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Review article

A literature review-based evaluation framework for maintenance strategy selection in heavy vehicles

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ABSTRACT

Effective maintenance strategies are critical for ensuring operational reliability, minimizing downtime, and optimizing resource utilization in fleet-based industrial operations. Among these, mining truck fleets represent a particularly high-risk, high-cost context where equipment failures can lead to substantial productivity losses and safety hazards. Despite the operational importance, existing literature lacks a structured framework to guide maintenance strategy selection that considers the practical constraints of data availability, diagnostic capability, and operational variability. To address this gap, this study proposes an evaluation framework that supports the selection and implementation of appropriate maintenance strategies. The framework is developed through a critical literature analysis, which is synthesized using a Frame of References approach. Unlike generic taxonomies, this model classifies maintenance strategies based on decision logic, response timing, data dependency, required infrastructure, and alignment with organizational capabilities. Building upon this structure, a two-level decision-support framework is introduced. The first decision tree assists practitioners in determining the appropriate class of maintenance strategy—corrective, planned, proactive, or predictive—based on operational constraints and system criticality. The second tree refines this selection by mapping available technological resources and data maturity to suitable analytical methods (e.g., rule-based, statistical, or AI-driven). While the framework is demonstrated in the context of mining truck operations, its modular design makes it applicable to other asset-intensive sectors, including logistics, construction, and heavy manufacturing. By bridging analytical insights with real-world constraints, this study offers a practical tool for organizations seeking to develop scalable, reliable, and context-sensitive maintenance strategies.

1. Introduction

The mining industry plays a vital role in global economic development by providing essential natural resources, including minerals, metals, and coal. These resources serve as the backbone of critical sectors such as infrastructure, manufacturing, and energy production. With increasing global demand, improving efficiency, sustainability, and cost-effectiveness in mining operations has become a key priority [1]. Efficiency in mining is not only vital to maximize productivity but also to reduce environmental impact, manage costs, and enhance worker safety. This need has led to ongoing advancements in technology and operational practices aimed at optimizing resource extraction and processing methods. Among the many aspects that influence operational efficiency, the availability and reliability of mining equipment—especially hauling trucks—are crucial, as they are tasked with transporting vast quantities of materials, often over challenging terrain and within strict timelines [2].

To achieve high levels of availability, performance, and safety, mining trucks require a well-structured maintenance policy. A robust maintenance strategy not only minimizes unexpected failures but also reduces operational costs and improves overall efficiency. Traditional maintenance approaches, which rely on reactive, failure-driven interventions, are increasingly being replaced by proactive and predictive strategies that optimize resource utilization and reduce downtime [3,4].

Maintenance strategies in the mining industry can be broadly categorized as [4]:

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- Reactive Maintenance (also known as corrective maintenance) – This strategy follows a "break-fix" principle, where repairs occur only after failure has taken place. It is simple to implement but often leads to higher repair costs, longer downtimes, and lower Overall Equipment Effectiveness (OEE).
- Planned Maintenance (also known as preventive maintenance)– In this approach, maintenance activities are performed at pre-scheduled intervals to reduce failure risks and improve OEE. However, it does not account for the truck's actual health, leading to unnecessary maintenance, increased costs, and reduced availability. Additionally, it lacks real-time adaptability to changing operational conditions.
- Proactive Maintenance (also called condition-based maintenance - CBM) – This strategy relies on monitoring equipment condition in real-time and performing maintenance when specific degradation indicators are detected. It helps reduce unnecessary interventions while extending component lifespan.
- Predictive Maintenance – The most advanced strategy, predictive maintenance leverages AI, predictive models, and real-time sensor data to forecast failures before they occur. This strategy ensures higher OEE, cost savings, and reduced unplanned downtime [5,6].

An overview of each maintenance approach and how they correspond to different OEE ranges is presented in Fig. 1.

As maintenance strategies continue to evolve, the next step beyond predictive maintenance is prescriptive maintenance. Unlike predictive maintenance, which answers "What will happen and when?", prescriptive maintenance goes further to address "How should a specific event happen?", providing actionable recommendations for optimizing operational and maintenance practices [7]. By integrating advanced AI, Internet of Things (IoT), and decision-support systems, prescriptive maintenance enables proactive decision-making, minimizing downtime and optimizing resource utilization. This emerging strategy represents the future of maintenance in the mining industry, providing a data-driven framework for maximizing equipment reliability and efficiency.

Several studies have shown that transitioning from corrective to predictive maintenance leads to significant improvements in asset reliability and cost efficiency [8]. However, mining companies face challenges in adopting advanced maintenance strategies, including integration of digital technologies, workforce training, and cost constraints [9].

In order to better understand the challenges faced by mining companies, this study emphasizes the critical role of maintenance in mining operations, as selecting the right maintenance strategy for hauling trucks directly affects operational efficiency, cost management, and safety [10]. Despite the growing body of research on mining equipment maintenance, there is limited comparative analysis that systematically evaluates the effectiveness of different maintenance strategies. This study seeks to address this gap by answering the following key research questions:

- What maintenance strategies for mining trucks are addressed in the existing literature?
- What are the objectives, quantified indicators, intervention actions, and evaluation processes for each strategy?
- How can the implementation of different maintenance strategies enhance the efficiency and reliability of mining trucks?
- What is the most appropriate maintenance strategy to follow for a specific case in the context of mining trucks?

To address these questions, this study introduces a comprehensive evaluation framework designed to classify, compare, and assess maintenance strategies systematically. Unlike conventional literature reviews that solely summarize existing research, this study provides structured guidance on selecting the most effective maintenance approach and corresponding methodology. The framework consists of three key components:

1. Systematic Literature Review (SLR): A structured review process to collect and analyze relevant research articles on mining truck maintenance strategies.
2. Frame of References (FoR) Approach: A structured classification framework that synthesizes quantification methods, intervention approaches, and evaluation criteria, enabling a comparative assessment of different maintenance strategies.
3. Evaluation Framework: A structured decision-support model that assists practitioners in selecting the most suitable maintenance strategy by considering operational impact, data availability, resource constraints, and performance objectives.

The remainder of this paper is structured as follows: Section 2 (Methodology) details the SLR process and the FoR framework used to classify maintenance strategies. Section 3 (Analysis of Results) provides an overview of the statistical analysis, literature review, and comparative assessment of the reviewed studies. These analyses contribute to the

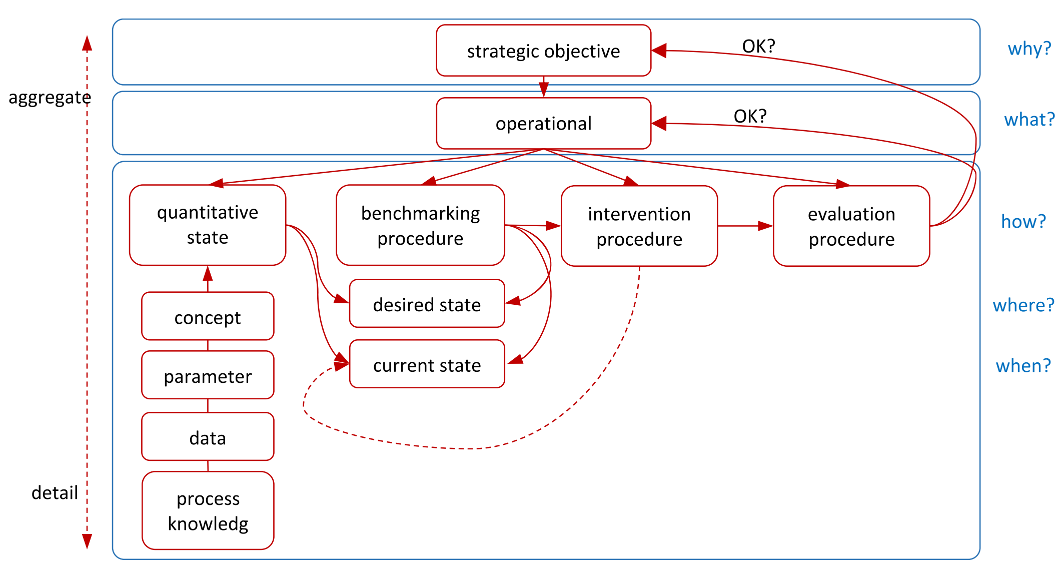

Fig. 1. Maintenance strategies [4].

development of a literature synthesis and an evaluation framework, including a decision tree model that guides the selection of maintenance strategies and methodologies. Section 4 (Discussion) interprets the findings, examines the implications of different maintenance strategies, and outlines future research directions. Finally, Section 5 (Conclusion) summarizes the key insights and provides recommendations for both industry practitioners and researchers.

2. Methodology

To develop a comprehensive insight into classifications of maintenance strategies for mining trucks and the existing knowledge gaps, this study adopts a Frame of Reference (FoR) approach coupled with a Systematic Literature Review (SLR). These two approaches help us understand the current state and research directions in this field, categorize the problem in relation to maintenance strategies, and explore the various aspects of each strategy, including objectives, methodologies, and evaluation criteria.

