

Optimisation of mining machinery maintenance in modern mining enterprises through text mining and machine learning techniques

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ABSTRACT

The efficiency of planning processes is fundamental to the success of modern mining enterprises, particularly in maintaining competitiveness in the raw materials market. This paper addresses the critical challenge of optimising production lines, encompassing strategic arrangement of mining fronts and the management of drilling, transport, and auxiliary machinery. Given the dynamic and often challenging conditions of underground mining, mitigating random disruptions that can lead to machine downtime is crucial for sustaining productivity. This study highlights the importance of leveraging large volumes of diverse data to achieve situational awareness and facilitate informed decision-making under uncertainty. We explore how text mining and machine learning techniques can extract valuable insights from unstructured data, such as equipment failure reports, which often contain complex and ambiguous information. By developing a classification system that categorises failure descriptions into actionable insights, we aim to improve data interpretation and support predictive maintenance strategies. Furthermore, we propose an integrated approach that consolidates data from various sources, including downtime logs and repair records, to establish a comprehensive database for analysis. The proposed methods not only streamline data management but also enhance the accuracy of predictive models, ultimately enabling mining companies to optimise their operations and increase overall productivity.

INTRODUCTION

Given the ever-changing nature of the extraction process and the often challenging operating conditions in most underground mines, one of the key aspects of mine management is addressing the random factors that can slow down or disrupt production. A major challenge in this area is reducing machine downtime caused by equipment failures or incorrect set-up of transport machinery, which can create production bottlenecks (Stefaniak *et al*, 2023; Skoczylas *et al*, 2025). For smaller mining operations, achieving situational awareness is not particularly difficult, as data validation, standardisation, and analysis can be handled manually by a small team. However, the situation becomes more complex for large, multi-site operations with extensive fleets of machines.

An intriguing solution was presented in Balaraju, Govinda Raj and Murthy (2020), where the authors aimed to uncover the underlying relationships leading to critical potential failures. They applied statistical reliability analysis to assess the performance of mining trucks, using the Kolmogorov-Smirnov test to identify the best-fitting data distribution. Subsystem reliability metrics for each subsystem of LHD machine were estimated using a Reliability Block Diagram (RBD) approach, structured in a series configuration, to determine the overall reliability of the LHD machine. Another study by Barabady and Kumar (2008) used reliability analysis to identify production bottlenecks and components or subsystems with low reliability compared to their designed expectations. This case study focused on a crusher reliability assessment in a bauxite mine in Iran, revealing that the conveyor subsystem and secondary screen subsystem were critical for the crusher's reliability, while the conveyor subsystem and secondary crusher subsystem were essential for the machine's availability. In Ghodrati, Hoseinie and Kumar (2018), the authors developed a method to estimate the Mean Residual Life (MRL) for mining equipment, aiming to optimise maintenance planning. They employed a statistical modelling approach to estimate the MRL, incorporating a Weibull proportional

hazard model (PHM) with time-independent covariates to model the hazard function. The method was verified using historical failure data from the hydraulic system of an LHD machine in a Swedish mine. A similar study in Rahimdel *et al* (2013) analysed the reliability of drilling machines in a copper mine in Iran, where failures led to delays in blasting operations. The authors used the Markov method for their reliability analysis. In contrast, Paithankar and Chatterjee (2018) highlighted the limitations of Markov models in estimating Remaining Useful Life (RUL), particularly the assumption of a specific statistical distribution for failure time data. The authors proposed a hybrid approach for RUL estimation based on a neural network and genetic algorithm. Their case study focused on an LHD machine, showing the developed method's superiority over traditional techniques. Martinsen *et al* (2023) explored the reliability assessment of mining process automation using Bayesian networks (BN). The experimental research demonstrated that autonomous haulage route planning can outperformed expert-designed routes. However, it also revealed that autonomous loading and haulage machines had shorter lifespans for tires, brakes, and bearings. A similar study on a fleet of haulage trucks operating in mining environments was presented in Rahimdel (2024). In Jakkula and Ch (2020), reliability analysis results for LHD machines were presented, using a renewal approach to evaluate fleet performance. The Kolmogorov-Smirnov test was applied to match the distribution to the data, and reliability for each subsystem was calculated according to the best-fitting distribution. Preventive maintenance schedules were developed based on these results, targeting a reliability level of 90 per cent. This study focused on evaluating the performance of four highly mechanised LHD systems using reliability, availability, and maintainability (RAM) modelling, identifying the causes of performance decline for each machine and offering recommendations to improve the efficiency of this capital-intensive equipment. In Özfirat, Yetkin and Özfirat (2019), the authors proposed a method for identifying bottlenecks in the circular haulage process due to LHD machine failures. A risk index was used to develop a repair scheduling method, employing Failure Modes and Effects Analysis (FMEA) to assess the associated risks.

