Predictive Maintenance in Underground using artificial intelligence

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Abstract – The article addresses predictive maintenance (PdM) applied to underground mining equipment using artificial intelligence, a crucial approach for improving efficiency and reducing operating costs. The objective is to optimize the equipment's lifespan through early fault detection, avoiding costly repairs and unplanned downtime. The challenge lies in the extreme conditions and intensive use of the equipment, which makes it difficult to predict failures using traditional methods. The methodology includes continuous monitoring of key parameters (temperature, pressure, oil analysis, thickness measurement) through sensors and real-time data analysis. This data is processed using artificial intelligence and machine learning techniques to identify patterns that precede failures. The results show that PdM can reduce maintenance costs by 8% and increase equipment availability by 10%, leading to greater productivity and safety in underground mining operations

Keywords - Predictive maintenance, Underground mining, Artificial intelligence, Sensors, oil analysis.

1. Introductión

In underground mining, growth is evident in the real-time monitoring of mobile assets, improving their efficiency, condition and performance. [1]. The importance of improving mining roads to optimize equipment performance and reliability is emphasized. Poor road conditions accelerate tire and structural wear, and negatively impact equipment performance. [2]. In addition, equipment stops in the mining sector generate a high impact on production and therefore economic losses [3]. However, in open pit mining, low efficiency and failure of ore hauling trucks generate a significant impact on the economic indicators of mining [4]. The lack of PdM in underground mining equipment contributes to poor decision making, lack of planning and therefore high maintenance costs and low equipment reliability [5]. An alternative to improve the reliability of underground mining equipment is the implementation of PdM with advanced techniques. Low availability of mining equipment can have a high impact on the mining operation process. Therefore, the maintenance of mining equipment can reach between 35% and 50% of the mine budget, despite having preventive and predictive maintenance strategies, when the equipment suffers frequent failures, it impacts the operation [6].

The problem of low equipment availability is due to the lack of new failure analysis techniques, inadequate planning and implementing it will optimize maintenance costs and improve the useful life of the equipment and therefore improve the availability of mining equipment [7]. Maintenance strategies such as Preventive Maintenance (PM), Corrective Maintenance (CM) and PdM are crucial to improve the availability of equipment in mining and reduce operating costs [8]. However, the lack of monitoring and the lack of historical data records and maintenance management systems in equipment generates a neglect of equipment monitoring [9]. The absence of monitoring and poor decision making can deteriorate the operational condition of the equipment. Therefore, the importance of using new predictive maintenance techniques to efficiently predict failures and maintain the operability of the equipment.

Many researchers have proposed several predictive maintenance techniques. In they propose a hybrid model with metaheuristic algorithms to predict the failure time in mining equipment, achieving an R^2 accuracy of 0.99 [10]. On the other hand, the use of the data mining technique for haul trucks in mining, where it is possible to diagnose critical failures and predict the useful life of the trucks [11]. In they use condition monitoring based on autoregressive fault detection in underground mine electrical machines, managing to detect failures and improving reliability and reducing operating costs [12]. Similarly, of use lubrication condition monitoring (LCM) to support the diagnosis and prognosis of maintenance failures, highlighting approaches and techniques that facilitate decision making through lubricant analysis [13]. Applying oil analysis to assess the health of a machine and detect failures in advance, using sensors such as capacitive, inductive, acoustic and optical, online, that measure lubricant properties such as wear residue, water, viscosity and sulfur content [14].

Critical fault detection parameters: elevated temperature signals friction/lubrication issues; viscosity reduction indicates contamination/degradation; metallic particles reveal component wear. Together, they enable proactive maintenance before failure occurs. However, using the Internet of Things to predict the maintenance needs of machines, where the use of real-time data is essential to develop predictive models [15]. These data, which include detailed information on component condition and operational performance, enable proactive fault anticipation and targeted maintenance scheduling, thereby optimizing maintenance strategies and minimizing equipment downtime

Despite the importance of using predictive maintenance in mining, predictive techniques were only found used in some mining equipment, however, it is necessary to cover other equipment that is considered in the mineral extraction process, specifically in underground mining. Therefore, it is worth using new predictive techniques in accordance with technological advances. The purpose of this study is to use artificial intelligence to optimize predictive maintenance, to improve the ability to predict equipment failures before they occur, optimizing resources and reducing maintenance and repair costs. This will allow equipment interventions to be scheduled in a timely manner, avoiding unexpected downtime, increasing the useful life of the equipment and improving equipment availability.

