifying the Remaining Useful Life (RUL) of ROS and onboard components, and evaluating forecasting models to predict failure intervals more accurately. The study also investigates operational factors within the GBC underground mining environment that contribute to high failure frequencies and seeks to develop a forecast-based decision-making framework for optimal component replacement timing. The main stakeholders involved include operators and ROS officers, maintenance teams, Asset Management and Reliability Engineering divisions, mine operational management, Health and Safety departments, and component suppliers. Each stakeholder plays an important role in ensuring that forecasting results can be translated into proactive maintenance actions, improved spare parts planning, and reduced operational risks.

This research is specifically limited to autonomous loaders operating in the GBC Mine area and focuses on ROS-related and onboard components that have shown repeated degradation in historical records. The analysis primarily relies on historical component replacement data from 2023 and part of 2025, which may not fully capture long-term degradation trends. Additional limitations include incomplete real-time degradation parameters, varying operational workloads between units, fluctuating underground environmental conditions, and dependence on the consistency and quality of maintenance records. As a result, the findings are most relevant to the GBC operational environment and may not be directly generalizable to other mining areas such as DMLZ or DOZ, or to other mining companies with different operational conditions. Despite these limitations, the study provides a strong foundation for developing a predictive and data-driven maintenance framework aimed at minimizing downtime, reducing maintenance costs, and improving the sustainability of autonomous loader operations.

METHOD

Research Design

This research adopted a quantitative case study design conducted at the Grasberg Block Cave (GBC) Mine, PT Freeport Indonesia, focusing on autonomous loader operations that depend heavily on the integration of the Remote Operating Station (ROS) and multiple onboard components. The case study approach allows for an in-depth examination of component degradation phenomena within a real operational environment characterized by extreme underground mining conditions, continuous equipment utilization, and high reliance on automation-based systems. Quantitative analysis is performed using historical component replacement data and downtime event records to identify degradation patterns, analyze failure intervals, and conceptually estimate Remaining Useful Life (RUL) based on observed trends. Reliability engineering principles are applied to interpret degradation patterns in relation to wear-out mechanisms, environmental exposure, and operational intensity, particularly for critical ROS-related components such as onboard control and sensing systems. This study does not employ qualitative methods such as interviews or questionnaires; instead, all analyses are based solely on historical operational data obtained from maintenance and asset management systems. The integration of forecasting analysis, reliability engineering, operational risk, downtime impact, and component criticality supports the development of a Forecast-Based Decision Framework to determine the optimal timing of component replacement, with the objective of reducing unplanned downtime, minimizing production losses, and improving system reliability. The research design is structured around four main research questions concerning degradation patterns, operational failure factors, forecasting accuracy, and decision framework development, each supported by appropriate analytical methods, data sources, and evaluation techniques.

Data Collection Method

This study employs a structured data collection approach to support the analysis of component degradation, forecasting accuracy, and the development of a forecast-based decision framework for autonomous loaders operating at the Grasberg Block Cave (GBC) Mine, PT Freeport Indonesia. Data were collected both on-site in the GBC underground mining area and through company maintenance and asset management systems, covering historical records from 2023 to 2025 based on availability and relevance to recurring component failure patterns under continuous underground operations and varying maintenance cycles. The primary data source consists of historical component replacement records, including replacement dates, affected components, failure descriptions, and root cause classifications, with particular emphasis on ROS-related onboard components such as joysticks to identify failure trends, analyze degradation patterns, and estimate failure intervals for forecasting and Remaining Useful Life (RUL) estimation. In addition, operational and maintenance records were collected to provide contextual information regarding equipment utilization, maintenance activities, and underground operational conditions, enabling the analysis of how factors such as dust, vibration, humidity, and continuous operation contribute to component degradation and failure frequency. The data scope is limited to autonomous loaders operating within the GBC Mine area during the selected period, and data reliability was ensured through consistency checks, completeness reviews, data cleaning, and validation procedures to maintain the integrity and accuracy of the analysis.