Data can be collected in various formats, with different standards applied during the collection process. In the case of data related to failures and repairs, even when recorded using forms in ERP systems, the data often consists of complex, unstructured textual descriptions (Stachowiak *et al*, 2021). Analysing this type of data is challenging and requires additional processing. In Blanco *et al*, (2019) the authors propose a method for analysing failure downtimes using wind turbines as an example. In practice, assessing the condition of turbines begins with an expert reviewing the service history, which is a time-consuming task because the expert must examine each entry individually. To automate this process, the authors used text-mining techniques and developed classifiers to assist the expert, allowing them to focus on analysing turbine systems and subsystems to optimise their performance. Meanwhile, the study in Brodny *et al* (2017) applied the Overall Equipment Effectiveness (OEE) model to assess the availability of selected mining machines. The analysis relied on SCADA logs as the primary data source, from which the authors evaluated the availability of machines in the mechanised longwall system of an underground coalmine. Dindarloo (2016) proposed a novel approach to estimating the Time Between Failures (TBF) for Load-Haul-Dump (LHD) machines using support vector machine regression based on a genetic algorithm. A different approach was presented in Sellami *et al* (2020), where the authors developed a model to predict operational events and safe operating times based on chronicles identified in the data set using unique sequential patterns over time. A key part of the analysis was identifying frequent event sequences that contributed to the most significant downtimes and then determining the time between these events to predict the one that triggers a failure. The authors suggested using the LSTM deep learning algorithm to predict failures and the remaining time to failure.

Text-mining techniques can extract valuable insights from data sources that were previously considered useless or irrelevant because they were not connected to other data (Stefaniak *et al*, 2022). The paper highlights an important application of these techniques for analysing text data from failure and repair monitoring of mining machines. By combining information about faults and repairs, a complete history of the machine can be created, enabling the calculation of reliability indicators for the machines and their components based on the classification developed by the authors. These indicators are derived from reliability formulas based on the register of shift states of mining machines.

DATA PREPARATION AND MERGING

The data in this research was collected as part of the NetHelix project (2022). The primary data source consists of textual notes detailing condition irregularities, failures, and service work performed. This data is unstructured and requires thorough analysis, including proper validation and classification based on the specific structure of systems and components. The work involves applying advanced text mining techniques and developing procedures to decompose complex entries into distinct activities, standardise them into a consistent and accurate format for seamless integration with other data sources, and enable further classification. The classification process must encompass critical dimensions such as the system, component, location of the element, symptoms or causes of irregularities, and the type of service work performed.

The data originates from a communication platform that facilitates information exchange within the mine, specifically focusing on operational oversight and production reporting. The system was implemented with the primary objective of reducing workload and enhancing communication across the mine. It serves critical functions across key areas of the mine's operations, including personnel and machinery management, while ensuring seamless electronic information flow-throughout all mining sites. This data contains text notes about the work performed on machines during their operation and technical breaks. In addition, there is a database that contains detailed information about the machine's activities during each work shift, categorised into seven distinct statuses:

1. BS – breakdown stop.
2. ERP – emergency repair.
3. PRP – planned repair.
4. PRD – in production.
5. PR – planned readiness.
6. UPR – unplanned readiness.
7. PS – periodic service.

