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Challenges and Cases of Artificial Intelligence Applied to Assist Predictive Maintenance in the Industry, Respectively in the Mining Sector

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Abstract

Unscheduled maintenance events have a crucial role in the industry's value chain. Predictive maintenance is becoming notorious in the mining sector because of improving downtime planning, operation effectiveness, and asset reliability. Although data analysis is widely used in other sectors, it is still necessary to deepen studies and applications for the mining industry. Therefore, the objective of this study is to identify, in the current state of the art, the existing challenges and solutions for Machine Learning techniques applied as an aid for predictive maintenance and, finally, present recent studies that used Artificial Intelligence in the mining industry to aid maintenance. The challenges reflect the natural world's complexity, such as dealing with limited, imbalanced, and noisy data, real-time extensive data monitoring, identifying relevant predictors, and ensuring data security. Existing solutions comprehend Machine Learning, Artificial Intelligence, and other techniques used in Industry 4.0.

Keywords: Artificial Intelligence, Mining industry, Predictive maintenance.

INTRODUCTION

Predictive maintenance is based on the continuous monitoring of the asset, allowing the detection of failures in early stages, generating cost reductions due to more efficient planning, either by extending the remaining life of assets or reducing downtime. Its purpose is to collect process data and the asset's parameters and physical health aspects (Fekete, 2015; Çınar *et al.*, 2020).

In the mining industry, a large mining company must maintain production distribution at competitive prices across continents. Mining activity is responsible for attracting investors and raising the Gross Domestic Product of cities that are part of the production process. The inspection of assets is often performed visually, with damage being detected at a more advanced stage, reducing the time for maintenance planning. An unexpected stop entails financial losses due not only to the high cost of equipment but also to the unavailable time for ore processing.

In this context, predictive maintenance shows up as a growing trend in the mining industry, in the era of Industry 4.0, with the potential to bring benefits, such as improved planning and increased productivity, reliability, and safety. Data analytics has been broadly used to help organizations transform data into useful information, but it is still in its infancy in mining. The mining industry is ideal for digital transformation, as it is a challenge to assess asset conditions concerning maintenance schedules since it has large environments and many assets, in addition to the unique opportunity to reduce costs, optimize processes and modernize (Zhou *et al.*, 2017; Tehran, Agrawal e Midha, 2018; Dave, 2021).

Machine learning (ML), Big Data, Artificial Intelligence (A.I.), and statistical techniques have been used in forecasting, diagnosis, and classification tasks. These are considered promising in the literature for applications to aid predictive maintenance in industrial environments. With the trend of implementing Industry 4.0 in the mining industry and the increasingly better sensing of assets, generating a growing volume of monitoring data, which include, among others, vibration, temperature, and pressure, there is a need to transform the acquired data into knowledge. Less than 1% of data generated by mining assets is analyzed (BAKER HUGHES, 2021 apud Davite, 2021, p. 5).

It is a challenge for industrial applications, when it comes to predictive maintenance, to achieve predictively or detection accuracy well above 90% due to the scarcity of data and the imbalanced data found in this environment. In addition, the intelligibility and understanding of A.I. methods need to be improved. Therefore, research is required to resolve open questions such as techniques for handling missing data, development of algorithms with low errors, and methods with less need for configuration and engineering to make A.I. applications intuitive and understood. A successful application implies confidence in data-driven models, which can be reached from the explainability of the models (*Technology Scenario "Artificial Intelligence in Industrie 4.0"*, 2019; Vollert, Atzmueller e Theissler, 2021).

This study aims to explore the A.I. landscape in industry focused on the mining industry about the application of ML methods to aid predictive maintenance. This paper primarily identifies the main challenges of applying ML techniques for predictive maintenance in the industry and then presents studies that deal with one or more found gaps.

IMPORTANCE OF AI IN THE INDUSTRY

Industrial A.I. application areas include Predictive Maintenance, Process Optimization, Collaborative Robotics, Workforce Training, Ergonomics, and Quality Control. The pillars of Industrial A.I. are scalability, context awareness, decentralization, modularity, real-time, robustness, human-in-the-loop, interoperability, service orientation, cybersecurity, interpretability, and continuous engineering. The enabling technologies of Industrial A.I. can be split into five categories:

- Data Technology: context and standardization in acquisition and exchange of the large volume of generated data;
- Analytics Technology: adding value from raw data, e.g., processing data at different levels, real-time data flow, and ML using self-learning and self-optimization mechanisms;
- Platform Technology: enable the remaining technologies, facilitating the interconnection between different elements and ensuring system integrity with cybersecurity;
- Operations Technology: create value from the knowledge provided by the decision support systems, leading to maintenance based on data and optimized operational management;
- Human-Machine Technology: the interaction between people and systems must be established in a practical, intuitive, and continuous manners, such as through virtual or augmented reality formaintenance, assembly, and remote diagnostics.