Data Analysis Method

This study applies a structured quantitative data analysis approach to examine component degradation behavior, evaluate forecasting model performance, and develop a forecast-based decision framework for ROS and onboard component replacement in autonomous loaders operating at the GBC Mine, PT Freeport Indonesia. The analysis begins by identifying failure trends and degradation patterns of critical components, particularly joysticks, through historical replacement data to observe recurrence frequency, failure intervals, and dominant failure modes, determining whether failures occur randomly or follow wear-out patterns consistent with reliability engineering theory. Based on these patterns, Remaining Useful Life (RUL) estimation is performed using historical replacement and failure interval data to assess the expected operational lifespan of components and support replacement planning. Time-series forecasting methods are then applied to predict component failure intervals and future replacement needs, with model performance evaluated using accuracy metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), while residual diagnostic testing using the Ljung–Box test ensures that model residuals are independently distributed and that the temporal structure of the data is adequately captured. To strengthen the operational relevance of the forecasting results, an operational risk and impact assessment is conducted by evaluating downtime duration, production loss, operational disruption, and component criticality, ensuring that replacement decisions account not only for predicted failures but also for business and operational priorities. Finally, forecasting outputs, RUL estimates, and operational risk considerations are integrated to formulate replacement decision rules that determine whether components should be replaced immediately, scheduled for replacement, or monitored further. These rules form the foundation of the Forecast-Based Decision Framework proposed in this study, providing a structured and proactive maintenance planning approach based entirely on quantitative analysis, statistical methods, forecasting outputs, and reliability engineering principles without the use of qualitative methods such as interviews or surveys.

RESULT AND DISCUSSION

Degradation Patterns and Estimated Remaining Useful Life (RUL) Identified Through Forecasting Models for ROS and Onboard Components

Based on the presented down event forecasting results, it can be identified that the degradation pattern of the ROS and on-board components of the autonomous loader at GBC Mine tends to be gradual and does not exhibit sudden failure characteristics. The fluctuation pattern of historical data followed by the relatively stable results of model estimation and forecast projections indicates that component degradation occurs gradually along with the intensity of use and exposure to the underground working environment. This finding is in line with the characteristics of electronic and mechatronic systems in modern mining equipment, where performance degradation generally occurs progressively before reaching a functional failure condition.

Forecasting results for critical on-board components such as Ladar, Camera, Communication, and RSM show that despite a spike in downtime events during certain historical periods, the forward projection trend remains relatively controlled and does not indicate a significant escalation of failures. This pattern reflects that these components have not yet entered a critical degradation phase simultaneously, but are instead in a wear progression phase that can still be mitigated through appropriate maintenance strategies. Thus, the forecasting results serve as an early indicator to identify the direction of degradation without having to wait for actual failure.

In Remaining Useful Life (RUL), although this study does not calculate the RUL value quantitatively, the RUL estimate can be interpreted conceptually through the trend of the forecast results. The stability of the forecast value within the confidence limit indicates that the component still has remaining operational life before reaching a condition that requires immediate replacement. Conversely, sharper historical fluctuations in some parts indicate that

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the RUL is relatively shorter than other components, thus requiring more intensive attention in maintenance planning. This interpretive approach is relevant in industrial case studies with limited real-time condition data and a focus on trend-based decision-making.

Specifically for the joystick component as part of the ROS control system, the recurring down event pattern in historical data indicates a degradation mechanism influenced by usage intensity, vibration, and ergonomic factors in operation. Although the joystick was not modeled separately in the quantitative forecasting in this study, its degradation pattern can be inferred through its association with disturbances in the ROS system and other on-board components. This indicates that the joystick has a degradation characteristic that tends to be cumulative, so that a forecasting approach based on the disturbance event trend can be used as a proxy to estimate its remaining operational lifespan.

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Operational Factors in the GBC Underground Mining Environment Significantly Contribute to the High Frequency of Failures of ROS Components and Related Onboard Devices

The underground working environment at the GBC Mine has extreme and complex operational characteristics, significantly impacting the reliability of the ROS and onboard components of the autonomous loader. Mining activities at great depths using block caving methods cause equipment to operate under conditions of high vibration, intense exposure to mineral dust, and relatively high humidity. These conditions create continuous environmental stress on electronic components, sensors, and control systems, accelerating the degradation process compared to more controlled operating environments.

Mechanical vibrations from blasting activities, rock mass movement, and repeated tool cycles are among the main factors influencing the failure of ROS components and on-board devices. Continuous vibrations can cause wear on connectors, solder joints, and internal components of electronic modules such as the RSM, communication module, and Ladar sensors. Over the long term, these conditions contribute to an increase in the incidence of intermittent downtime events before they develop into more serious functional failures.

In addition to vibration, exposure to fine mineral dust is a very dominant environmental factor in the GBC area. Dust can penetrate electronic component housings and mechanical interfaces, disrupting electrical contacts, and degrading the accuracy of optical sensors such as radars and cameras. Undetected dust accumulation often leads to gradual performance degradation, reflected in recurring downtime patterns in historical data. This explains why some components exhibit relatively high fluctuations in downtime, even though they are not always followed by total failure.