This can be used to comprehensively track the entire machine history. The next step was to figure out how to connect all these information. Because broken parts can be repaired at different times and for varying durations, it was impossible to connect the databases directly by dates and machine codes. The solution here was to use text mining tools with machine learning. Machine learning was applied to divide the information into categories while text mining tools allowed for proper text preparation. Since the Greek language is characterised by extensive inflection, usually each individual word undergoes case inflection. Additionally, the presence of mining jargon, spelling and stylistic errors, synonyms, and proper names further complicates text processing. For this reason, the results of the qualitative and quantitative analysis were used to develop a specialised dictionary of concepts and to define the target structure of the systems and classification rules. As a result, the following categories were proposed:

- System
- Detailed component/element
- Type of fault
- Work performed
- Cause/symptom
- Location
- Description of fault.

The adopted classification required the creation of five machine learning models for first five categories and two procedures based on logical rules defined for the various combinations of expressions. The seven-stage classification process is preceded by validation algorithms including, among others, lemmatisation, removal of unnecessary words, punctuation correction, capitalisation standardisation,, autocorrection, and text-to-numerical conversion. All corrections and changes of

words written in jargon help to bring the words to their correct version. Then, lemmatisation allows to reduce words to one simple form. Words prepared in this way will be properly understood and connected by the model. As a result, a short text note is transformed into categorised information that enables the integration of different databases.

Connecting data sources about failures repair work and shift statuses allows to obtain complete information about history of the machine. The previously proposed categories, assigned to each row of information, allow the combination of information from different databases into a single data set. The linking method involves the following steps:

- Check whether failure and repair entries from the same shift for a machine have been classified in the same way. If so, the cases are merged into single entry.
- Join shift statuses occurring on a given day for a given machine to the corresponding entry.
- Verify whether failure and repair cases are divided into multiple entries or if both occur within the same shift but to different elements. If this happens, the working day is divided into as many segments as there are failures and repairs, distributing time evenly.

Data prepared and combined in this way provides a comprehensive overview of a machine's operational history and enables tracking of all machine-related events, determination of reliability and operational indicators, calculation of the repair duration and assessment of downtime following failure.

RELIABILITY ANALYSIS

The integration of data enabled the calculation of operational and reliability indicators for a selected component, machine system, or group of elements. Using recorded statuses, time spent by the selected group on repairs or stops can be calculated. The formulas are shown below:

$$\text{REPAIRS} = \sum(\text{PRD}, \text{ERP}) / \sum(\text{BS}, \text{ERP}, \text{PRP}, \text{PRD}, \text{PR}, \text{UPR}, \text{PS}) \cdot 100\% \quad (1)$$

$$\text{STOP IN BREAKDOWN} = \sum(\text{BS}) / \sum(\text{BS}, \text{ERP}, \text{PRP}, \text{PRD}, \text{PR}, \text{UPR}, \text{PS}) \cdot 100\% \quad (2)$$

$$\text{UNPLANNED DOWNTIME} = \sum(\text{BS}, \text{ERP}) / \sum(\text{BS}, \text{ERP}, \text{PRP}, \text{PRD}, \text{PR}, \text{UPR}, \text{PS}) \cdot 100\% \quad (3)$$

By integrating status information with the identification of failure start and end times, derived from the fusion of failure and repair databases, it is possible to determined reliability indicators. The calculated reliability indicators include the Mean Time to Failure (*MTTF*), Mean Time to Repair (*MTTR*), and Mean Time Between Failures (*MTBF*):

$$\text{MTTF} = \sum(\text{PRD}) / \# \text{BLOCK } E \quad (4)$$

$$\text{MTTR} = \sum(\text{ERP}, \text{BS}) / \# \text{BLOCK } M \quad (5)$$

$$\text{MTBF} = \text{MTTF} + \text{MTTR} \quad (6)$$

where *BLOCK E* represents the number of periods of continuous operation for a given component or machine system (*PRD* status) and *BLOCK M* represents the number of periods of continuous malfunction for a given component or machine system (*BS* or *ERP* status). The logic behind of determining the elements *BLOCK E_i* and *BLOCK M_i* of the sets is presented schematically in Figure 1.