2.1. Frame of reference (FoR)

The Frame of References (FoR) approach provides a structured methodology for analyzing, designing, and evaluating dynamic policies, supporting both strategic and operational objectives through quantification, benchmarking, and intervention planning. It serves as a decision-making tool that helps stakeholders define measurable goals, identify conflicts, and guide resolution throughout implementation phases [11]. According to the FoR, every decision-making problem requires specifying the following factors.

- A strategic objective shows the long-term perspective of the system's desired state, considering the uncertainties, and serves as a comprehensive goal that policies aim to achieve.
- An operational objective that is specific and measurable and designed for achieving goals in daily operations using the actionable stages of problem-solving.
- A quantitative state concept is defined for each operational objective using quantifiable parameters as building blocks for decision-making.
- A benchmarking procedure consisting of a comparison between the quantifiable parameters and reference points helps in assessing if the system is performing properly regarding its strategic and operational objectives.
- Use of an intervention procedure to address the gaps between the current and desired states in the system.
- An evaluation procedure consisting of determining whether the objectives are met after implementing the intervention actions. It is also used as a feedback-receiving tool that measures the effectiveness of strategies and policies.

Fig. 2 represents a basic schema for the implementation of the FoR approach.

In mining truck maintenance, the FoR approach offers a structured framework that links strategic objectives with operational execution. By quantitatively defining problems, benchmarking current versus desired performance, and evaluating the impact of interventions, FoR supports continuous monitoring and informed decision-making. It integrates conceptual models, relevant parameters, and datasets to assess the effectiveness of maintenance strategies, ensuring alignment with business goals and operational reliability. Its application includes the following key aspects:

1. Quantitative State Concept: Defining a quantitative state concept by identifying parameters like equipment types, failure rates, and operational characteristics, along with relevant datasets to address maintenance challenges.
2. Benchmarking Process: Benchmarking current maintenance performance against desired targets to highlight performance gaps after implementing interventions, such as improved maintenance schedules or reduced failure rates.
3. Interventions and Evaluation Process: Monitoring and evaluating interventions to ensure alignment with goals such as reduced downtime and improved resource use.
4. Differentiating Maintenance Strategies: Distinguishing maintenance strategies based on equipment, operating conditions, and failure patterns to support more precise and effective planning.

2.2. Systematic literature review (SLR)

The SLR approach is used to explicitly search for the most relevant literature, select the best criteria for extracting the articles, and analyze the results [13,14]. To conduct an SLR, this study uses the following iterative steps to identify and filter data before being analyzed.

1. **Generating search queries:** Search keywords are adopted to generate useful queries, including generic keywords to determine the main scope of the research and specific keywords to narrow down the

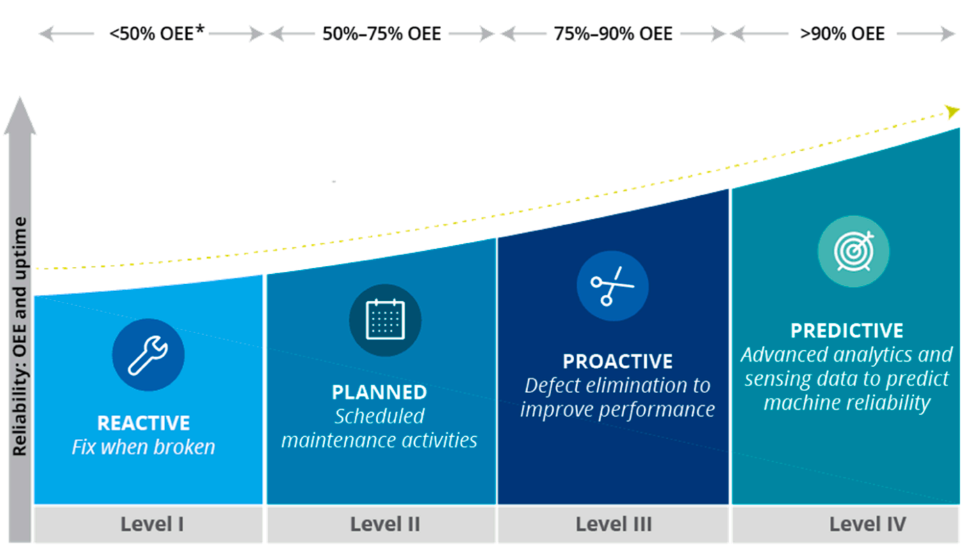

Fig. 2. Fundamentals of the FoR approach [12].

search into different sub-categories. Logical operators (OR, AND, and NOT) are used to combine these keywords and generate queries.

2. **Selecting databases:** Among the most well-known academic datasets (Scopus, Web of Science, Google Scholar, etc.), a dataset is selected for collecting the references based on a trial and error, on which of these datasets results in the highest number of relevant articles.
3. **Collecting articles:** An initial pool of articles is generated when searching for the search queries. At this stage, inclusion and exclusion criteria are defined to find the target articles based on timeframes, subjects, publishers, etc.
4. **Analyzing articles:** The remaining articles after implementing the inclusion and exclusion criteria are analyzed to identify the problem classification, recent trends of each subject, and remaining knowledge gaps.
5. **Interpreting the findings:** The findings of the research are evaluated in the context of the FoR to define the problem objectives, performance indicators, and assessment criteria.
6. **Filtering and updating:** An iterative process is used to repeat the abovementioned stages continuously to refine and re-collect the most relevant articles in the scope of this study.

The search query is defined in a way that encompasses the maintenance of mining trucks while dividing the problem scopes into maintenance, mining industries, and trucks when using the most generic and inclusive keywords for each scope. The search query is used when searching for articles on the Web of Science (WoS) and Scopus on 10 October 2024. Articles are filtered and refined using multiple exclusion and inclusion criteria based on selecting the most relevant accessible articles published since 2000. Table 1 summarizes the exclusion and inclusion criteria along with the query used in the search process.

The exclusion criteria mainly focus on removing the articles published before 2000, non-accessible articles, and articles not written in English. Besides, refining the initial pool based on the WoS and Scopus categories, research area, and document type results in a more relevant pool of articles before going through them one by one and excluding the ones that don't fit within the scope of this study. The additional articles that are not Scopus or WoS-indexed but discuss the main topic of this study are then included in the final stage after finding them from Google Scholar.

3. Analysis of results

The results obtained from the literature study are summarized in this section based on the exclusion and inclusion criteria used for data filtering. The final pool of publications is analyzed concerning the most recent subjects addressed, authors' affiliations, and publishers' contributions. Two main categories of maintenance for mining trucks are identified (corrective and preventive maintenance), and each category is thoroughly analyzed to illustrate the latest trends and knowledge gaps, and classify the problem based on the FoR framework.

Table 1
Exclusion (EXC) and inclusion (INC) criteria for data collection and refinement.

Criterion	Description
EXC1	Excluding the articles published before 2000.
EXC2	Excluding the non-accessible articles.
EXC3	Excluding the articles written in a language other than English.
EXC4	Excluding the articles that are not classified as relevant WoS and Scopus categories or research areas.
EXC5	Excluding review articles, early access articles, retracted publications, meeting abstracts, and letters.
EXC6	Excluding the articles that don't fit the scope of maintenance strategies for mining trucks.
INC1	Including the in-scope articles not indexed in the WoS and Scopus but in other academic databases.

Query: ((maintenance) **AND** (mine **OR** mining) **AND** (truck **OR** (heavy **AND** (vehicle **OR** equipment)) **OR** mobile equipment)).

3.1. Statistical analysis

The articles were searched on the Web of Science (WoS) and Scopus, as these databases were more successful in resulting in the most relevant published works; however, the leftover articles aligned with the scope of this research are added to the final pool of articles using a single inclusion criterion. Fig. 3 shows a total of 51 articles reviewed in this study after implementing all the exclusion and inclusion criteria.

Analyzing the final pool of articles shows a significant increase in the number of published articles over the last 10 years compared to the period before 2015, as displayed in Fig. 4. It means that considerable attention has been paid to the topic of maintaining mining trucks during the last decade, while the subject had been rarely investigated before that period. The most significant increase in the number of articles is shown in the last five years.

A geographical analysis of the final pool of articles categorizes the countries based on the affiliated authors. Results shown in Fig. 5 demonstrate high attention towards the subject from affiliated authors based in Iran (8), Canada (8), Chile (5), and Russia (4), while Brazil, China, India, Australia, and USA (3) are also the countries where the authors investigated this research scope very often. High contribution in the mentioned regions can be related to their large-scale mining operations, where enhancing cost-efficiency and minimizing downtimes play an important role in selecting maintenance strategies.

Distribution of the final pool of articles in terms of their publishers is shown in Fig. 6, showing that Springer, IEEE, Elsevier, and articles published by universities have the most contributions to the subject. This analysis, based on the publishers with at least four articles, shows that most of the well-known publishers, such as Elsevier (8 articles), IEEE (7 articles), and Springer (6 articles), covered this subject.

A network of the most frequently used keywords in the selected articles is shown in Fig. 7, demonstrating a problem classification where articles investigated different themes of fleet selection, truck performance, reliability analysis, and smart methods (such as AI and decision-support systems). Analyzing these keywords helped us in reviewing the articles based on which segment of trucks they focused on, what methods they adopted, and whether they validated the results using a real-world case.