Humidity and temperature variations also play a significant role in accelerating the degradation of ROS components and on-board devices. High humidity in underground environments can increase the risk of corrosion in connectors and circuit boards, while temperature changes resulting from equipment operating cycles can trigger repeated expansion and contraction of materials. This combination of factors contributes to the long-term degradation of electronic system reliability and increases the probability of operational disruptions, particularly in communication systems and control modules.

In addition to environmental factors, the intensity of operations and usage patterns of autonomous loaders at the GBC Mine contribute to the high frequency of component failures. Near-continuous operation with dense work cycles results in a cumulative workload on the ROS and on-board components, including the joystick as part of the control system. Repeated human-system interactions, high workloads, and limited maintenance intervals accelerate functional degradation. Thus, the high frequency of ROS and related component failures is inextricably linked to the combination of extreme underground environmental factors and the operational characteristics of the GBC Mine, which collectively reinforce the urgency of implementing a forecast-based maintenance and component replacement strategy.

Accuracy of the Selected Forecasting Model in Predicting Component Failure Intervals Based on Historical Replacement Data

The accuracy of the forecasting model in this study was evaluated based on its ability to consistently represent downtime event patterns and predict component failure intervals, rather than solely using numerical error indicators. This approach was chosen because the data used was event count with a limited number of observations and the research objective was oriented towards operational decision-making. Therefore, model accuracy was assessed through the results of residual diagnostic tests, the pattern match between actual data and model estimation results, and the stability of forecast projections against historical data patterns.

The results of the diagnostic evaluation using the Ljung–Box test on all modeled on-board parts show a significance value above the 5 percent confidence level. This finding indicates that the model residuals are random (white noise) and do not contain significant autocorrelation, so that the main temporal dependency structure in the failure event data has been successfully captured by the ARIMA (1,0,1) model. With no remaining systematic patterns found in the residuals, the model can be said to have adequate accuracy in representing component failure intervals based on historical data.

In addition to residual testing, the model's accuracy was also evaluated through visual observation of a comparison graph between the actual data (observed) and the model's estimated results (fit). The observation results show that the model's estimated line follows the general trend of the actual data pattern without exhibiting repeated extreme deviations. The absence of a consistent deviation pattern between the estimated results and the actual data indicates that the model does not experience significant underfitting or overfitting, thus being able to represent the dynamics of down events stably.

In the context of failure interval prediction, the forward forecasting results show a relatively stable trend and are within acceptable confidence limits. This reflects the model's ability to adequately project the timing of the next disruption without producing predictions that are either too aggressive or too conservative. Thus, although the model is not designed to provide absolute precision failure time estimates, the forecasting results still provide relevant information for anticipating periods of increased risk of operational disruption

Based on this evaluation, it can be concluded that the ARIMA (1,0,1) model has an adequate level of accuracy to be used as a tool to predict component failure intervals in the context of autonomous loader operations at the GBC Mine. The model accuracy in this study is functional and applicable, meaning it is sufficient to support forecast-based component maintenance and replacement decisions. Therefore, the forecasting results can be relied upon as the primary input in developing a forecast-based decision framework, which is the main contribution of this study.

Decision-Making Framework to Integrate Forecasting Results in Determining the Optimal Timing for Component Replacement on Autonomous Loaders

The downtime forecasting results analyzed in the previous subchapter demonstrate that trend-based and projection-based information plays a strategic role in supporting maintenance decision-making. However, forecasting outputs cannot be directly translated into replacement actions without a structured interpretation mechanism. Therefore, this study develops a decision-making framework that integrates ARIMA-based forecasting results with operational risk considerations and component criticality assessment, ensuring that replacement decisions are not solely triggered by actual failures but also informed by early degradation signals identified through time-series modeling.

The framework positions forecasting results as the primary input in evaluating component condition and failure probability. Information generated from the ARIMA model, including fluctuation intensity, forecast trend direction, confidence intervals, and historical degradation patterns, is used to estimate the likelihood of future failure. These probabilistic insights are then combined with operational impact levels, representing the consequence dimension of risk, to determine replacement priority. Through this approach, components exhibiting increasing degradation trends and high criticality can be identified before functional breakdown occurs.