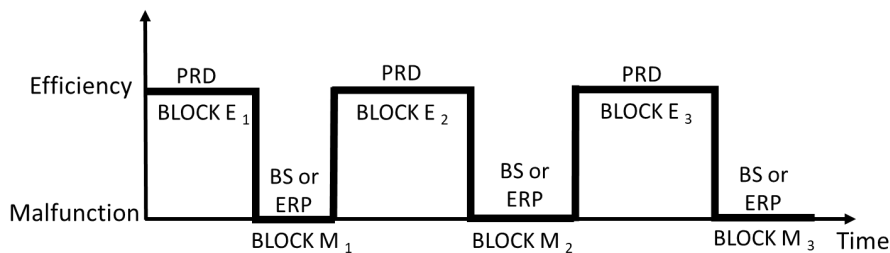


FIG 1 – Machine operation diagram.

Determining the start and end points of blocks was only possible after integrating the data. With the help of the MTBF indicator, the probability of survival and the probability of failure can be determined. They are described by the following formulas:

$$R(t) = e^{-\lambda t} \quad (7)$$

$$F(t) = 1 - e^{-\lambda t} \quad (8)$$

where t is time, λ is failure rate (Meeker, Escobar and Pascual, 2022). The formulas above are based on the assumption of a constant failure rate, which holds true under normal machine operation, excluding the initial break-in and wear-out phases. Therefore, for mining loading and haulage machines, it is reasonable to assume a constant failure rate, which can be estimated as follows:

$$\lambda = 1/MTBF \quad (9)$$

$$P = 1 - e^{-T/MTBF} \quad (10)$$

where T is the failure-free operation time from the last component failure t_0 to the last work shift t_n : $T = \sum_{t_0}^{t_n} PRD$. The $MTBF$ indicator value is determined by selecting an appropriate group of machines with a similar expected failure rate for a given component. This group can be defined by machine type and the mining division to which it belongs. To determine the coefficient correctly, it is important to use data from a sufficiently long period to account for the recurrence of failures that occur infrequently.

RESULTS

The following analysis covers data collected over an 11-month period, detailing the failures and repairs of two types of machines across multiple mining divisions. The data has been processed and integrated as described in the previous section. The results presented here offer an evaluation of the reliability indicators for both machine types, highlighting differences across various systems. Additionally, the analysis includes a detailed examination of the Mean Time Between Failures (MTBF) coefficient, observing its fluctuations over time. The analysis also explores the MTBF values for identical machine components, but differentiated by their positions on the machines, offering a deeper understanding of performance variations based on component location. First, Table 1 presents the reliability indicator values for each designated system for both types of machines.

TABLE 1
Reliability indicators for each system.

Machine	System	Repairs	Stop in breakdowns	Unplanned downtime	MTTF	MTTR	MTBF
Type 1	drive system	4.24%	0.31%	0.64%	59.74	0.78	60.52
Type 2		3.28%	0.18%	0.39%	108.92	0.87	109.80
Type 1	construction elements	2.79%	0.18%	0.31%	91.38	0.62	92.00
Type 2		2.85%	0.13%	0.20%	143.12	0.66	143.78
Type 1	fire extinguishing installation	0.18%	0.01%	0.02%	316.60	0.35	316.95
Type 2		0.22%	0.00%	0.02%	378.72	0.64	379.36
Type 1	electrical installation	1.77%	0.07%	0.18%	111.07	0.47	111.55
Type 2		0.84%	0.09%	0.14%	206.00	0.84	206.84
Type 1	cooling system	0.77%	0.05%	0.11%	202.05	0.69	202.74
Type 2		1.06%	0.09%	0.15%	231.15	1.11	232.26
Type 1	brake system	0.59%	0.04%	0.10%	197.10	0.66	197.76
Type 2		0.46%	0.02%	0.07%	270.52	0.69	271.21
Type 1	air conditioning system	0.95%	0.08%	0.17%	131.40	0.56	131.96
Type 2		0.68%	0.05%	0.10%	236.70	0.75	237.45
Type 1	hydraulic system	0.74%	0.05%	0.13%	176.35	0.69	177.04
Type 2		1.19%	0.05%	0.11%	198.52	0.64	199.16
Type 1	actuator system	1.52%	0.13%	0.26%	102.31	0.60	102.91
Type 2		2.00%	0.17%	0.27%	135.26	0.84	136.10
Type 1	wheel system	1.95%	0.11%	0.24%	106.65	0.59	107.24
Type 2		1.28%	0.15%	0.21%	165.77	0.88	166.65