The findings presented above are derived from the statistical analysis of the final pool of articles. To gain deeper insights, the next section provides a descriptive analysis, offering a structured review of the articles based on their classification under Corrective, Planned, Proactive, and Predictive maintenance strategies, their focus areas within mining truck operations, the methodologies employed, and the case studies examined. This analysis contextualizes the existing literature within a comprehensive FoR framework, helping to identify the key factors influencing maintenance strategy selection.

3.2. Descriptive analysis

This section presents a detailed literature review of the selected studies, examining how each maintenance strategy—Corrective, Planned, Proactive, and Predictive—has been implemented in mining truck operations. Each subsection analyzes the methods used, the effectiveness of the strategies, and their limitations, providing a critical perspective on the existing research.

3.2.1. Corrective maintenance

Corrective maintenance (also called Reactive maintenance), often referred to as run-to-failure maintenance, involves addressing component failures only after they occur. This approach is unplanned and inherently inefficient, leading to high costs, unexpected downtimes, and potential collateral damage to other components. Despite its drawbacks, corrective maintenance remains common in mining operations due to its

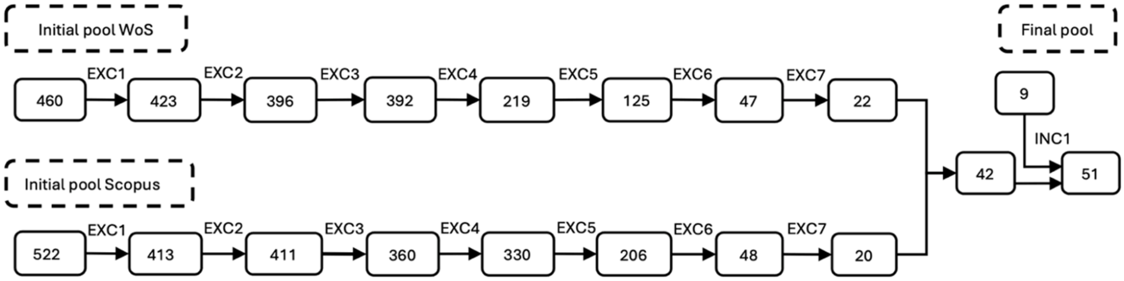

Fig. 3. Article collection procedure.

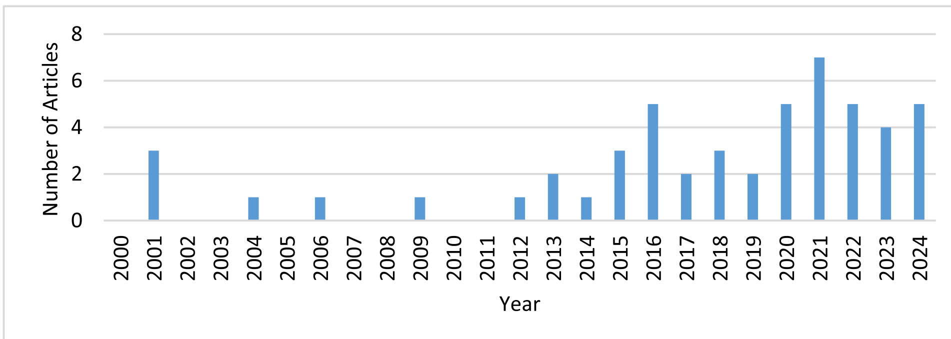

Fig. 4. Year-wise analysis of the articles.

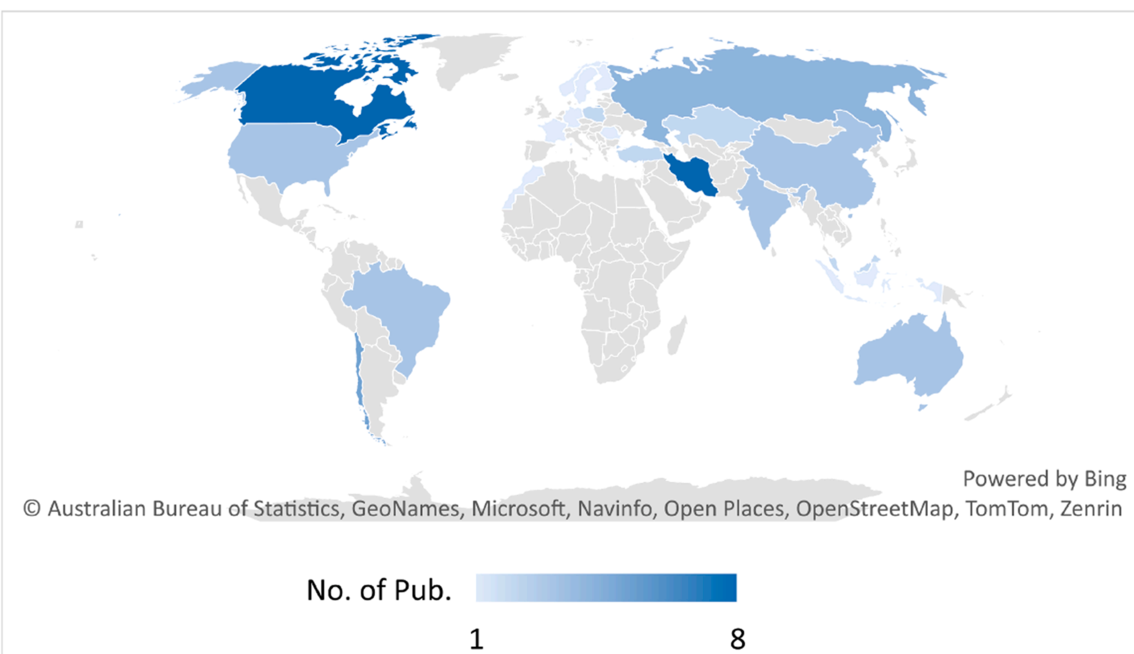

Fig. 5. Country-wise analysis of the articles.

low initial investment and simplicity. However, as mining equipment—such as trucks—operates under extreme conditions, this approach frequently results in cascading failures that extend downtime and escalate maintenance costs [3]. However, it is important to recognize that corrective maintenance may be economically viable under certain conditions. For example, for non-critical components with low failure impact or short replacement times, the cost of preventive or predictive maintenance may outweigh the benefits. In these cases, a run-to-failure strategy can offer a cost-effective solution, especially when the failure of such components does not compromise overall system safety or productivity.

A few studies have examined the consequences of relying on corrective maintenance for mining truck components. Knights and Boerner [15] investigated tire failures in mining trucks and demonstrated that failure frequency increases significantly in specific haul route conditions, particularly in loading and discharging zones. Their application of a Poisson distribution model highlighted patterns in failure frequency; however, the study lacked a practical dimension, as it

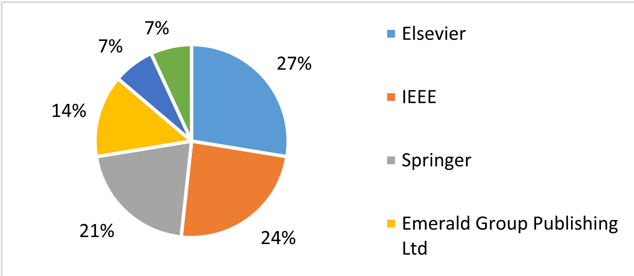

Fig. 6. Publisher-wise analysis of the articles.

did not explore how predictive techniques might reduce such failures or assess the economic trade-offs of different maintenance strategies.

Lhorente et al. [16] analyzed four years of wheel motor armature failure data from a Chilean mining fleet to develop an age-based maintenance strategy. Their study combined real operational data with a simulation model to find the optimal preventive replacement interval and compare it with a run-to-failure approach. While the results showed that corrective maintenance can be nearly as cost-effective as preventive replacement for non-critical components, the proposed policy was not tested through full implementation on site. This leaves open questions about practical challenges, such as scheduling and administration, that can affect the actual cost savings of corrective versus planned maintenance in real operations.

These studies highlight the inefficiencies of corrective maintenance, but a significant limitation in the literature is the lack of a comprehensive cost-benefit analysis. While these works document the high frequency and cost implications of corrective maintenance, they fail to provide alternative solutions or a transition pathway toward more proactive approaches. Moreover, many of these studies rely on historical failure data without considering how technological advancements in diagnostics and monitoring could mitigate these failures.

3.2.2. Planned maintenance

Planned maintenance, a structured time-based approach, aims to prevent failures before they occur by scheduling maintenance activities at predefined intervals. Unlike corrective maintenance, which responds to unexpected breakdowns, planned maintenance attempts to balance cost efficiency and asset reliability by reducing the likelihood of catastrophic failures. However, this approach has notable limitations: it does not account for the truck's actual health condition, leading to maintenance interventions that may not be necessary. This can result in higher maintenance costs and reduced fleet availability without significantly improving reliability [17].