Table 1 Decision-Making Framework for Component Replacement Based on Forecasting Results

No	On-Board Component	Historical Event Down Pattern	Forecasting Results	Operational Impact Level	Estimated RUL Condition	Recommended Replacement Strategy
1	Ladar	High frequency with recurring fluctuations	Stable with variations within confidence limits	Very high (navigation & safety)	Gradually decreasing	Preventive replacement based on forecasting results and time intervals
2	Camera	Moderate to high frequency, fluctuating	Stable without extreme spikes	High (visualization & control)	Relatively stable	Condition-based replacement with intensive monitoring
3	Communication	Sharp fluctuations during	Stable during the	Very high (ROS connectivity)	Moderate	Conditional replacement based on

		specific periods	forecasting period			forecast trends and recurring disturbances
4	RSM	High fluctuation with sporadic spikes	Stable after the historical period	High (system control)	Irregularly decreasing	Scheduled replacement with periodic evaluation based on forecasting results

Source: Results of ARIMA forecasting analysis and research discussion, 2026

As presented in Table 4.13, the framework translates forecasting outcomes into structured replacement strategies for each onboard component. Rather than relying exclusively on historical failure occurrences, the model integrates projected downtime trends, component criticality, and estimated Remaining Useful Life (RUL) conditions. High-criticality components such as Ladar and Communication are prioritized for preventive or conditional replacement based on forecast behavior, while components with stable projected trends, such as Camera and RSM, are managed through condition-based or scheduled replacement strategies. This structured interpretation enables optimized replacement timing, reducing the risk of sudden failure while avoiding premature maintenance actions.

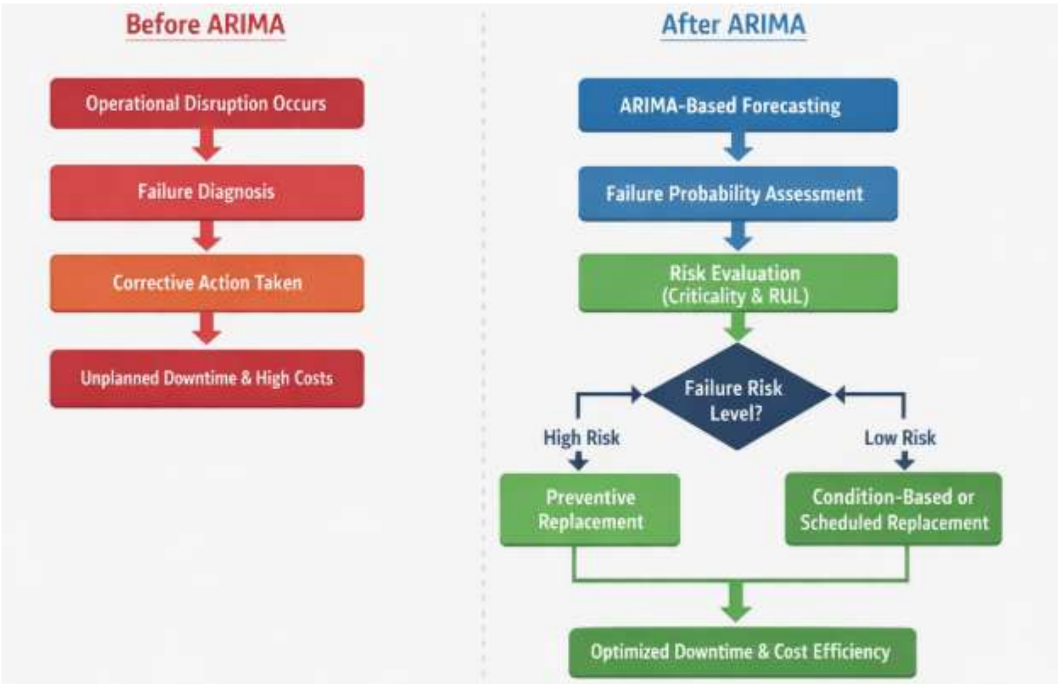

Figure 1 Component Replacement Decision Process Before vs After ARIMA

Figure 1 illustrates the conceptual transition from a reactive maintenance approach to a forecast-informed predictive maintenance framework supported by ARIMA-based forecasting. This framework demonstrates how forecasting outputs can be translated into structured maintenance decision processes that minimize operational disruption and improve equipment reliability.

Before the implementation of ARIMA-based forecasting, component replacement decisions at the GBC Mine primarily followed a reactive or corrective maintenance approach. Replacement actions were initiated only after operational disruption occurred, particularly when failures directly affected ROS stability, navigation accuracy, or system control. While this approach addressed immediate breakdowns, it lacked the capability to anticipate degradation trends, thereby increasing the exposure to unplanned downtime and operational instability. Following the integration of ARIMA forecasting, historical downtime events could be modeled to capture temporal dependency and emerging failure tendencies. This enabled a transition from corrective maintenance to forecast-informed predictive maintenance, where replacement timing is determined based on projected risk levels rather than solely on observed failures. The primary operational benefits include reduced unexpected downtime, improved maintenance timing accuracy, enhanced cost efficiency, and increased system reliability in the underground mining environment.