A.I. adds value to the industry by enabling it to perform unforeseen tasks requiring adaptation and problem-solving skills, supporting agile action, leveraging increased efficiency and safety, and reducing the use of resources and operating costs. However, applications for predictive maintenance using these technologies are still developing in the mining industry. Mining still lags behind other industries as regards A.I. implementation and digital transformation. Development, in the sense of this revolution, depends on the digitization of all information, which must be correctly acquired and carefully processed so that it can guarantee the efficiency of data analysis and control, with relevant and applicable results for the industry, allowing for better planning of activities and maintenance, aiding decision making and improving productivity (Bumblauskas *et al.*, 2017; Nanda, 2020; Sánchez e Hartlieb, 2020; Dave, 2021).

Forecasts of future asset states based on present-time monitoring can help decision-making regarding equipment maintenance and operation. When it comes to data collection n an ideal scenario, there is the availability of data on the history of failures and suspension of the asset, as well as healthy and homogeneous data. However, the reality can be quite different, especially in the mining industry. The heterogeneity, unavailability, and unreliability of the acquired data by sensing the assets make it difficult to process and apply the collected data. In the literature, possible solutions have been presented and discussed for the challenges encountered, whether regarding data acquisition, ML techniques, A.I., or forecasting methods. However, the application of A.I., respectively ML methods to aid predictive maintenance in natural industrial environments is still scarce (*Technology Scenario "Artificial Intelligence in Industrie 4.0"*, 2019; Kruczek *et al.*, 2019; Çınar *et al.*, 2020; Dalzochio *et al.*, 2020).

AI CHALLENGES IN PREDICTIVE MAINTENANCE

Besides providing a reduction in maintenance costs due to more efficient planning, predictive maintenance can also extend the remaining useful life (RUL) of assets, increase productivity, reduce downtime, increase the time between stops and improve product quality. Its objective is to collect process data and its parameters and physical health aspects of the asset, such as vibration, temperature, and viscosity, among others (Fekete, 2015; Çınar *et al.*, 2020).

The application of techniques used to assist planning and decision-making in predictive maintenance is a relevant topic that has been studied recently by several authors. In their studies, challenges and existing solutions for this topic are presented. Table 1 briefly describes the challenges of implementing Big Data and ML techniques in applications for predictive maintenance (Yan *et al.*, 2017; Cho *et al.*, 2018; Çınar *et al.*, 2020; Dalzochio *et al.*, 2020; Serradilla *et al.*, 2020).

Although there are numerous solutions for applying Big Data and ML techniques, it is not feasible to develop a single model capable of dealing with all the scenarios found in a company (Dalzochio *et al.*, 2020). In addition to difficulties with data and models, barriers to implementing predictive maintenance can also come from financial factors, the management, or the company's philosophy. The main challenges for its implementation, raised by Wagner and Hellingrath (2019), were cost and benefit, still in the concept phase, real-time access in the operationalization stage, and reluctance regarding the human factor.

Table 1 - Challenges in the application of techniques to aid predictive maintenance

Challenge	Description
Real-time monitoring	Processing a large volume of data that is generated, especially from sensors
Ensure latency, scalability, and bandwidth	Set of assets simultaneously processing and sending a large volume of data
Data acquisition	Difficulty obtaining good quality data and interpreting it
Difficulty quantifying qualitative or limited detection factors	Health status of assets, the capacity of operators, environmental conditions of the workspace
Data variability	Machine behavior with the exact specification varies according to environment and operation.
Lack of a "universal" model	Modeling is typically done for a specific application, limited to an asset, forecast, or rating type.
Lack of data	Incomplete notes regarding machine status or maintenance history

Challenge	Description
Imbalanced and heterogeneous data	Data type and format vary by data source, impacting the accuracy of ML models.
The computational cost of more generic models	Feasibility of training processing and application of less specific models
Need for expert	Prior knowledge of data context and parameters
Identification of the relevant data to collect	Identify in the enormous volume of data what can add value
Obtaining the necessary dataset	It permeates the correct choice of an ML algorithm and the availability of input data for this algorithm.
Enhanced data science	Choosing the correct method for analyzing data and presenting results
Data security	Access protection primarily on critical equipment and security of all connected assets

Source: Cho et al. (2018), Çinar et al. (2020), Dalzochio et al. (2020), Yan et al. (2017), Serradilla et al. (2020), (Lee, Kim and Choi, 2019).