Several studies have attempted to optimize planned maintenance scheduling in mining operations. Topal and Ramazan [18] developed a stochastic integer programming model to optimize multi-year fleet maintenance scheduling, aiming to minimize maintenance costs while meeting production targets. Their approach effectively considered uncertainties in operational demands, yet the model was static and did not account for real-time failure patterns, reducing its adaptability in changing mining conditions.

De Toledo et al. [19] introduced the Arithmetic Reduction of Age (ARA) and Arithmetic Reduction of Intensity (ARI) models for planned maintenance scheduling, analyzing failure records from five mining trucks. These models successfully optimized maintenance intervals, but their reliance on historical data limited their applicability in real-time decision-making scenarios. The study also assumed that past failure behavior would persist under evolving operational loads, which may not hold in dynamic mining environments. Kishorilal [20] explored the impact of scheduled engine overhauls on mining truck reliability, introducing Mean Time to Overhaul (MTTO) as a key metric for planned maintenance optimization. While their results confirmed that engine overhauls reduce breakdown frequency, the study assumed that all

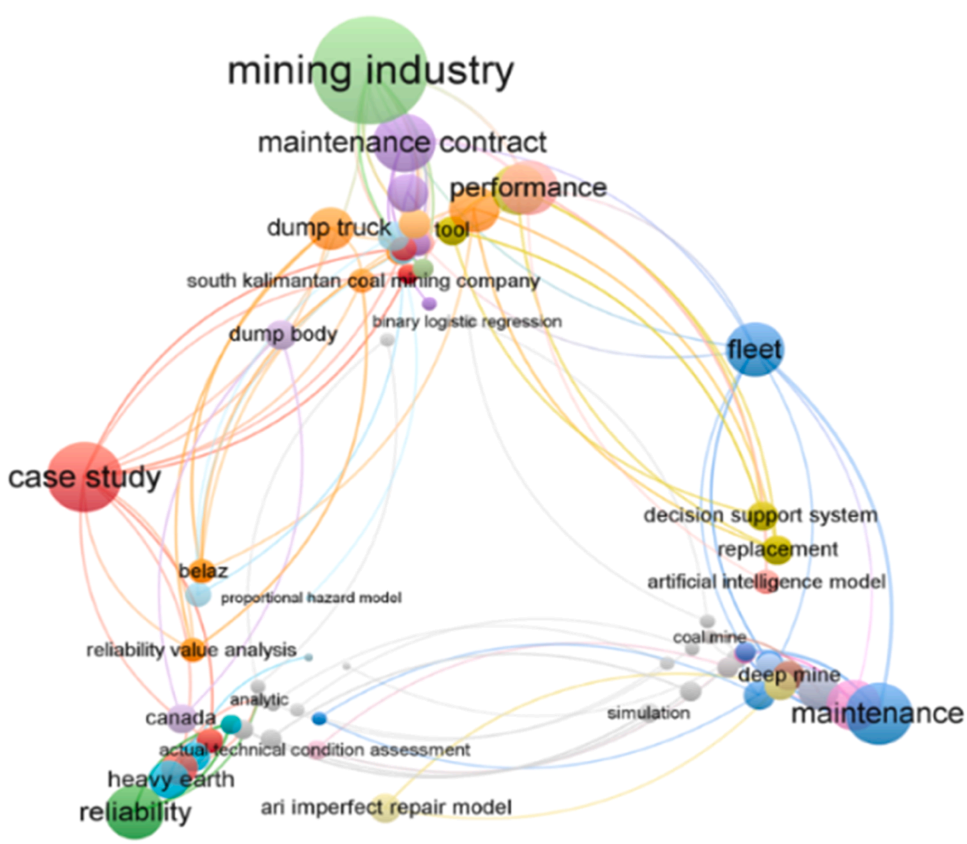

Fig. 7. Network map of keywords used in the reviewed articles.

overhauls restore engines to near-original conditions, ignoring the cumulative effects of wear and diminishing returns on repeated servicing. This idealization may lead to overestimation of planned maintenance benefits, particularly in aging fleets.

Silva et al. [21] estimated the required hours for both corrective and planned maintenance to assess truck availability and develop component replacement plans. Their study applied statistical modeling based on historical failure data, which provided a structured approach to predicting maintenance needs. However, a major shortcoming of this work is its reliance on past failure trends rather than real-time monitoring. Mining environments are highly dynamic, and static models based on historical data often fail to account for sudden operational changes, environmental conditions, or evolving failure mechanisms. A more theoretical approach was taken by Said and Taghipour [22,23], who analyzed repairable mining truck systems using a non-homogeneous Poisson process to compare corrective and planned maintenance scenarios. Their results suggested that planned maintenance significantly reduces failure risks, but their study assumes a perfect maintenance system, ignoring practical constraints such as technician availability, spare part logistics, and unexpected delays in servicing. This oversimplification limits the applicability of their model in real-world mining operations, where logistical and human factors play a critical role in maintenance effectiveness. In addition, their evaluation does not assess whether planned maintenance remains superior under cost constraints or in remote operations with limited support infrastructure.

Chaowasakoo et al. [24] proposed a truck dispatching simulation model that evaluated age-based maintenance strategies in open-pit mines. The study demonstrated that fixed maintenance schedules impact truck availability and production rates, but it failed to address operational variability, such as fluctuating workloads and changing haul routes, which significantly affect optimal maintenance timing. Without integrating these variables, the practical utility of their model in operational planning remains limited.

Doyen et al. [25] introduced a Virtual Age (VA) model to assess maintenance strategies for mining truck engines. Their framework evaluated how scheduled maintenance affects component reliability, highlighting the trade-off between maintenance frequency and fleet availability. However, their model lacks empirical case studies to validate the efficiency of their proposed approach in reducing unplanned downtimes. The absence of real-world validation raises concerns about the robustness of their conclusions under actual operational stressors. Building on this, Angeles and Kumral [3] refined the VA approach through a two-step optimization method for setting inspection intervals and separating physical from virtual aging effects. Although their model enhances planned maintenance scheduling, it still does not fully address the issue of unnecessary interventions leading to potential over-maintenance or delayed repairs. Furthermore, it overlooks the cost-benefit trade-offs of performing inspections that yield no actionable findings.

Rahimdel and Mirzaei [26] utilized a multi-criteria decision-making (MCDM) framework under a fuzzy environment to determine optimal planned maintenance schedules for mining trucks. Their study focused on reducing vibrational health risks for operators, which was a novel contribution. However, their approach still relied on fixed maintenance schedules and did not account for real-time monitoring, limiting its responsiveness to unexpected component degradation. This weakens the applicability of the framework in conditions where failure mechanisms evolve unpredictably. Nouri Qarahasanlou et al. [27] analyzed production losses due to planned maintenance scheduling, comparing constant vs. cyclic maintenance intervals. Their study effectively showed that environmental conditions, such as road quality, influence maintenance effectiveness, but it did not propose a dynamic adjustment mechanism for maintenance intervals based on real-time performance metrics. Such mechanisms are essential for adapting schedules to variations in operational severity.

Atmadyaya et al. [28] studied fleet readiness optimization through engine oil change intervals, demonstrating that optimally timed oil changes improved truck performance and reduced contaminants. However, their study did not incorporate real-time lubricant quality analysis, meaning that oil changes might still be performed prematurely or too late, leading to inefficiencies in maintenance execution. Wibowo and Santosa [29] investigated tire replacement schedules for mining trucks, integrating tire lifetime estimations, maintenance costs, and truck downtime into a goal programming model. Their results demonstrated optimal maintenance scheduling for different tire types (new, re-tread, rental). However, their model failed to consider real-time tire wear indicators, such as load conditions, temperature, and terrain variability, which significantly affect actual tire degradation rates.

Botyan et al. [30] examined maintenance scheduling for mining truck suspension systems, incorporating route conditions and material transport logistics. Their approach effectively determined the most suitable servicing intervals based on operational usage patterns, but it lacked an adaptive mechanism to adjust maintenance timing dynamically in response to unexpected wear and tear. This limits its ability to respond to early indicators of failure or unanticipated stress events. Myrzabekov et al. [31] proposed an optimization strategy for scheduled maintenance, analyzing the productivity, cost implications, and safety trade-offs of different maintenance intervals. Their findings showed that improperly scheduled maintenance can lead to over-servicing, increasing costs without significant reliability improvements. However, the study did not integrate condition-based monitoring, meaning its optimization strategy remains vulnerable to premature or delayed interventions. This omission reduces its relevance in modern fleets where real-time monitoring is increasingly feasible.