The main contribution of the article is to provide the use of artificial intelligence to optimize the PdM of underground mining equipment. The remainder of the article is organized as follows. Section 2 reviews new trends in PdM in mining. Section 3 develops the methodology; the results are presented in Section 4. Finally, the conclusions are presented in Section 5.

2. Review

PdM stands out for its ability to predict failures and optimize the operation of mining equipment through early failure detection. Unlike MP, which prevents the failure, and MC, which acts after the failure occurs, PdM offers a proactive solution. Many studies have proposed different advanced predictive techniques to improve the operation of mining equipment. The use of the Internet of Things (IoT) to monitor equipment in a coal mine, achieving greater operational efficiency [16].

On the other hand, the propose implementing real-time condition monitoring in ore hauling trucks, reducing equipment downtime and maintenance costs [17]. However, consider that MP and MC are not sufficient for critical equipment, especially in mills of the mineral concentration plant, so they propose the use of PdM using mathematical algorithms to optimize the maintenance of critical equipment [18]. Furthermore, in use laser scanning to predict the wear of ball mill liners [19]. On the other hand, PdM is used to predict fatigue fractures in turbocharger axles of mining trucks [20].

While proposing a hybrid model for miners achieving a 10.9% reduction in fuel consumption [21]. On the other hand, integrating PdM with the Weibull distribution improves sustainability and optimizes resources in the maintenance area [22]. To increase availability, reduce maintenance costs and optimize equipment life, the implementation of PdM in combination with other techniques is essential [23].

The application of machine learning models, powered by artificial intelligence (AI) techniques, offers more detailed and interpretable results for decision making, significantly improving spare parts management [24]. Specifically, AI facilitates the prediction of critical moments in the operation of underground mining machinery, such as sharp turns, as well as the analysis of dynamic overloads [25]. Techniques such as logistic regression and Random Forest have proven to be effective in this context. Additionally, the use of digital twins has revealed high accuracy in fault prediction, surpassing the performance of conventional models such as CNN and LSTM [26].

Furthermore, with the integration of Digital Twins (DT), (IoT) with predictive maintenance has transformed the manufacturing industry, optimizing production up to 30% and reducing costs up to 40% [27]. These technologies enable real-time monitoring, advanced simulations and predictive decision making, improving the resilience and visibility of the supply chain in the era of Industry 4.0. On the other hand, for the same sector, Explainable AI (XAI) and sensor fusion with techniques such as Random Forest and Fourier Transform (FFT) achieved 95% accuracy in fault detection, reducing downtime and improving operational efficiency and resilience in the supply chain and driving a reliable maintenance strategy in the era of Industry 4.0 [28].

In the mechanical industry, a deep learning approach and Wavelet transformation were applied to analyze the health of gearboxes. This allowed faults to be detected with 97.11% accuracy, outperforming traditional methods and improving reliability, reducing costs and downtime [29]. In the automotive industry, a methodology based on DT, data-based maintenance prioritization, genetic optimization and dispatch rules was implemented. This allowed the optimization of the allocation of maintenance tasks, reducing downtime, increasing productivity and improving operational efficiency in production lines [30].

3 Methodology

For the development of this work, historical data on mining machine failures, as well as oil analysis and equipment failure reports, will be used. Figure 1 shows the development methodology.

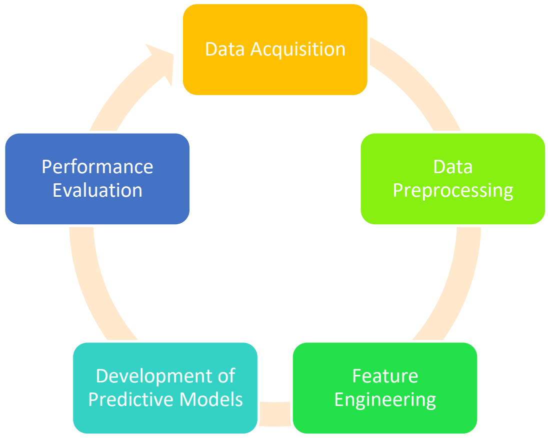

Fig. 1. Methodology

3.1. Data Acquisition: First, system shutdown records for each piece of equipment, engine system oil analysis data, and failure reports will be collected. The data will cover from January 2023 to May 2024.

For the development of this study, an exhaustive collection of historical data on mining machine failures will be carried out, covering detailed records of downtime and failures classified by system in each piece of equipment. Additionally, engine system oil analysis reports will be analyzed, allowing not only to evaluate the current state of the equipment, but also to adjust the frequency of preventive maintenance based on observed wear trends and specific operating conditions.