In the mining industry, it is challenging to obtain reliable data that are statistically robust in sample size, have quality, satisfy model constraints, and are available and accessible (HODKIEWICZ et al. 2014 apud H.O., 2015).

Table 2 lists the techniques used in state of art with the gaps they aim to fill, such as the lack of prior knowledge of the failure threshold, limited or low-reliability data, equipment integration, determination of equipment integrity in a non-intrusive, predicting and suggesting maintenance actions, determining patterns that signal failures, imbalanced data and large amounts of data. The solutions proposed by the authors can be seen from the perspective of enabling Technologies of Industrial A.I., which are related to the techniques used in each study with the following identification: Data Technology (D.T.), Analytics Technology (AT), Platform Technology (P.T.), Operations Technology (O.T.), Human-Machine Technology (HMT).

Table 2 – Proposed solutions to meet the demands of the industry

Author	Objective	Object of study	Addressed gap	Technics [Enabling Technology]	Results
(Huang *et al.*, 2019)	Provide an accurate RUL forecast	Commercial Modular Aero-Propulsion System Simulation (C-MAPSS)	No need for prior knowledge of the failure threshold	Generative Adversarial Networks(GAN) + Long Short-term Memory Networks (LSTM) [AT]	Up to 71% decrease in RUL prediction mean absolute error (MAE)
(Kahraman, 2018)	Maintenance plan based on failure prediction	Mining trucks	Find patterns that indicate failures	Big data Data analysis [AT]	The detection rate of more than 90% in the last five events of a shift
(Li *et al.*, 2019)	RUL estimation	Rotary machines	Diagnosis and prognosis of incipient failures regarding the future working conditions of the system	EWMA-Pearson MGM-PF [AT]	EWMA (Exponentially Weighted Moving Average)-Pearson was able to identify relevant predictors for incipient fault identification with a better contribution rate than Pearson; MGM-PF (Metabolism Grey Forecasting Model with Particle Filter) had a superior performance for RUL prediction than LSTM and ANIFS

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Author	Objective	Object of study	Addressed gap	Technics [Enabling Technology]	Results
(Wang *et al.*, 2020)	Failure Prognosis / RUL	Wind turbine bearings	Handle limited data	Wavelet transform and particle filter Bayesian inference [AT]	The length of the forecast steps determines the amount of previous information. Therefore, the longer the prediction steps, the greater the uncertainty of the RUL prediction. The result was within the expected 90% reliability.
(Velásquez e Lara, 2018)	The tradeoff between cost and reliability	Series capacitor bank	Lack of reliable data on equipment reliability and the cost of power outages	State Space; Monte Carlo; Reliability, Availability, Maintainability (RAM) [AT+OT]	Obtaining equipment availability, identifying the main contributor to forced outages, and planning maintenance to reduce forced shutdowns.
(Rahimdel, Ataei e Ghodrati, 2020)	Subsystems reliability and availability analysis	Drilling machine (mine)	Need to ensure continuity of operation and improve maintenance plan	Kolmogorov – Smirnov Test; Monte Carlo [AT+OT]	Improvement of 3.78% and 29.56% in the reliability of each machine.
(O’donovan *et al.*, 2015)	Features a system architecture and data acquisition for a maintenance plan and asset diagnostics	Architecture for predictive and intelligent maintenance system for assets in general whose data are time series	Existing real-time maintenance systems were unable to predict and suggest specific maintenance actions.	Big Data; Distributed architecture [DT+PT]	The significant data pipeline facilitated seamless data integration, so facilities started intelligent manufacturing without requiring extensive technology replacement.
(Kruczek *et al.*, 2019)	Cloudy technology applied in predictive maintenance	The underground mining transport system	Use of corrective maintenance due to lack of component failure’s prediction	Cloudy technology; ML; RFID [DT+PT]	Easy access to data and its use in maintenance, as well as allowing the processing of data acquired by cloudy technology
(Lee, Bagheri e Kao, 2014)	Predictive life monitoring	Robots on a production line	Challenge for PHM algorithms to determine robot health in a non-invasive way	Big Data Cloudy technology Web interface [AT+PT+HMT]	Data – torque, speed, and calibration parameters – from all robots used as initial input for each one individually, cloud processing, infographics for health visualization
	Car battery health management	Hybrid or electric car batteries	Need to predict battery life in real-time considering external conditions with visualization for the user and sending diagnostic data	Cyber-physical battery model [AT+PT+HMT]	The cyber-physical model allowed the visualization of information by the user and the maintenance team in real-time with transmission to a logistics center to assist in fault diagnosis.
(Zhou *et al.*, 2017)	Investigate IIoT (Industrial Internet of Things) applications in the mining industry	Mining equipment	Transform collected data into useful information	IIoT Big Data [AT+PT+OT]	Connecting equipment and systems in mines make it possible to improve safety and remote diagnostics processes. Various assets and sensors can be integrated into IIoT systems with little or no modification.