To demonstrate the operational impact of the forecasting-based decision framework illustrated in Figure 4.10, a comparative analysis between the reactive maintenance approach (Before ARIMA) and the forecast-informed predictive maintenance approach (After ARIMA) is conducted. The comparison focuses on three operational indicators: downtime duration, potential production loss, and maintenance-related operational cost.

Baseline Operational Condition (Before ARIMA)

Prior to the implementation of forecasting-based maintenance planning, component replacement decisions were primarily triggered after operational disruption occurred. This corrective maintenance approach required immediate troubleshooting and component replacement once failures affected autonomous loader performance. Based on historical maintenance records, the average repair duration for critical onboard component failures ranges between 3–5 hours, depending on component accessibility and troubleshooting complexity. In this analysis, an average repair duration of 4 hours per event is assumed.

Considering that an autonomous loader in the GBC Mine has an average hauling capacity of 230 tons per hour, each downtime event results in a significant potential production loss.

Downtime Impact Calculation (Before ARIMA)

Production Loss = Hauling Capacity × Downtime Duration

Production Loss = 230 tph × 4 hours

Production Loss = 920 tons per event

Assuming that critical component failures occur approximately 10 events per month across autonomous loader operations, the estimated production loss becomes:

Monthly Production Loss = 920 × 10

Monthly Production Loss = 9,200 tons

This situation indicates that the reactive maintenance approach potentially causes 9,200 tons of disrupted material flow per month, which directly impacts hauling productivity and operational efficiency.

Forecast-Informed Maintenance Scenario (After ARIMA)

Following the implementation of ARIMA-based forecasting, the maintenance strategy shifts from reactive intervention to forecast-informed predictive maintenance. Instead of waiting for failures to occur, maintenance teams can schedule preventive replacement during planned maintenance windows when forecasting results indicate an increasing probability of failure.

This proactive approach reduces unplanned downtime and shifts part of the maintenance activities to scheduled replacement intervals, which typically require less operational interruption. In scheduled preventive maintenance scenarios, component replacement can often be performed within 1–2 hours, as troubleshooting is minimized and spare parts are prepared in advance. For this analysis, an average preventive maintenance downtime of 1.5 hours per event is assumed.

Downtime Impact Calculation (After ARIMA)

Production Loss = 230 tph × 1.5 hours

Production Loss = 345 tons per event

Assuming that the same number of maintenance interventions occurs but under planned conditions:

Monthly Production Loss = 345 × 10

Monthly Production Loss = 3,450 tons

Downtime Reduction and Production Efficiency

Table 2 summarizes the comparison between reactive maintenance and forecast-informed predictive maintenance.

Table 2 Comparison of Operational Impact Before and After ARIMA Implementation

Indicator	Before ARIMA (Reactive Maintenance)	After ARIMA (Forecast-Based Maintenance)
Average repair duration	4 hours	1.5 hours
Production loss per event	920 tons	345 tons
Estimated events per month	10	10
Monthly production loss	9,200 tons	3,450 tons
Downtime reduction	-	62.5% reduction
Production loss reduction	-	5,750 tons saved per month

The comparison highlights the practical advantage of integrating forecasting models into maintenance decision-making processes, particularly in high-intensity mining operations where equipment downtime directly impacts production throughput. The results indicate that the implementation of forecasting-based maintenance planning can potentially reduce downtime-related production loss by approximately 62.5%, representing a significant operational efficiency improvement.

The implementation of forecasting-based maintenance provides several forms of operational improvement within the autonomous loader system. One of the most evident improvements is the reduction of unplanned downtime, as component replacement decisions are no longer triggered only after failures occur but are instead scheduled based on forecasting indications of potential degradation. By anticipating failure trends earlier, maintenance teams are able to intervene before operational disruption happens. This proactive approach also contributes to shorter repair durations because preventive replacement eliminates the need for extensive troubleshooting processes that usually occur in reactive maintenance situations. In addition, forecasting enables better maintenance preparation, including more effective spare part availability planning and improved maintenance crew scheduling. As a result, maintenance activities can be conducted more efficiently and with minimal interruption to production operations. Furthermore, the forecasting results indicate that operational disruption patterns tend to stabilize, as demonstrated by projected downtime trends that remain within controlled confidence limits. These improvements collectively contribute to more stable autonomous loader operations, reduced operational risk, and improved reliability of mining equipment operating in the extreme underground environment of the GBC Mine.