As can be seen in Table 1, the Type 1 machine experiences failures more frequently across each system. In some cases, differences are minor, as in the case of the hydraulic system, while in others, they are significant, such as the electrical system, which fails twice as often. The most critical system from repair perspective appears to be the drive system, which has highest total unplanned downtime. It is also the system with the most frequent failures. Conversely, the fire extinguishing system is the least prone to failures.

Similarly, these statistics can be calculated for more precise elements on machines. Due to the large number of components,, this article does not present a complete table. However, the results indicate that the most common failures in both machines occur in tires and cylinders. Among Type 2 machine-specific components, the bucket is the most failure-prone, while for the Type 1 machine, the most frequently failing components are various covers and joints. The most time-consuming repairs involve tires and the gearbox. Unique components requiring extensive repairs include the cargo box in Type 1 machines and the bucket in Type 2 machines. The analysis can be further refined by adding additional information. In some cases, certain components exist in multiple instances on the machine. Sticking to the case that occurs quite often, ie tires from wheels, they can be further separated by adding information about their position on the machine. Figure 2 illustrates the failure probability function for each wheel as a function of shifts worked.

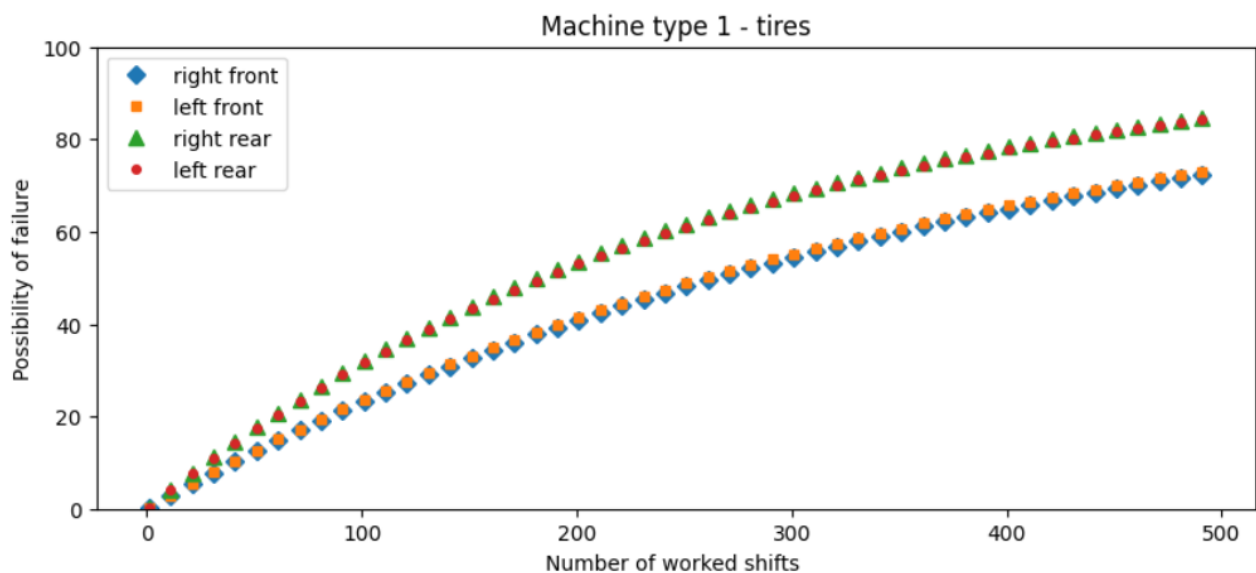


FIG 2 – Likelihood of failure over time for different tires on Type 1 machine.