Author	Objective	Object of study	Addressed gap	Technics [Enabling Technology]	Results
(Ghodrati, Hoseinie e Kumar, 2018)	EstimateMean Residual Life (MRL) by integrating operational environment with reliability analysis	Hydraulic systems of loading and unloading machines	Natural prediction systems remain rare in the mining industry	Weibull Proportional-hazards model [AT]	System reliability is best when the excellent condition of the covariates decreases slightly (only based on time) and decreases dramatically when the covariates are in the worst need. Results can help plan preventive maintenance based on conditional failure probability or MRL

MINING INDUSTRY APPLICATIONS

Gaurav et al. (2019)analyzed the reliability of a coal mine universal drill to identify the fact responsible for the reduction in reliability in the machine from historical maintenance data for 44 months, containing the operating hours, time failure, and repair time of the devices. The K-S test was done to find the best distribution of the data, resulting in the Weibull distribution. The authors identified the cause of the low reliability of the machine, which was overheating, leading the engine and hydraulic pump to fail.

Pereira (2018)developed a methodology to establish the reliability of a component and then related the reliability and availability of equipment with the cash flow of the mining company. He aimed to fill the gap in mining companies not having models, tools, or protocols to assess component reliability and quantify the cost impact of choosing components. Deterministic (Analytical) and stochastic (Monte Carlo Simulation) approaches were applied in two case studies involving hydraulic hoses. The Monte Carlo Simulation was considered more realistic than the analytical model because it uses ranges of values in statistical distributions, dealing more effectively with uncertain parameters. For the analytical model, outliers in the data sets can introduce errors in calculating the estimated point of the mean and standard deviation. The author concluded that equipment downtime is usually significantly more significant than the cost difference between components on the market and that the lower the reliability of the database, the lower the availability of the equipment and, consequently, the more significant the loss of revenue from the mining company.

Kahraman (2018)proposed a mining truck maintenance plan based on sequential pattern mining techniques. The author selected the most relevant variables from the 9-month data history of 11 mining trucks and three different types of fault codes most related to alarms that caused the highest maintenance costs. Initially, patterns between the same two fault codes were discovered and computed. Subsequently, ways were found in the last three and five shifts preceding the failure, and confidence values were calculated for these shifts. Experimental results achieved a detection rate of more than 90% in the last five shift events, which indicates specific and identifiable groups of patterns that precede machine failures. However, it would be necessary to have larger and cleaner datasets for more accurate results. Sequential pattern mining was considered a suitable approach to discovering relevant fault information.

Zhou; He; Zhang (2021)proposed a real-time vibration monitoring and data acquisition platform to meet the demands of underground mines regarding layout flexibility with excessive data volume. The hardware design features storage for self-learning predictive maintenance algorithms and either an Ethernet interface – for data transmission to terrestrial servers or cloud platforms – or RS485 for large-scale data analysis. The software processes the collected signals eliminating possible interference and predicts and evaluates the operating state of electrical equipment. The platform made it possible to monitor equipment and components online and export the results of on-site fault diagnosis, satisfying the needs of layout and real-time monitoring to aid in maintenance decision-making and cost reduction.

Antonino-Daviu et al. (2018)proposed a transient-based approach to diagnosing the rotor condition of mining equipment motors by measuring electrical current. This method analyzes a motor's starting current using the Short-time Fourier Transform and the Discrete Wavelet Transform. This methodology allowed detection of the failure before it became severe, earlier than the traditional method of analyzing the motor's current signature.