Based on the forecasting analysis and the interpretation of component degradation trends, several strategic maintenance recommendations can be formulated. For components with high operational criticality, such as LADAR and communication modules, preventive replacement is recommended when forecasting results indicate an increasing disruption trend or when the projected failure probability reaches a critical level. Since these components play a key role in navigation accuracy and ROS connectivity, early replacement is essential to avoid system-wide operational disruption. For components with moderate operational impact, such as camera and RSM modules, a condition-based monitoring approach is recommended. In this strategy, component conditions are continuously monitored and replacement is performed only when degradation indicators exceed acceptable operational thresholds. In addition, forecasting results should be integrated into the existing maintenance planning systems used by the mining operation so that replacement decisions can be scheduled proactively rather than reactively. For future development, it is also recommended that additional condition-monitoring data, such as vibration, temperature, and sensor diagnostic parameters, be incorporated into predictive maintenance models. The integration of these additional data sources would further improve the accuracy and reliability of component degradation forecasting.

To operationalize the forecasting-based decision framework proposed in this study, several practical operational actions can be implemented within the autonomous loader maintenance management system. First, forecast-based maintenance scheduling should be established for critical onboard components to ensure that replacement activities are conducted during planned maintenance windows before failures occur. Second, ARIMA-based forecasting outputs should be integrated into maintenance planning dashboards to support real-time monitoring of component degradation trends and potential disruption risks. Third, a risk-based maintenance prioritization system should be implemented, where replacement priorities are determined based on component criticality, operational impact, and forecasting results. Finally, periodic evaluation of forecasting model performance should be conducted using updated operational data to ensure that the forecasting model remains accurate and relevant to changing operational conditions. Through the implementation of these actions, the forecasting model developed in this research evolves from a purely analytical tool into a practical decision-support system capable of supporting predictive maintenance strategies and improving the operational reliability of autonomous mining equipment.

In addition to supporting maintenance scheduling decisions, the forecasting results also provide important implications for spare parts procurement planning. By analyzing the projected trend of downtime events generated by the ARIMA model, the maintenance and asset management teams can estimate the potential demand for critical onboard components in future operational periods. This forecasting-based procurement approach allows the company to anticipate spare part requirements earlier and avoid delays caused by material shortages during maintenance activities.

For example, the forecasting trend for LADAR-related downtime events indicates a relatively stable but recurring disturbance pattern throughout the projected period, suggesting that at least two replacement units should be prepared within the next three months to ensure availability during scheduled preventive maintenance. Similarly, the projected failure pattern for the RSM module indicates moderate fluctuation with potential recurrence in the mid-forecast period, suggesting that approximately two spare units should be prepared before the fourth month of the forecast horizon. For communication modules, the forecast trend shows occasional spikes associated with operational disturbances; therefore, maintaining a minimum inventory level of two units within the next two to three months is recommended to mitigate unexpected system disruptions. Meanwhile, the camera component exhibits relatively stable forecasting results, indicating lower immediate replacement urgency, but it is still recommended that one to two spare units be prepared within the next four months to support preventive replacement if degradation signals increase.

By integrating forecasting outputs with procurement planning, the maintenance management system can transition from reactive spare-part ordering to a more strategic and data-driven inventory planning approach. This enables the company to optimize spare part availability, reduce emergency procurement costs, and improve maintenance readiness for autonomous loader operations. As a result, forecasting not only supports predictive maintenance decisions but also contributes to more efficient supply chain management for critical mining equipment components.

Based on the projected downtime frequency generated by the ARIMA forecasting model, an estimated spare part procurement plan can be developed to ensure material availability for preventive maintenance activities. The estimated spare requirement is derived from the projected failure frequency of each critical onboard component within the forecasting horizon. Components with higher forecasted disturbance frequency, such as LADAR and communication modules, require a larger number of spare units within earlier procurement periods to prevent operational disruption. Meanwhile, components with relatively stable forecast patterns, such as camera and RSM modules, require fewer spare units and can be scheduled for procurement in later periods within the forecasting horizon.