In the context of underground mining, mineral extraction involves multiple interconnected processes, with the mechanized support being the last link in the production circuit. Therefore, this study focuses on the analysis of the failures of this critical equipment, collecting data from January 2023 to April 2024. The information obtained will be essential to evaluate operational reliability and optimize maintenance strategies.

Figure 2 shows that the highest number of failures is concentrated in the engine system, followed by the hydraulic and electrical systems. These three systems accumulate more than 80% of the total failures, which suggests that they should be prioritized in maintenance strategies. The steering, additives and brake systems have a lower incidence of failures, contributing marginally to the accumulated total.

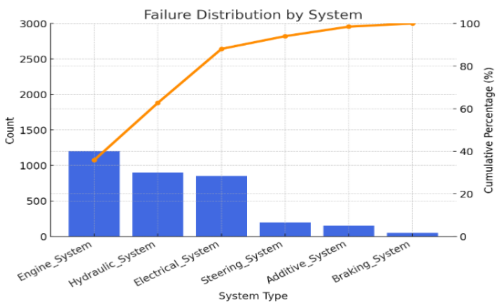

Fig. 2. Equipment failure report

3.2. Data Preprocessing: Data will be cleaned and transformed to ensure its quality and consistency. This will include handling missing data, correcting inconsistencies, and normalizing the data.

3.3. Feature Engineering: From the preprocessed data, key maintenance indicators such as mean time between failures (MTBF) and mean time to repair (MTTR) will be calculated. In addition, wear trends in internal diesel engine components will be analyzed from oil analysis, generating relevant features for prediction.

In the feature engineering stage, essential metrics will be calculated to evaluate the reliability and efficiency of the equipment. The Mean Time Between Failures (MTBF) will be determined, which quantifies the frequency of breakdowns, and the Mean Time to Repair (MTTR), which measures the efficiency in the execution of corrective actions. These metrics are critical to optimizing equipment availability and refining maintenance planning.

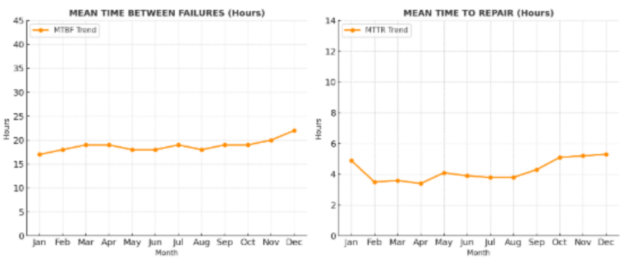

Fig. 3. MTTR y MTBF

The MTBF analysis reveals an upward trend throughout the year, suggesting an improvement in system reliability, with failures occurring increasingly spaced out over time. In contrast, the MTTR exhibits a slight downward trend, indicating an overall reduction in the time required to repair breakdowns throughout the year (see Figure 3). These trends will allow us to understand the behavior of the equipment and prioritize maintenance actions.

3.4. Development of Predictive Models: For failure prediction, the ARIMA (Autoregressive Integrated Moving Average) algorithm will be used, which is effective in modeling and forecasting future events based on historical patterns. This approach will allow trends and behaviors to be identified in past failure data. The application process of this algorithm is illustrated in Figure 4.

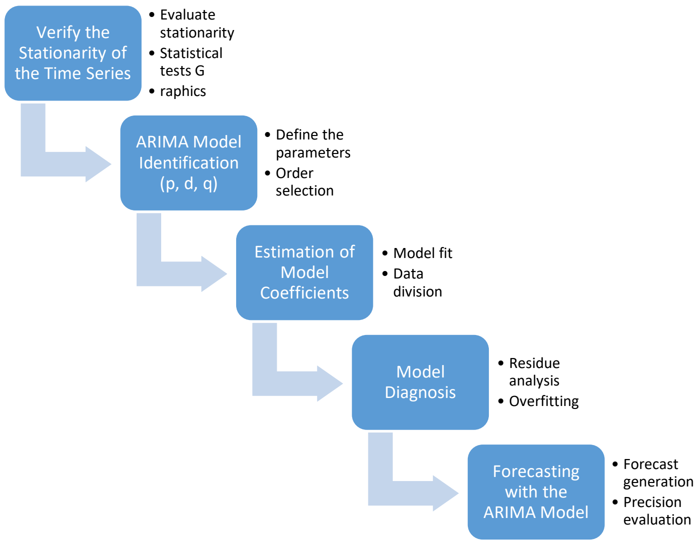

Fig. 4. ARIMA Modeling Flowchart

In addition to the ARIMA model, advanced machine learning techniques will be used to improve the accuracy of fault prediction. Models such as XGBoost, Random Forest and Recurrent Neural Networks (RNN) will be implemented, as well as Long Term Memory (LSTM) models. These approaches will allow you to anticipate the next failure by analyzing the historical behavior of the equipment, providing a more comprehensive and accurate view for maintenance planning.