Despite broad research efforts in planned maintenance strategies, several critical gaps remain unresolved:

1. Over-Reliance on Historical Data: Most studies depend on failure records and statistical distributions, which do not account for real-time operating conditions [18,19,21,24,25].
2. Limited Consideration of Practical Constraints: Many models assume ideal maintenance execution, overlooking workforce availability, supply chain issues, and unpredictable external factors [22,23]. In real-world mining operations, delays in spare part deliveries, insufficiently skilled labor, and operational disruptions frequently affect maintenance execution, yet many optimization models fail to account for these uncertainties, reducing their practical applicability.
3. Lack of Dynamic Adjustment Mechanisms: Many studies assume fixed maintenance schedules, ignoring the impact of variable environmental conditions and fluctuating operational loads [27,30]. In practice, trucks operating under harsher conditions (e.g., heavy loads, extreme temperatures) require more frequent servicing, yet most models do not dynamically adjust schedules based on actual equipment stress levels.
4. Oversimplified Cost vs. Reliability Trade-Offs: While some studies optimize maintenance costs, they often assume that increasing maintenance frequency always improves reliability, failing to consider diminishing returns on excessive servicing [29,32]. Over-maintenance not only increases operational costs but may also introduce unnecessary downtime and labor inefficiencies.
5. Lack of Empirical Validation: Several studies propose mathematical optimization models without testing them in real-world mining operations, raising concerns about practical applicability [3,25]. Theoretical models often assume perfect maintenance execution and predictable failure patterns, yet mining operations are highly unpredictable. Without empirical validation, the reliability of these models remains questionable.
6. Missed Opportunity for Integration with Emerging Technologies: Most existing research does not incorporate IoT-based condition monitoring or machine learning techniques, which could significantly improve maintenance scheduling accuracy [26,31]. While

planned maintenance relies on static scheduling, integrating real-time diagnostics and predictive analytics could allow for more adaptive and cost-efficient servicing.

Overall, planned maintenance remains a structured yet rigid approach, requiring integration with real-time monitoring and adaptive scheduling to reduce unnecessary interventions and improve cost efficiency. The next section will explore proactive maintenance, which enhances planned maintenance by incorporating real-time sensor data to optimize servicing intervals dynamically.

3.2.3. Proactive maintenance

Proactive maintenance refers to strategies that use real-time monitoring and diagnostics to assess equipment condition and schedule maintenance only when necessary to prevent failures. This category includes Condition-Based Maintenance (CBM) and Reliability-Centered Maintenance (RCM) as follows:

- CBM focuses on continuous monitoring of asset health using sensors and diagnostics to determine the optimal time for maintenance interventions. Common applications in mining trucks include vibration analysis, oil condition monitoring, real-time tire pressure tracking, and emissions analysis [33,34].
- RCM extends CBM by incorporating systematic reliability assessments to prioritize maintenance actions based on failure modes, criticality, and operational risks. It integrates risk-based decision-making and engineering evaluations to ensure maintenance planning is aligned with system reliability and operational needs, optimizing resource allocation and failure prevention [35,36].

Unlike planned maintenance, which follows predefined schedules, proactive maintenance responds to actual asset conditions, reducing unnecessary servicing while ensuring timely intervention. However, despite its advantages, CBM and RCM face significant challenges related to high data-processing demands, sensor reliability, and implementation costs. Recent work by Tan et al. [37] shows that applying CBM to large, complex systems can increase model intractability and computational cost due to inspection uncertainties and system interactions, highlighting the need for more robust collaborative solutions.

Early work on CBM for mining trucks focused on oil condition monitoring, with Jardine et al. [38] developing a decision model for wheel motor maintenance. By continuously analyzing oil degradation, their approach aimed to determine whether motors should continue operating or undergo servicing. While effective in demonstrating the benefits of real-time diagnostics, the model did not account for external contaminants such as dust and moisture, factors that could significantly influence oil condition and lead to inaccurate predictions in harsh mining environments. Moreover, the study assumed stable operating conditions, which may not hold across diverse mine sites. Samanta et al. [39] expanded on this by introducing probabilistic models to evaluate truck reliability, demonstrating that condition-based interventions could reduce unnecessary maintenance. However, their study relied primarily on historical failure trends rather than real-time sensor validation, making it less applicable to mining fleets where operating conditions vary significantly over time.

Beyond oil condition analysis, Forbush [40] explored an emissions-based CBM strategy, monitoring carbon monoxide levels in truck engines to optimize fuel efficiency and engine performance. While this work introduced a novel emissions-driven diagnostic approach, it lacked integration with mechanical wear indicators, such as injector wear or air intake issues, limiting its effectiveness in predicting overall engine health. This single-variable focus reduces its predictive reliability for complex mechanical systems. Recognizing the need for a broader diagnostic approach, Wang et al. [41] connected CBM-driven spare part replacements to inventory management, proposing that oil condition monitoring could inform part ordering strategies. Although their findings showed cost savings in spare part procurement, the study relied solely on oil analysis and did not incorporate multi-sensor diagnostics, such as thermal monitoring or vibration analysis, which could further refine failure detection. Additionally, their model assumes high sensor accuracy, which is not always realistic in rugged mining environments.

To improve failure predictions, Moniri-Morad et al. [42,43] applied Monte Carlo simulation techniques to estimate component failure probabilities, integrating Reliability Block Diagrams (RBDs) to assess RCM strategy. While these simulation models provided useful theoretical insights, the research lacked real-world validation in mining fleets, raising concerns about its practical effectiveness in dynamic conditions. Similarly, Secara et al. [44] proposed Weibull and Exponential models for truck fatigue life estimation, deriving failure probabilities based on statistical distributions. However, their models did not incorporate real-time sensor data, meaning that actual degradation rates could deviate from predictions, reducing the reliability of maintenance scheduling decisions.

Advancements in computer-aided maintenance modeling were explored by Nikulin et al. [45], who developed a digital tool to optimize truck servicing schedules based on mine layout and operational data. While this structured framework improved decision-making for maintenance planning, it lacked real-time integration with CBM sensor data, making it less responsive to unexpected failures. Addressing the environmental impact of truck reliability, Peralta et al. [46] examined CBM-driven emissions reductions, concluding that improving fleet reliability through condition-based interventions could significantly lower fuel consumption. However, the study primarily focused on emissions as an outcome of maintenance effectiveness, rather than exploring a holistic CBM framework that integrates multi-sensor diagnostics for broader failure prevention. Integrating multi-sensor condition monitoring, such as vibration, thermal imaging, and oil analysis, would provide a more robust CBM strategy for optimizing truck reliability.

A shift toward software-based CBM decision systems emerged with Kalra et al. [47], who developed a CBM platform incorporating data acquisition, processing, and key performance indicators (KPIs) such as propeller time and environmental factors. While this approach introduced structured maintenance triggers, its reliance on static IF-THEN rules meant that it lacked adaptability to evolving failure patterns, reducing its effectiveness in complex operational environments. Expanding CBM diagnostics to motor-wheel gearboxes, Kudrevatykh et al. [48] introduced a multi-sensor monitoring model, incorporating thermal imaging, vibration analysis, and noise detection. While their approach demonstrated the effectiveness of multi-sensor diagnostics, their results were not extensively validated across different operating conditions, making it unclear whether their model could generalize to other mining environments.

Further refining CBM decision-making, Alla et al. [49] introduced performance indicators to assess maintenance effectiveness, incorporating data seasonality and reliability impact assessments. Their study provided valuable insights into long-term CBM outcomes, but it did not integrate advanced anomaly detection methods, which could have improved the accuracy of maintenance predictions. The reliance on predefined thresholds limits its performance in detecting early-stage degradation. The connection between CBM and inventory management was further explored by Motahari et al. [50], who developed a spare parts optimization model based on CBM-driven failure forecasts. Although their approach demonstrated cost reductions in inventory management, the model did not account for uncertainties in sensor accuracy, which could lead to inaccurate spare part demand predictions. This introduces risks of stockouts or overstocking in volatile operational settings.

Recent studies have begun integrating environmental factors into CBM frameworks, with Puzyrevskaya et al. [51] analyzing the impact of heavy rainfall on truck failure rates. While their work introduced weather-based CBM, it lacked real-time terrain assessment technologies, limiting its adaptability to other climate conditions. Shakenov et al. [52]

extended CBM diagnostics to off-road tire monitoring, applying temperature and pressure sensors to assess road conditions and tire durability. However, their study focused solely on tire wear, missing opportunities to integrate broader drivetrain and suspension diagnostics, which are also critical for fleet reliability.

Sarıgül [35] developed reliability-based maintenance policies for haul trucks by integrating failure data with statistical models to optimize preventive scheduling and truck availability. While effective in reducing downtime, the approach depends solely on historical data, lacking real-time condition monitoring and predictive analytics, which limits its applicability in dynamic mining operations.

Rahmani et al. [33] conducted a comprehensive reliability analysis of a mining truck fleet in Iran, applying Weibull distributions and reliability block diagrams to evaluate failure trends. Their approach successfully quantified the lifespan of key truck components, providing data-driven recommendations for maintenance scheduling. Despite these strengths, their study focused only on time-based failure patterns, omitting the influence of external environmental conditions, which are crucial in real-world mining operations.

Expanding the scope of RCM, Nouri Qarahasanlou et al. [34] investigated how operating environmental conditions impact the effectiveness of RCM strategies. Their findings highlighted that temperature fluctuations, humidity, and dust accumulation significantly alter failure probabilities and optimal maintenance intervals. While their research advanced RCM frameworks, it lacked sensor-based validation, which could have strengthened their reliability models.

Elbazi et al. [53] advanced CBM applications by implementing digital twin technology for real-time diagnostics of mining trucks, integrating sensor data with statistical process control to detect operational anomalies. Their approach demonstrated the potential for fleet-wide monitoring and failure detection, significantly improving maintenance decision-making. However, despite its effectiveness, the method poses challenges in large-scale deployment, as high computational demands and extensive data processing requirements may limit feasibility in resource-constrained mining environments.