A module to implement a Decision Support System for maintenance of the underground mine conveyor system with the development and implementation of data fusion and artificial intelligence techniques was proposed by Stefaniak, Wodecki, and Zimroz (2016). Data from more than 220 transporters were applied in a Self-Organizing Map Network to identify objects with similar characteristics based on clustering multidimensional indicators datasets. The module was able to assist in maintenance planning, identify assets in need of inspection and identify potential problems affecting the operation’s safety early.

In the study by Patil *et al.* (2021), failure prediction and remaining lifetime models were developed for underground mine trucks, prioritizing the model's explainability over accuracy. They dealt with the limitedand imbalanced failure data proposing a failure zone instead of failure point prediction;derived virtual sensor parameters from raw parameters aiming to relate the interaction between two or more predictors;and chose a model capable of *post-hoc* interpretation.The models output an asset life score in percentage, a binary indicator of whether or not there is a failure predicted for the next period, and the reason why the loss was averted. The resultwas a 9% improvement in the Overall Equipment Efficiency.

Davite (2021)developed an advanced decision tool to model complex scenarios in the mining and energy sectors using BayesianML. The author reached the following conclusions: target-based resource analysis to identify the most informative variables of the system reduces its complexity; the proposed tool with intuitive interfaces allows professionals to design data-driven business actions in real-time; BayesianML allows understanding the uncertainties associated with decision making and anticipating possible future results; and A.I. solutions must be accessible and auditable, leading to transparent, justifiable and reproducible forecasting models.

CONCLUSION

This article presents challenges for implementing predictive maintenance in the industry in the context of Industry 4.0. A.I. and ML techniques have been used to add value to the industry with their potential for problem-solving in support of agile action, also helping to plan maintenance based on asset conditions.

The following topics highlight the addressed gaps and solutions identified in the literature:

- Data integration can be affected by different communication protocols, making it hard to implement Big Data solutions;
- Despite being very faithful to reality, applications in simulation databases may not present the complexity of the real-world asset;
- The accuracy of fault detection and remaining life prediction results and associated uncertainties are directly related to the size and reliability of the dataset;
- It is possible to obtain a satisfactory result for maintenance assistance even without considering the effect of all operational and environmental conditions, which can be difficult to quantify due to its subjectiveness, or just not having data available;
- The purpose of an MLalgorithm can go beyond what it provides. As a result, e.g., identify the reason for a failure by predicting whether or not there is a failure. In this case, the explainability of forecasting algorithms aggregates relevant information for maintenance planning, so it is necessary to seek more minor forecast errors and the best tradeoff between explainability and performance.

The challenges identified in the literature reflect the complexity of the natural world, whose data are non-linear, imperfect - e.g., noisy, imbalanced, and incomplete. Also, the extraction of relevant information from these data is subject both to the way the asset behaves under similar and different operating conditions, as well as to the prior knowledge about this asset, such as its behavior in different scenarios, data history, maintenance and the context of data gathering. It is a challenge to distinguish between relevant and non-relevant data furthermore correctly choose the ML algorithm for the desired application. The individuality of each process means there is no rule to knowing beforehand which datasets and ML algorithms are best for each application, hence the importance of comparing different methods, architectures, and hyperparameters for each application. In addition to identifying and providing sensing in relevant parts of the assets and integrating the data, companies also need to be concerned with the security of the large volume of data generated and protecting access, especially in critical equipment.

The industrial context, focusing on the mining industry, lacked a history of reliable data and sufficient quantity for more accurate forecasts. If, on the one hand, the trend by sectors in the application of technologies can be noticed, on the other hand, companies may not know whether these technologies will bring a return on the investment made, either by increasing security, availability of assets, improving downtime planning for maintenance or another form of financial return.

A.I. applications have the potential to meet the needs of the mining industry in terms of helping predictive maintenance with reliability, even with existing limitations, such as data quantity and quality, lack of prior knowledge about the influence of variables in the system, data in real-time processing. Due to the characteristic of each process being different, each model to be developed has individual needs and specific challenges to meet, such as proper operating conditions, failure modes that are more likely to occur, and maintenance strategy. Therefore, combining single solutions to develop a model can bring satisfactory results and meet the demands of the industry. A.I. applied to maintenance systems is capable of making the processes safer and more reliable; assisting in the planning of maintenance strategies by allowing the identification of failure patterns; predicting the remaining life and alerting future failures in advance; predicting a range of future scenarios; identifying the reason for an imminent collapse, among others.

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