Additionally, oil analysis will be incorporated as a complementary technique to monitor the internal state of the systems, both engines and hydraulic systems. The oil analysis will act as a "window" into the interior of the machinery, allowing the frequency of current maintenance to be evaluated (Table 1), optimizing it and extending the useful life of the equipment (Figure 5).

TABLE 1.
Maintenance frequency

Tipe of plan	System	Duration (h)
A	Engine	5
B	Engine	6
C	Engine, Transmission	10
D	Engine, Transmission, hydraulic	12

Data derived from oil analysis, including concentrations of metals such as iron, copper and silicon, as well as lubricant viscosity, will be used as key predictor variables within our machine learning models. These critical parameters, which reflect the internal state and wear of the components, will be integrated with the historical failure data previously recorded on the equipment. The combination of these sources of information will be essential for the exhaustive training of XGBoost, Random Forest, Recurrent Neural Networks (RNN) models and, particularly, Long Short-Term Memory (LSTM) architectures.

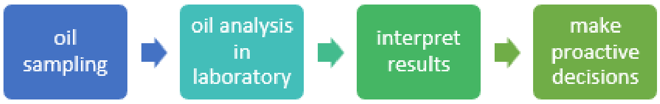

Fig. 5. Oil sampling flow.

The primary goal of this approach is for models to develop the ability to discern subtle patterns and establish meaningful relationships between trends observed in oil analyzes and the probability of future failures. Understanding these interconnections will enable more accurate and proactive prediction of failure events, which in turn will allow you to optimize preventive and corrective maintenance strategies, maximizing equipment life and minimizing unplanned downtime.

3.5. Performance Evaluation: Finally, the performance of the predictive system will be evaluated using precise metrics such as the mean square error (MSE), coefficient of determination (R^2), and accuracy. The results will be compared with historical records to validate the effectiveness of the model.

4. Results

In Figure 3, the need to optimize maintenance management is observed, since an increase in the Mean Time Between Failures (TMEF) is directly related to greater equipment reliability, while a reduction in the Mean Time to Repair (MTTR) suggests better maintainability of the equipment. To achieve these objectives, it is essential to implement artificial intelligence algorithms that allow future failures to be predicted accurately. This will facilitate more informed decision-making and contribute to improving the availability of mining equipment, optimizing the overall performance of operations.

Figure 6 represents the prediction of failures using an optimized ARIMA model. The training data, blue lines, exhibit high variability, while the real data, green, show more controlled fluctuations. However, future predictions, which are red, indicate that decisions must be made and new predictive maintenance strategies must be proposed for mining equipment. The failure projection was given for the month of May 2024.

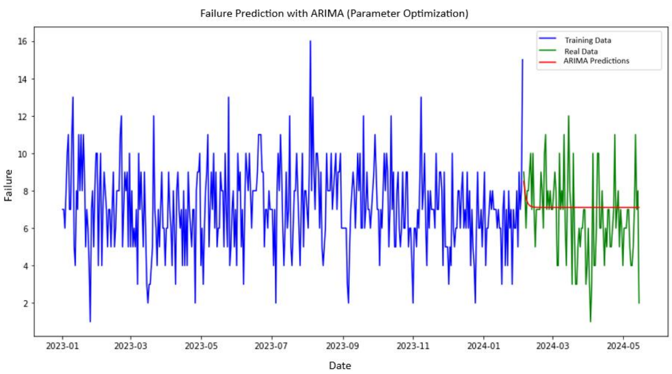

Fig. 6. Future failures in the month of May 2024.

Figure 7 shows the prediction of failures using an ARIMA model. Where the historical data, which is colored blue, presents significant fluctuations, while the real observations, those colored green, reflect a decreasing trend. However, the future predictions, orange lines, starting from June 2024, indicate a constant and flat projection.

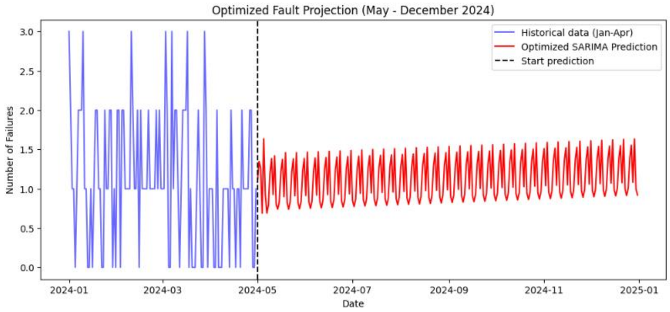

Fig. 7. Future failures throughout 2024

On the other hand, by applying machine learning to the data from the oil analysis results, the evolution of the kinematic viscosity of the oil at 100°C was verified as a function of the hours of use of the oil, comparing the "Before" and "Now" periods. It is observed that the viscosity values remain within acceptable limits (10.4 and 20.7 cSt), which indicates a stable behavior of the oil, although slightly more dispersed in the "Now" period, which could require closer monitoring to ensure operational stability. See Figure 8, this can be interpreted by increasing the maintenance frequency up to 250 hours.