Table 3 Forecast-Based Spare Part Procurement Plan Based on ARIMA Projection

Component	Average Historical Failure (events/month)	Forecasted Failure Trend	Estimated Spare Requirement	Recommended Procurement Period
LADAR	3 - 4 events	Recurring disturbance trend	2 - 3 units	Month 2 - 3
Communication	2 - 3 events	Occasional spikes	2 units	Month 2
RSM	1 - 2 events	Moderate fluctuation	2 units	Month 4
Camera	1 - 2 events	Stable trend	1–2 units	Month 4

The procurement plan presented in Table 3 demonstrates how forecasting results can be translated into practical inventory planning decisions. By estimating the expected failure frequency of each component, the maintenance management team can determine the number of spare units required and schedule procurement activities accordingly. This approach helps

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ensure spare part availability during preventive maintenance while avoiding excessive inventory levels. Consequently, forecasting-based procurement planning supports both maintenance readiness and cost efficiency in autonomous loader operations at the GBC Mine.

This transformation from reactive maintenance to forecast-informed predictive maintenance aligns with recent developments in predictive maintenance literature. (Dayo-Olupona, 2023) highlights the continued relevance of statistical time-series models such as ARIMA in mining equipment reliability analysis where failure data exhibit strong temporal dynamics. (Fatima, 2024) further emphasize that ARIMA remains effective in capturing short-term fluctuations in industrial systems characterized by non-stable event patterns. Similarly, (Di, 2025) demonstrates that autoregressive models outperform smoothing-based approaches when dealing with dynamic and event-driven industrial time series. From a strategic maintenance perspective, (Goli, 2025) underscore the importance of integrating risk evaluation with quantitative forecasting models to enhance maintenance decision effectiveness.

The decision-making framework adopted in this study is therefore grounded in established Risk-Based Maintenance (RBM) and Reliability-Centered Maintenance (RCM) principles, which are widely recognized in industrial asset management literature. Within this structure, ARIMA-based forecasting serves as a probability estimator, while operational impact levels represent consequence severity. By combining probability and consequence dimensions, replacement decisions are formulated based on quantified risk exposure, ensuring alignment with established maintenance engineering theory rather than relying on ad hoc or novel unvalidated conceptual models. This structure reflects the classical risk formulation where risk is defined as a function of probability and consequence, thereby operationalizing forecasting results within a structured maintenance decision paradigm.

Overall, the findings of this study demonstrate that the integration of ARIMA-based forecasting into maintenance decision-making provides a structured and data-driven approach for managing component reliability in autonomous mining systems. By transforming historical downtime data into predictive insights, the proposed framework enables maintenance teams to anticipate potential failures, optimize replacement timing, and improve operational preparedness. The quantitative comparison between reactive and forecast-informed maintenance scenarios also illustrates the potential operational benefits in terms of downtime reduction and production efficiency. Furthermore, the integration of forecasting results with spare-part procurement planning strengthens maintenance readiness and supports more efficient inventory management for critical onboard components. These results indicate that forecasting models can play a strategic role not only in predictive maintenance but also in broader asset management and operational planning within complex underground mining environments. Therefore, the forecast-based decision framework developed in this research provides a practical foundation for improving equipment reliability, reducing operational disruption, and enhancing maintenance governance in autonomous loader operations at the GBC Mine.

DISCUSSION

The findings of this study indicate that the degradation behavior of ROS and onboard components in autonomous loaders operating at the GBC Mine follows a non-random and progressive pattern. This observation suggests that component failures are not stochastic events but rather the result of cumulative operational stress and environmental exposure. This pattern is consistent with the principles of reliability engineering, where components transition into a wear-out phase characterized by increasing failure rates over time, as discussed by K. B. Misra (2008). The recurring failure trends observed in joystick and other onboard components reinforce the argument that degradation is systematic and predictable, supporting the suitability of forecasting-based approaches for maintenance planning.

However, while reliability engineering provides a theoretical explanation for degradation patterns, the practical challenge lies in translating these patterns into actionable maintenance decisions. In this context, the application of the ARIMA (1,0,1) model in this study demonstrates that statistical time-series methods are capable of capturing temporal dependencies in failure data. This finding aligns with the work of O. Dayo-Olupona (2023), who emphasizes that mining equipment failures often exhibit structured temporal behavior rather than purely random distributions. Similarly, S. S. Fatima (2024) highlights that ARIMA models remain effective for industrial systems with fluctuating and event-driven data, particularly when datasets are limited in size and complexity.

Despite this consistency, it is important to critically evaluate the limitations of ARIMA-based forecasting in the context of complex underground mining operations. While ARIMA performs well in capturing linear temporal patterns, it may not fully account for non-linear interactions between environmental variables, operational intensity, and component degradation. Previous studies, such as those discussed by J. Di (2025), suggest that machine learning approaches, including recurrent neural networks, may provide superior performance in handling non-linear and high-dimensional datasets. Therefore, although ARIMA is appropriate for the current study due to data limitations and interpretability requirements, its predictive capability may be constrained in more complex or data-rich environments.