Figure 2 shows a predictable increase in the likelihood of failure over time for different tires on the machine. Left and right rear tires fails the fastest, which may indicate higher stress on these components. Front tires show a slower increase in failure probability, suggesting better durability or less strain under normal operating conditions. This may be caused by uneven load distribution could place greater strain on the rear tires. The result obtained can be used to increase inspection and maintenance frequency after, for example 200 shifts, with greater focus on rear tires or using by leveraging an existing system to highlight critical areas. The mine conducts periodic tire inspection, and the results can help identify which machines and tires require more thorough examination. This is possible thanks to information about the last recorded failure of a specific component on the machine. Expanding on this idea, a list of potential risk areas can be prepared for mechanics to check during their work shift. This will help distribute the workload more effectively, focusing efforts on high-risk areas.

Table 2 shows three components with the highest failure probability for three selected machines from Machine Group 1. As can be seen, all failures occurred most recently in the first half of last year. A list prepared in this way for all machines within the given departments helps identify components that may require more detailed inspection or additional maintenance. It can be used in implementation of preventive and predictive maintenance, which leads to:

- Significant savings in maintenance costs.
- Reduction in the number of failures and downtimes, which translates into greater equipment availability.
- Extending the service life of components and entire machines.
- Improving work safety through early detection of potential faults.

TABLE 2

The elements with the highest probability of failure for three selected machines.

Name	System	Element	Data of last failure	Likelihood of failure
Machine 1	electrical installation	electrical boxes	2024/04/08	63.17%
	hydraulic system	cap	2024/03/21	69.84%
	drive system	driving gear	2024/03/19	72.75%
Machine 2	cooling system	combustion engine cooling system	2024/04/04	75.67%
	electrical installation	e-gas installation	2024/04/25	76.07%
	drive system	alternator	2024/05/21	76.22%
Machine 3	drive system	multi-ribbed belt	2024/04/25	50.66%
	air conditioning system	compressor-evaporator hose	2024/04/10	52.36%
	actuator system	steering cylinder hose	2024/04/30	57.39%

These benefits confirm that investments in modern technical condition monitoring and predictive analysis systems are profitable and contribute to increased operational efficiency in the mining industry.

It is important to acknowledge that the proposed solution represents an ongoing development effort rather than a finalised system. The dynamic nature of human language, as well as the continuous evolution of mining technologies and equipment, necessitates the regular revision and adaptation of classification models. Over time, new terminology and component types are expected to show, which will need to be reanalysed and classified. There is also the problem of applying the methods to data from other sources. Not all mining departments maintain equally detailed logs. In some cases, equipment shift status or failure cause may be missing, limiting the model's input completeness. These constraints suggest that, while the article demonstrates good results for this kind of database in the case of other type of data, in-depth analysis and appropriate preparation will be required to obtain the desired results.

SUMMARY

The article emphasises the importance of optimising planning processes in modern mining operations to maintain competitiveness. It focuses on enhancing production line efficiency through effective maintenance strategies. Given the unpredictable nature of underground mining, minimising machine downtime is critical. To improve situational awareness, the research employs text mining and machine learning methods to extract insights from unstructured failure reports. A classification system was developed to categorise failure descriptions, facilitating predictive maintenance. Data integration from downtime logs, repair records, and shift statuses creates a comprehensive database, enabling a complete analysis of machine performance. The study analysed 11 months of data on two types of machines, assessing reliability metrics like Mean Time Between Failures (MTBF). The results indicate notable differences between machine types, with more frequent breakdowns observed, particularly in electrical and drive systems – the latter being responsible for the longest downtime. Further analysis revealed that even identical components within the same machine type can exhibit different failure intervals. Tire failure analysis showed that rear tires on Type 1 machines deteriorate faster, suggesting the need for targeted maintenance and inspection strategies. These insights support proactive maintenance scheduling and workload distribution, ultimately enhancing operational efficiency.

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