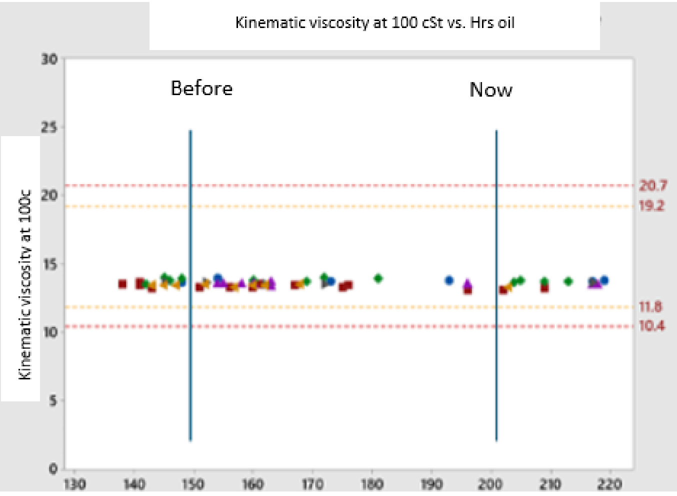

Fig. 8. Viscosity evolution according to working hours

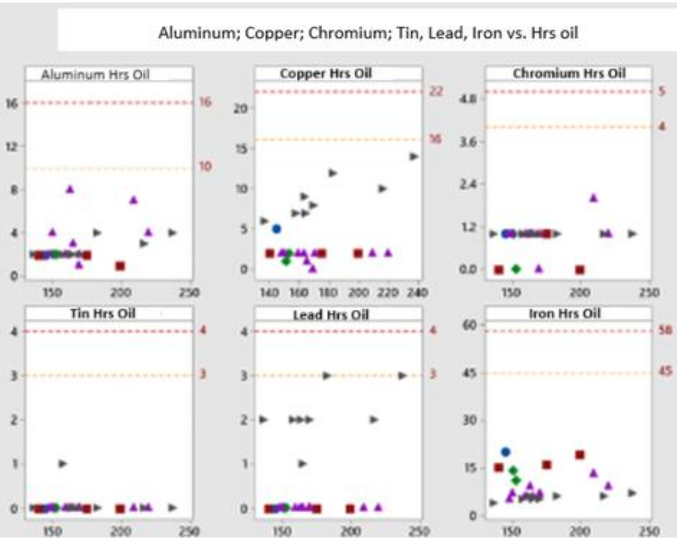

Fig. 9. Evolution of wear metals

Similarly, Figure 9 shows the evolution of six metals (aluminium, copper, chromium, tin, lead and iron) in the oil, compared to the hours of use. In general, the levels of the metals remain within acceptable limits, except for slight increases in iron and chromium, which could indicate wear on components.

From Figures 8 and 9, it can be seen that an increase in the frequency of preventive maintenance is feasible, which would benefit the availability, utilization, and reliability of equipment, as well as reduce equipment maintenance costs.

TABLE. 2
New maintenance frequency scenario.

Type of plan	System	Times per year (before) f=150	Times per year (Now) f=200	Times per year (Now) f=250
A	Engine	36	27	22
C	Transmission	9	7	5
D	Hydraulic	4	2	1

Figure 10 shows the trend of copper (Cu) wear in the diesel engine as a function of the hours of operation of a piece of equipment ("horometer"). Each blue dot represents a measurement of copper wear at a given time, while the red line indicates the overall trend over time, with a shaded area representing the confidence interval for this trend.