A key contribution of this study lies in extending the role of forecasting beyond prediction into decision-making. While prior research has largely focused on failure prediction or Remaining Useful Life (RUL) estimation, this study integrates forecasting outputs into a structured decision-making framework that incorporates operational risk and component criticality. This approach is consistent with the framework proposed by M. Goli (2025), which emphasizes that predictive models should be embedded within risk-based maintenance strategies to improve decision effectiveness. By operationalizing forecasting results into replacement strategies, this study addresses a critical gap between analytical modeling and practical implementation in maintenance systems.

From an operational perspective, the findings of this study provide empirical evidence supporting the effectiveness of forecast-informed maintenance. The estimated reduction of downtime-related production loss by approximately 62.5% demonstrates a significant improvement in operational efficiency when compared to reactive maintenance approaches. This result supports the findings of M. Ahern (2022), who argues that proactive maintenance strategies can substantially reduce unplanned downtime and enhance system reliability. However, it is important to note that the estimated impact in this study is based on modeled assumptions rather than real-time implementation data, which may introduce potential bias in estimating operational benefits.

Furthermore, this study highlights the critical role of environmental factors in influencing component degradation in underground mining environments. Unlike many

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industrial studies conducted in controlled environments, the GBC Mine presents extreme operational conditions, including high vibration, dust exposure, and humidity. These factors not only accelerate degradation but also introduce variability that may affect forecasting accuracy. This finding suggests that predictive maintenance models developed in controlled industrial settings may not be directly transferable to underground mining without incorporating environmental variables. Therefore, this study contributes to the literature by emphasizing the importance of contextualizing predictive models within specific operational environments.

Despite its contributions, this study has several limitations that should be critically acknowledged. First, the absence of real-time condition monitoring data limits the ability to perform precise RUL estimation, resulting in a reliance on trend-based and conceptual interpretations. Second, the use of historical event data may not fully capture the dynamic interactions between operational variables and component degradation. Third, the generalizability of the findings is limited to the GBC Mine context, as different mining environments may exhibit different failure characteristics.

Future research should address these limitations by integrating real-time sensor data, such as vibration, temperature, and system diagnostics, into predictive models to enhance forecasting accuracy and enable quantitative RUL estimation. Additionally, comparative analysis between statistical models and advanced machine learning techniques, such as Long Short-Term Memory (LSTM) networks, would provide deeper insights into model performance in complex industrial environments. Incorporating economic optimization models into the decision framework would also strengthen its practical applicability by balancing maintenance costs and production risks.

CONCLUSION

This chapter presents the main conclusions derived from the research on the development of a forecast-based decision framework for the replacement of Remote Operating System (ROS) and onboard components in autonomous loaders at the Grasberg Block Cave (GBC) Mine, PT Freeport Indonesia. Based on the analysis of historical down event data, ARIMA time series forecasting, reliability engineering, and operational risk analysis, the study concludes that ROS and onboard components—especially joysticks—experience progressive degradation rather than random failure, with repeated replacements indicating that these components have entered the wear-out phase and allowing implicit estimation of Remaining Useful Life (RUL). Operational factors in the underground mining environment, including high vibration, mineral dust exposure, humidity, and intensive work cycles, significantly accelerate component degradation and increase failure frequency. The ARIMA (1,0,1) model proved sufficiently accurate in predicting component failure intervals, supported by Ljung–Box test results showing random residuals, indicating the model effectively captures temporal patterns of down events and can be reliably used for maintenance planning. This research also produced a forecast-based decision framework integrating forecasting results, degradation estimates, and operational risk analysis to determine optimal replacement timing, shifting maintenance strategies from reactive to proactive and improving operational efficiency. Key findings further reveal that critical components such as radar, camera, communication, and RSM contribute most to system downtime and therefore require prioritized maintenance attention. Practically, the forecasting-based approach enables earlier maintenance actions, more accurate spare parts planning, reduced unplanned downtime, and more stable hauling operations. Therefore, it is recommended that PT Freeport Indonesia integrate this framework into its existing maintenance system, improve maintenance data quality and consistency, optimize spare parts inventory based on forecasting outputs, and strengthen coordination among maintenance teams, reliability engineers, and operators. For future research, expanding data coverage, integrating condition monitoring and environmental data, applying sensor-based RUL estimation, and comparing ARIMA with machine learning and deep learning methods are recommended to enhance prediction accuracy and support a more sustainable, proactive, and data-driven maintenance system in complex underground mining environments.

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