Jardine [54] traced the evolution of vibration monitoring, showing how integrating proportional hazard models improves cost-efficient maintenance planning, particularly in electric wheel motors of mining trucks. Nonetheless, the study centered on vibration data alone, overlooking complementary CBM methods like oil or thermal analysis that could enhance its accuracy. Relying on a single failure signal reduces diagnostic confidence in complex systems.

While proactive maintenance strategies such as CBM and RCM significantly enhance fleet reliability, research in this area still faces several limitations, as:

1. Over-Reliance on Single-Sensor Diagnostics: Many studies focus on a single monitoring parameter (e.g., oil condition, emissions, vibrations) rather than integrating multiple sensor types for improved diagnostic accuracy [36,38,52,54–56].
2. Limited Real-World Implementation: Several studies rely on simulations or statistical models without extensive validation in operational mining fleets, raising concerns about practical applicability [33–35,42–45].
3. Static Rule-Based Decision Models: Many CBM frameworks use predefined IF-THEN rules for maintenance alerts, which do not adapt dynamically to changing failure conditions [47,49,51].
4. Lack of Machine Learning Integration: Most CBM studies do not incorporate AI-driven predictive models, missing the opportunity to advance toward predictive maintenance strategies [46,50].
5. High Implementation Costs & Data Processing Challenges: Real-time CBM systems require expensive sensor networks and significant data processing capabilities, which can be prohibitive for smaller mining operations [53].

Although CBM and RCM offer significant improvements over planned maintenance, they still lack the predictive foresight needed to estimate the remaining useful life of the studied system, thereby limiting the optimization of maintenance practices. The next section will explore predictive maintenance, which enhances proactive strategies by leveraging AI, machine learning, predictive models, and historical data to forecast equipment failures before they occur.

3.2.4. Predictive maintenance

Predictive maintenance is a highly advanced maintenance strategy that leverages historical data, sensor readings, and predictive models to anticipate failures before they occur, enabling timely interventions while minimizing downtime and maintenance costs. Unlike CBM, which detects existing degradation and initiates maintenance when a threshold is reached, predictive maintenance forecasts the progression of degradation, allowing maintenance teams to intervene at the optimal moment to prevent failures while optimizing costs and operational efficiency. In contrast, RCM differs from both CBM and predictive approaches by focusing on failure classification based on consequences, such as safety, operational, and economic impacts, rather than detecting or predicting failures. Instead of relying solely on real-time condition monitoring, RCM utilizes historical failure data, expert judgment, and risk assessments to identify the most effective maintenance actions for different failure modes. It serves as a structured decision-making framework to determine the most effective and necessary maintenance actions. Predictive maintenance is particularly valuable for mission-critical truck components, such as engines, transmissions, suspension systems, and brakes, where unexpected failures can lead to severe operational disruptions and financial losses.

The application of data analytics to predictive maintenance was first explored by Cheng [57], who demonstrated how historical and sensor data could be used to predict failures in engines, suspensions, and transmission components. However, this early research lacked adaptive learning models, relying on rule-based estimations, making its predictions less precise in dynamic mining environments. Advancing this approach, Phillips et al. [58] applied big data analytics to optimize oil change intervals for mining trucks. Their model utilized binary logistic regression and a cascade-correlation neural network to classify oil samples and predict engine health in real-time. While their findings improved lubrication management efficiency, their approach relied solely on oil analysis, failing to incorporate vibration, temperature, or pressure readings, which could provide a more comprehensive understanding of engine health. The computational complexity of the model may also pose scalability issues for fleets lacking advanced data infrastructure.

Silva et al. [59] expanded on predictive maintenance by developing a forecasting model to estimate mining truck availability based on historical preventive and corrective maintenance data. Their statistical approach enabled long-term planning by predicting the required maintenance hours and optimizing equipment replacement schedules. However, their reliance on past operational data rather than real-time condition monitoring limited the model's adaptability to sudden failures or dynamic operating conditions. Unlike data-driven predictive methods, their approach did not incorporate sensor-based diagnostics, reducing its ability to capture real-time equipment health variations. Despite these limitations, their study remains relevant for fleet management and availability forecasting, offering a foundation for integrating data-driven predictive maintenance strategies with statistical reliability assessments. This limits its usefulness for small or newer fleets where sensor investment is not feasible.

Beyond engine oil analysis, He et al. [60] addressed predictive maintenance for exhaust valves, which experience thermal and mechanical stress leading to increased maintenance costs. Their data-driven failure prediction model categorized exhaust valve degradation into risk groups, estimating failure likelihood using value-at-risk assessments. While this approach improved lifespan estimation, it lacked real-time sensor integration, meaning it could not adjust predictions based on evolving operating conditions. Moreover, the model's dependency on categorized failure data restricts adaptability for enterprises with minimal failure logs.

To expand predictive capabilities to suspension systems, Ali and Frimpong [61] developed an AI-based model incorporating Artificial Neural Networks (ANNs) and Mamdani Fuzzy Logic (MFL) to predict the performance of hydro-pneumatic struts in mining trucks. Their results demonstrated high accuracy in forecasting suspension performance degradation, leading to optimized maintenance scheduling. However, their model required extensive labeled training data, making it challenging to deploy in fleets with limited historical records.

Machine learning applications were further explored by Demyanov et al. [62], who developed intelligent predictive models for various truck components, aiming to reduce maintenance costs and increase reliability. Their research introduced logistics system optimization, but their model lacked adaptability across different truck types and mining conditions, reducing its scalability. The model also assumes uniform data availability, which may not reflect real-world constraints.

Focusing on motor-wheel gearbox reliability, Kudrevatykh et al. [63,64] presented mathematical models integrating vibration, noise, and thermal analysis to predict failure-prone conditions. While their multi-sensor approach improved diagnostic accuracy, it was highly sensitive to data noise, meaning that minor sensor inaccuracies could lead to false failure predictions, triggering unnecessary maintenance actions. Such sensitivity may be impractical for smaller fleets unable to maintain frequent sensor calibrations or redundant systems. A broader IoT-driven predictive maintenance framework was introduced by Patil et al. [9], who analyzed underground and off-road mining trucks using IoT data, statistical approximations, and machine learning algorithms. Their approach enabled real-time failure forecasting, yet their model produced a high number of false positives, reducing trust in automated failure predictions.

A different predictive approach was taken by Kahraman et al. [65], who applied sequential pattern mining to real-time alarm and sensor data. Their model identified which alarm patterns were most strongly correlated with future failures, allowing early intervention strategies. While effective, their method depended on having an extensive historical dataset of failures and alarms, limiting its usefulness for newer fleets without sufficient operational data. This reliance on large-scale data may limit applicability in low-volume or newly established mining operations.

Moving beyond mechanical failures, Rau et al. [66] investigated electrical fault prediction in mining trucks, applying machine learning models to classify fault severity in diesel engine control systems. Their study provided an innovative approach to non-mechanical failure forecasting, yet it did not integrate environmental factors such as temperature fluctuations, moisture levels, or electrical load variability, which could significantly impact electrical fault risks.

Predicting tire lifespan under different environmental conditions, Rahimdel [67] used a proportional hazard model to estimate tire reliability and conditional failure rates. Their research contributed to better tire change scheduling, yet it did not incorporate sensor-based real-time monitoring, meaning that actual road conditions or tire pressure variations were not factored into the predictions. A more comprehensive predictive maintenance approach was explored by Stefaniak et al. [68], who assessed how dynamic loads in different mining environments affected truck structural components. Their model linked mining conditions with structural fatigue risks, yet it lacked integration with onboard vehicle diagnostics, meaning that actual truck behavior (such as acceleration patterns or braking frequency) was not included in the failure predictions.

A real-time predictive maintenance system was proposed by Canelón et al. [10], who developed a remote assistance model for diagnosing and repairing critical truck failures. Their augmented reality and data analytics platform significantly reduced downtime by enabling real-time expert guidance for on-site technicians. However, their approach required continuous high-speed internet connectivity, which may not be feasible in remote mining locations with limited network infrastructure. This infrastructure requirement is particularly challenging for small or remote mining operations with limited network capabilities.

While predictive maintenance significantly enhances failure forecasting and operational efficiency, several challenges remain unresolved:

1. High Sensitivity to Data Quality: Many predictive models rely on AI and machine learning, which require large, high-quality training datasets. Incomplete or noisy sensor data can lead to false positives, triggering unnecessary maintenance actions [9,64].
2. Limited Generalization Across Different Fleets: Many models are trained on specific truck types and operating conditions, making them less effective when applied to different fleets or mines [62,66].
3. Over-Reliance on Single-Factor Analysis: Some studies focus on one failure type, such as oil degradation or vibration analysis, without integrating multi-sensor diagnostics, which limits prediction accuracy [58,60,67].
4. High Computational and Implementation Costs: AI-based predictive models require significant computing power, making large-scale adoption challenging for smaller mining operations [10,69].
5. Dependence on Historical Data: Some predictive models require extensive historical failure data, which may not be available for newer truck fleets, limiting the effectiveness of AI-based predictions [21,61,65].
6. Infrastructure and Connectivity Constraints: Real-time predictive maintenance systems require high-speed data transmission, which is often unavailable in remote mining sites, affecting implementation feasibility [10].