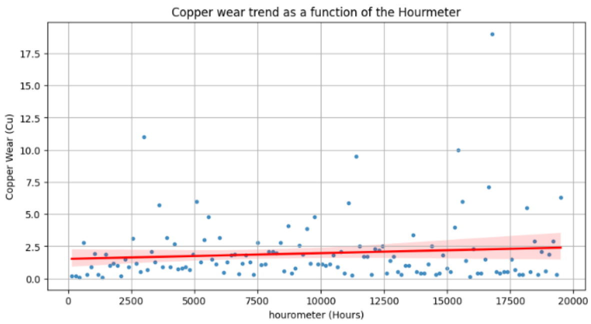

Fig. 10 Copper trend

Figure 11 shows the trend of the presence of silicon in the diesel engine as a function of the hours of operation of a piece of equipment ("hour meter"). Each blue dot represents a measure of the amount of silicon that exists in the oil, while the red line indicates the general trend over time, and a shaded area represents the confidence interval for this trend. Mention that an increase in silicon can generate wear of internal engine components, which is why this trend will allow us to identify preventive measures to avoid further damage to the diesel engine.

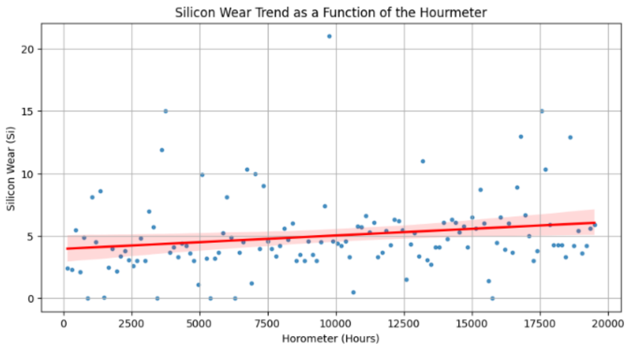

Fig. 11 Silicon trend

Figure 12 shows the iron wear trend in the diesel engine as a function of the hours of operation of a piece of equipment ("hour meter"). Each blue dot represents a measure of the amount of iron that exists in the oil, while the red line indicates the general trend over time. Mention that an increase in iron particles in an oil analysis can indicate several negative consequences for the health and operation of the engine, where it is an indicator of wear of internal engine components.

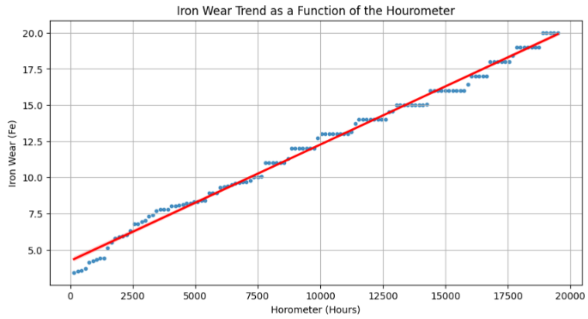

Fig. 12 Iron trend

Figure 13 shows the behavior of oil viscosity in the diesel engine as a function of the hours of operation of a piece of equipment ("hour meter"). Each blue dot represents a measure of the amount of iron that exists in the oil, while the red line indicates the general trend over time, and the shaded area a reliable working area. Mention that an increase in the viscosity value makes the oil more viscous and takes longer to lubricate the engine components, especially during cold starts, which can cause greater wear of the parts.

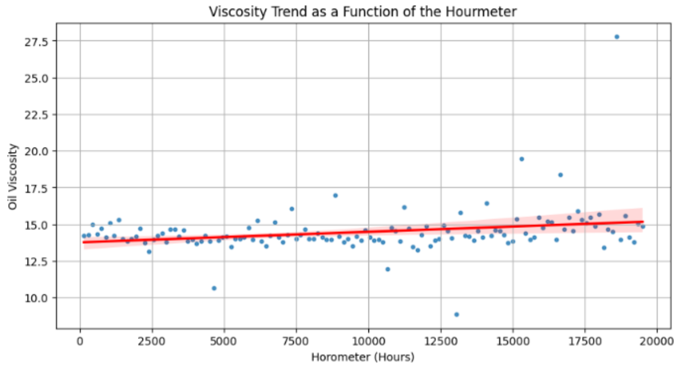

Fig. 13 Viscosity trend

Figure 14 shows the prediction of Fe wear particles with the Random Forest model, where this model is capable of modeling the relationship and making the prediction on the amount of Fe in the future.

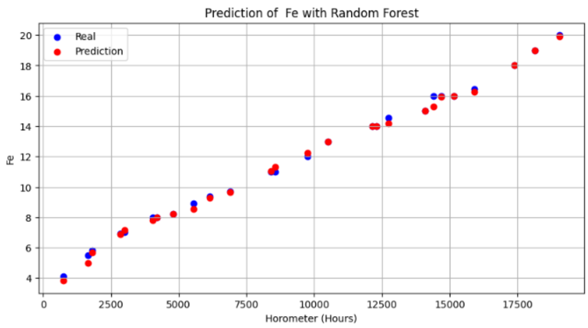

Fig. 14 Model Random Forest

In the same way, it can be seen in figure 15, where the XGBoost model manages to model correctly and therefore a good prediction will be obtained.

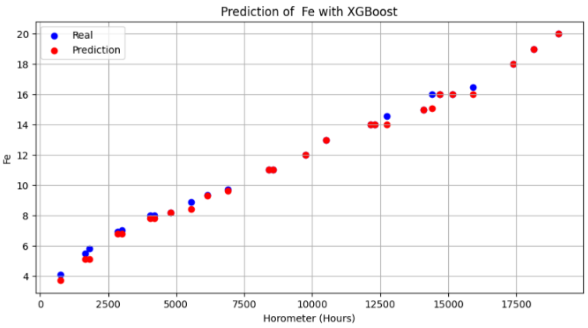

Fig. 15 Model XGBoost

In the same way, it can be seen in Figure 16, where the LSTM model manages to model, but has a greater error compared to the other two models, which is why the prediction made by this model is not more appropriate.

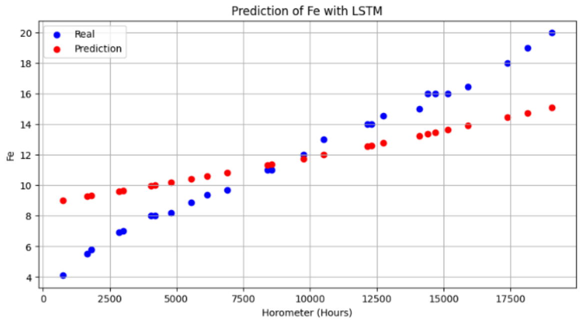

Fig. 16 Model LSTM

Table 3 shows the metrics MAE (Mean Absolute Error), MSE (Mean Squared Error) and R2 Score (R-squared).

TABLE. 3
Summary of model metrics.

Model	MSE	R^2	MAE
Random Forest	0.053193	0.997259	0.148269
XGBoost	0.098789	0.994909	0.184454
LSMT	6.671285	0.656177	2.246763

Figure 17 compares two machine learning models: Random Forest (left) and XGBoost (right), in their ability to predict copper (Cu) wear as a function of time (Horometer).

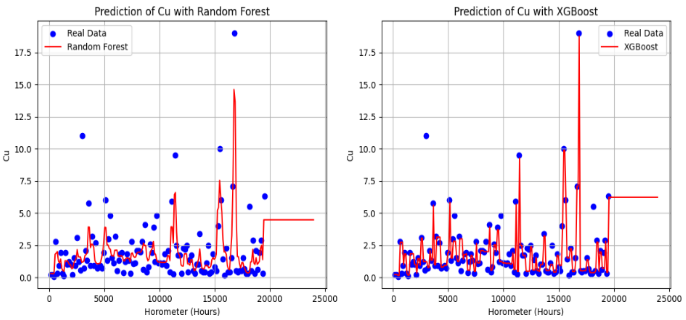

Fig. 17 Prediction Model of Cu

Figure 18 compares two machine learning models: Random Forest (left) and XGBoost (right), in their ability to predict silicon (Si) wear as a function of time (Horometer).

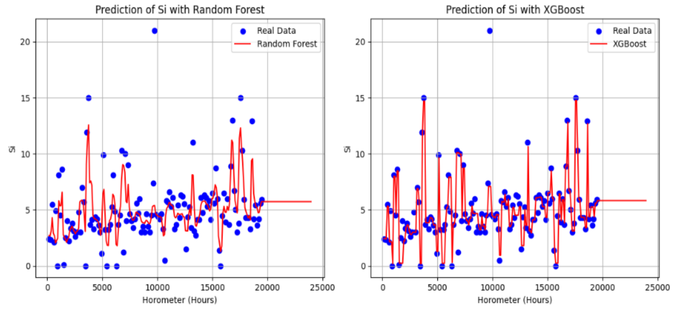

Fig. 18 Prediction Model of Si

Specialized literature documents significant advances in predictive maintenance across industrial sectors. In textile manufacturing, AdaBoost achieves 92% accuracy in fault classification [31]. For discrete manufacturing, Random Forest demonstrates superior performance (98.26% accuracy) in multiclass failure identification [32]. In regression applications, deep neural networks yield $R^2 = 0.86$ and RMSE = 0.097 for textile quality control [33], suggesting transfer learning potential to mining equipment through integrated vibration and wear debris analysis of critical components.