Although predictive maintenance outperforms corrective, planned, and proactive strategies, addressing these technological and implementation challenges is essential for maximizing its potential. Future advancements should focus on multi-sensor fusion, improved anomaly detection, and reduced model sensitivity to data inconsistencies to further refine failure predictions and optimize mining fleet reliability. In this context, recent studies have also emphasized the importance of fleet-level predictive approaches. For example, Yang et al. [70] propose a global group maintenance policy that combines real-time health prediction with dynamic scheduling across multiple components, improving system-level precision and efficiency. Similarly, Yang et al. [71] highlight how integrating condition monitoring with system age can support risk-informed actions, such as mission abort or adaptive scheduling, to enhance safety and cost efficiency in mission-critical operations.

3.3. Comparative analysis

This section provides a comparative analysis of the reviewed maintenance strategies to highlight research trends, industry focus, and the relative attention given to each approach. By examining the distribution of studies across Corrective, Planned, Proactive, and Predictive Maintenance, we identify which strategies have been prioritized in the literature and how maintenance research has evolved over time.

As illustrated in Fig. 8, proactive and predictive maintenance strategies have been the primary focus in recent research, reflecting the industry's shift toward data-driven decision-making. Among proactive strategies, CBM has been widely studied, while RCM has received comparatively less attention. Predictive maintenance—despite being a relatively newer approach—has shown significant research growth, driven by advancements in AI and IoT-enabled prognostics. In contrast, corrective maintenance has been the least studied, aligning with industry trends aimed at reducing unplanned failures and transitioning toward more efficient, reliability-centered maintenance strategies.

The reviewed studies have primarily focused on the overall

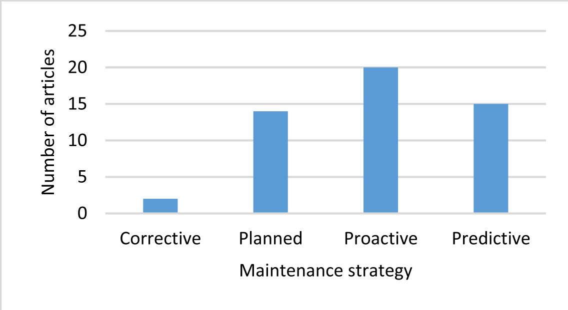

Fig. 8. Strategy-wise analysis of the articles.

performance of mining trucks, with particular emphasis on engine reliability, as engine failures tend to cause the most significant operational disruptions

(see Fig. 9). Additionally, engine performance is influenced by multiple factors, including regular maintenance schedules, oil quality, and operating conditions, making it a critical area of study for optimizing fleet efficiency and reducing downtime.

Fig. 10 illustrates the distribution of maintenance strategies across different truck components, highlighting the predominant focus areas in existing research. Proactive maintenance strategies are the most studied, particularly in overall truck performance. Predictive maintenance shows a strong emphasis on engine performance and transmission reliability, demonstrating its role in early fault detection. In contrast, corrective maintenance is minimally explored, with only one study each focusing on tire and transmission failures. These trends suggest a shift towards proactive and predictive strategies for optimizing fleet reliability and reducing unplanned downtimes.

To facilitate structured decision-making in maintenance strategy selection, particularly for the decision tree framework, the methodologies used in the reviewed articles are categorized into five distinct approaches. Each serves a specific function in maintenance analysis, differing in underlying principles, data requirements, and applications.

1. Statistical Methods – These approaches rely on mathematical and statistical techniques to analyze historical failure, assess reliability, and model maintenance schedules. Common methods include regression analysis (for trend identification), reliability modeling (to assess system lifespan), and non-homogeneous Poisson processes (NHPP) for modeling time-dependent failure rates.
2. Probabilistic Methods – Unlike statistical methods, probabilistic approaches incorporate uncertainty and risk modeling to estimate failure distributions and maintenance needs under varying conditions. Key techniques include Weibull analysis (for life estimation), Cox Proportional Hazard Models (Cox PHM) (for analyzing risk factors), Poisson distribution models (for discrete failure events), and virtual age modeling (to account for past maintenance effects).

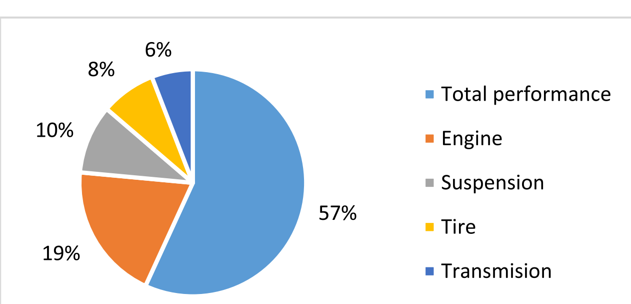

Fig. 9. Distribution of articles focuses on mining truck segments.

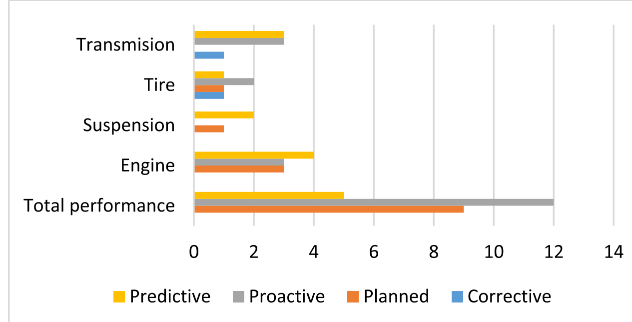

Fig. 10. Distribution of Maintenance Strategies in Mining Trucks by Component Focus.

3. AI-Driven and Intelligent Methods – Leveraging machine learning, expert systems, and data mining to identify complex failure patterns and enhance predictive accuracy. Unlike statistical and probabilistic methods, AI-based techniques continuously learn from real-time and historical data, adapting to new failure conditions. Common applications include Artificial Neural Networks (ANN) (on-linear failure prediction), Support Vector Machines (SVM) (classifying failure patterns), fuzzy logic (handling uncertainty in maintenance decisions), digital twins (real-time virtual models), and expert systems (rule-based decision-making).
4. Optimization and Decision-Support Models – These methods aim to optimize maintenance planning by balancing costs, resources, and operational goals. Unlike AI models that predict failures, optimization techniques determine the best maintenance scheduling and resource allocation strategies. Approaches include goal programming (optimizing multiple conflicting maintenance objectives), simulation-based optimization (testing maintenance scenarios under different conditions), joint optimization (integrating maintenance scheduling with logistics planning), genetic algorithms (GA) (evolutionary-based optimization for complex maintenance problems), and simulated annealing (searching for near-optimal maintenance solutions).
5. Uncertainty-Based Stochastic Models – These methods incorporate randomness and variability in maintenance decision-making by simulating different possible outcomes based on uncertain operating conditions. Unlike probabilistic methods, which estimate failure likelihoods based on known distributions, stochastic models generate multiple possible scenarios to account for variability in equipment performance. Common techniques include Monte Carlo simulations (simulating a range of potential maintenance outcomes), Proportional Hazard Models (PHM) (adjusting failure predictions based on changing risk factors), and stochastic process modeling (modeling unpredictable fluctuations in maintenance needs).

The distribution of methodologies in the reviewed literature is presented in Fig. 11, showing the relative proportion of research dedicated to each approach, while Fig. 12 highlights their evolution over time. The analysis reveals a clear transition toward data-driven and AI-powered techniques, particularly in the last decade, aligning with the industry's increasing focus on predictive maintenance solutions.

Among the methodologies, statistical methods account for the largest share (33 %), reflecting their long-standing role in failure analysis, reliability assessment, and maintenance scheduling. Their consistent presence across different periods indicates their continued relevance, especially for planned and predictive maintenance strategies. In contrast, AI-driven and intelligent methods (21 %) have experienced rapid growth, particularly in the last four years, highlighting the industry's transition toward real-time, data-driven decision-making. Probabilistic methods (18 %) and stochastic models (12 %) play a crucial role in risk assessment, failure prediction, and handling

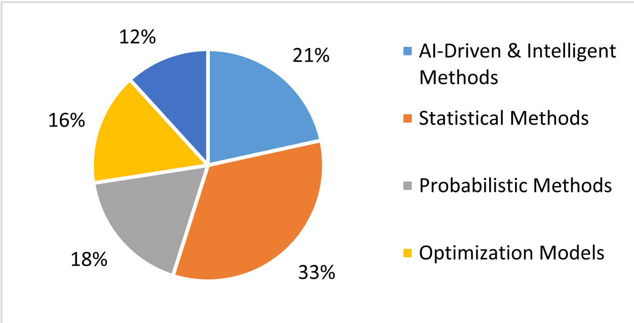

Fig. 11. Distribution of Methodologies in Mining Truck Maintenance Studies.

operational uncertainties, making them valuable for planned and proactive maintenance strategies. Additionally, optimization and decision-support models (16 %) have shown steady growth, emphasizing the increasing focus on cost-effective maintenance planning and resource allocation.