5. Discussion

The Figure 7 presents the historical series of failures recorded between January and April 2024, represented in blue, along with the prediction of failures for the period from May to December 2024, illustrated in red. It can be seen that the prediction generated by the SARIMA model exhibits an oscillatory trend with notable periodicity, which indicates that the model has captured a seasonal component in the analyzed data.

This predictive behavior suggests that the number of future failures will fluctuate in a repetitive pattern around a mean value. This variability may be influenced by the structure of the training data used. However, it is important to note that this oscillation does not appear to fully align with the distribution of historical faults, indicating that there are opportunities to improve model accuracy.

Random Forest and XGBoost show excellent performance, with very low MSEs (close to zero) and R^2 close to 1. This indicates that these models are very good at predicting the Fe variable. In contrast, the LSTM model has a higher MSE and lower R^2 compared to Random Forest and XGBoost, suggesting that it is less accurate in predicting the Fe variable in this context, as shown in Figure 16.

The results demonstrate the superiority of tree-based models (Random Forest: R^2=0.9972; XGBoost: R^2=0.9949) over deep learning architectures (R^2=0.86 [33]) in predicting mechanical wear. This advantage aligns with textile industry applications, where Random Forest achieves 98.26% accuracy in fault classification [32]. The high R^2 values confirm their suitability for regression analysis in mining, particularly in vibration monitoring and component wear assessment. While these models exhibit cross-industry transferability, their implementation requires feature selection adaptations for specific operational conditions while maintaining robustness across diverse production environments.

The superiority of Random Forest y XGBoost over LSTM in this context stems from three key factors: (1) LSTMs rely on temporal dependencies absent in the data, diminishing their effectiveness; (2) their high computational cost and demand for optimal hyperparameters render them impractical with limited data; and (3) their performance degrades rapidly with noise or class imbalance. In contrast, tree-based models implement automated feature selection, natively handle missing data, and maintain predictive stability even with small samples. These properties, combined with their computational efficiency, establish them as the optimal choice for tabular problems lacking temporal dominance.

However, in the case of Cu, Random Forest seems to soften the predictions, which may explain why it does not capture the peaks well. On the other hand, the XGBoost model seems to be a little more aggressive in capturing some peaks, but still has difficulty predicting the highest values accurately. This can be seen in figure 17. the XGBoost model appears to perform slightly better than Random Forest, capturing some peaks more accurately. However, the choice between Random Forest and XGBoost often depends on the nature of the data and the optimization of the hyperparameters.

Unlike the results observed for copper, the silicon analysis reveals greater agreement between modeled predictions and empirical data, particularly in the low to medium value range. Both models demonstrate a better ability to reproduce the general trend of silicon data compared to copper. However, discrepancies remain in the prediction of prominent peaks and valleys. Specifically, the Random Forest model exhibits smoother and more generalized predictions, consistently following the main trend of the data. In contrast, the XGBoost model shows greater sensitivity to fluctuations in silicon levels, reflected in its ability to capture peaks and valleys. While this sensitivity can be advantageous in identifying subtle changes, it also carries a potentially greater risk of overfitting, as shown in Figure 18

The selection of Random Forest and XGBoost is justified by their proven robustness against noise, exceptional handling of multivariate datasets, and classification efficiency for industrial maintenance data. The LSTM model was incorporated specifically for its demonstrated capability to detect complex temporal patterns characteristic of progressive wear sequences.

6. Conclusions

Random Forest and XGBoost models demonstrated promising potential for predicting silicon wear as a function of time. In particular, the XGBoost model appeared to offer slightly better performance by more accurately capturing peaks and valleys in the data. However, it is essential to consider the risk of overfitting associated with the higher sensitivity of this model, and rigorous validation is required to ensure its robustness and generalizability.

While the Random Forest and XGBoost models showed some predictive potential for time-dependent copper erosion, both have limitations in attempting to capture the inherent variability and characteristic peaks present in the empirical data. These findings suggest the need for additional research focused on the optimization of the models, with the aim of improving their ability to accurately reproduce the dynamics of copper wear.

where these Random Forest and XGBoost models demonstrated superior predictive capacity for the Fe variable compared to the LSTM model. Specifically, Random Forest and, to a greater extent, LSTM exhibited substantially inferior performance, evidenced by a high MSE (Mean Squared Error) and a low R^2 (Coefficient of Determination). These results suggest that LSTM fails to effectively capture the relationship between the predictor characteristics and the Fe variable.

The oscillations observed in failure prediction using the ARIMA model (Figure 7) indicate that fine tuning of seasonal parameters, together with the incorporation of relevant exogenous variables such as workload, weather conditions and maintenance cycles, could significantly optimize failure management and anticipation. This improvement would allow for more effective implementation of preventive and predictive maintenance strategies.

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