Overall, Fig. 12 illustrates a progressive shift from traditional statistical approaches toward AI-driven techniques, while optimization-based methods are gaining traction as industries seek efficiency and reliability improvements. This trend underscores the growing reliance on advanced analytics and predictive modeling in modern maintenance strategies.

3.3.1. Literature synthesis

To provide a structured understanding of maintenance strategies in mining truck operations, the FoR approach is adopted to analyze how different strategies can be effectively operationalized. The insights obtained from the SLR, together with findings from the comparative analysis, contribute to a comprehensive framework that enables practitioners to:

- Understand explicit definitions of the four maintenance strategies: Corrective, Planned, Proactive, and Predictive Maintenance.
- Differentiate the decision-making processes involved in implementing each strategy.
- Identify KPIs and quantitative measures, such as Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), failure rates, and cost-effectiveness, to assess their impact and effectiveness.

The comparative analysis, alongside the literature review, further strengthens this framework by highlighting trends, gaps, and interconnections between different strategies, providing a clearer roadmap for maintenance planning.

Table 2 presents a structured comparison of these strategies using the FoR framework, categorizing them based on their strategic intent, KPIs, quantification metrics, benchmarking processes, intervention triggers, and evaluation methods. This table goes beyond presenting information—it serves as a practical guide for decision-makers aiming to transition from reactive to intelligent maintenance systems. For instance, a practitioner currently relying on Corrective Maintenance can consult the benchmarking and evaluation rows to understand how performance is measured and validated in Predictive Maintenance. By doing so, they can identify which operational metrics—such as Remaining Useful Life (RUL) or anomaly detection—must be introduced to support the transition. Similarly, if an organization already uses Planned Maintenance, the table highlights how integrating equipment health indicators and real-time monitoring (as emphasized in Proactive Maintenance) can bridge the gap toward fully predictive strategies. This structured approach supports a stepwise, evidence-based progression in maintenance planning, helping practitioners align interventions with technological readiness, operational needs, and long-term strategic goals.

Several published case studies show how these strategies have improved real fleet KPIs in mining operations. For example, Jardine et al. [38] demonstrated that applying a proportional hazards model to optimize oil analysis for haul truck wheel motors at Cardinal River Coals in Canada led to clearer overhaul decisions and estimated a 20–30 % reduction in overhaul costs while extending MTBF. Similarly, Lhorente [16] used four years of actual failure data from Komatsu haul trucks in Chile to develop an age-based maintenance strategy for wheel motor armatures. By analyzing failure distributions and modeling different preventive intervals, the study compared corrective and preventive scenarios in terms of mean time between failures (MTBF), fleet availability, and maintenance cost per operating hour. The results showed that applying an optimal preventive interval of 14,500 operating hours could increase MTBF consistency, save about US$163,000 annually, and improve fleet availability rate by 2.3 % compared to the existing run-to-failure (Corrective Maintenance) approach. These practical examples illustrate how real mining sites have validated condition-based and planned maintenance policies by tracking performance indicators such as MTBF and overhaul costs, supporting the value of applying this framework in practice.

Additionally, to provide a holistic understanding of the current research landscape, Table 3 presents a summary of all reviewed studies, enabling practitioners and researchers to quickly identify patterns, gaps, and opportunities for future investigation. The studies are categorized according to:

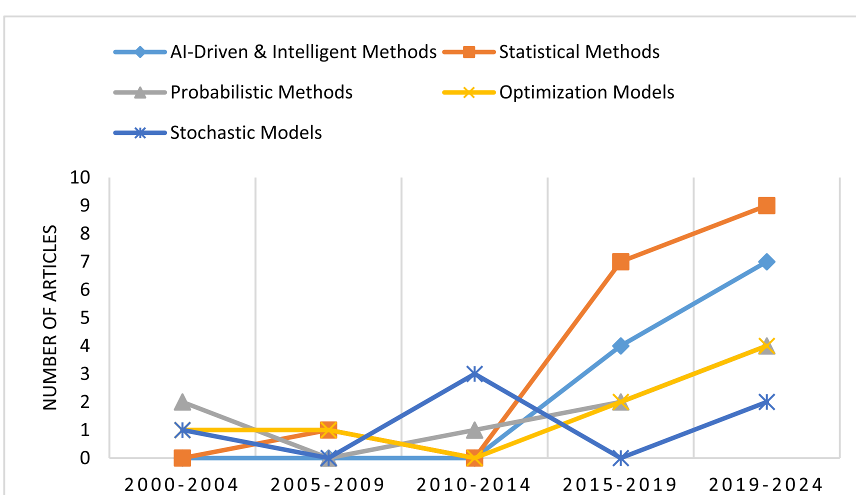

Fig. 12. Evolution of Research Methodologies in Mining Truck Maintenance Studies.

Table 2
The FoR framework for maintenance strategies of mining trucks.

Procedure	Maintenance strategy			
	Corrective Maintenance	Planned Maintenance	Proactive Maintenance	Predictive Maintenance
Strategic objective	Address failures as they occur to restore operations quickly.	Perform maintenance based on a pre-defined schedule to minimize failures.	Monitor asset conditions and intervene when signs of degradation appear.	Use data analytics and predictive models to anticipate failures before they occur.
Operational objective	No deviation between failure occurrence and repair response.	No deviation between scheduled maintenance and actual interventions.	Optimize asset performance and unplanned downtime based on the current degradation level.	Optimize asset performance and reduce unexpected failures using predictive insights.
Quantitative state concept	Mean Time to Repair (MTTR), downtime impact on productivity, and cost of unscheduled repairs.	Mean Time Between Failures (MTBF), truck availability rate, and maintenance cost per operating hour.	Equipment health indicators, degradation rate analysis, and early failure detection metrics.	Predictive failure models, RUL, anomaly detection metrics.
Benchmarking process	MTTR should ensure that productivity losses and repair costs remain within budget.	Scheduled maintenance should be benchmarked against actual MTBF to ensure alignment with the expected failure rate.	Real-time monitoring should accurately detect early degradation trends.	Predictive models should consistently provide accurate failure forecasts and improve asset reliability.
Intervention process	Just-in-time repair based on operator reports, failure diagnosis, and resource allocation.	Pre-scheduled maintenance activities based on historical failure data and manufacturer guidelines.	Data-driven inspections and repairs triggered by real-time condition monitoring.	Operational data-driven maintenance decisions based on predictive analytics and failure pattern recognition.
Evaluation process	Assess the responsiveness of maintenance teams and restoration efficiency.	Evaluate how effectively scheduled maintenance prevents failures.	Validate the accuracy of diagnostics and, effectiveness of early interventions.	Validate predictive models, analyze false positives/negatives, and refine failure predictions.

- The maintenance strategy they address (Corrective, Planned, Proactive, or Predictive).
- Their focus components in mining trucks (general performance, engine, suspension, transmission, tire).
- The methodologies applied (AI-Driven and Intelligent Methods, Statistical Methods, Probabilistic Methods, Stochastic Models, and Optimization Models).
- Whether the study includes real-world case validation or remains theoretical.

By synthesizing these insights, this section provides a decision-support foundation for practitioners and researchers to understand existing literature trends, gaps, and opportunities in maintenance strategy development. The next section further translates these insights into an actionable evaluation framework, guiding decision-makers on the optimal maintenance strategy based on operational constraints and technological capabilities.

3.3.2. Evaluation framework

Building on the findings from the systematic literature review and comparative analysis, this study develops an evaluation framework to guide practitioners in selecting the most appropriate maintenance strategy for mining trucks, based on operational impact, downtime costs, resource availability, and technological readiness. The framework consists of two interconnected decision trees: the first proposes the optimal maintenance strategy by evaluating operational risks and cost considerations, while the second refines the choice by recommending the appropriate methodology based on data availability and technological capabilities. The two decision trees are sequential and interdependent—first identifying the best-fit maintenance strategy and then determining the most suitable methodology to support its implementation. By systematically linking operational realities, resource constraints, and data readiness to strategic decisions, this evaluation framework ensures informed, evidence-based maintenance planning that enhances reliability, minimizes downtime, and optimizes resource utilization.

The first decision tree (Fig. 13) supports the selection of the most appropriate maintenance strategy by systematically evaluating three key dimensions:

1. The critical impact of failures on operations.
2. A comparison of:
   a. Downtime costs: Refer to financial losses resulting from production interruptions or halted operations.
   b. Maintenance costs: Include expenses associated with labor, spare parts, tools, and servicing activities.
   c. Asset utilization costs: Refer to losses from underusing an asset's full potential due to early replacement or repair, and also include indirect costs related to project delays or contractual penalties caused by extended downtime.
3. The availability of expertise and resources to implement advanced technologies.

The decision process begins by assessing whether a failure has a critical impact on operations. Here, criticality refers to the severity of potential safety risks (such as accidents or environmental hazards) and financial consequences (including repair costs, production losses, and downtime-related expenses). While this framework considers criticality in terms of safety and financial impact, it does not prescribe fixed thresholds for what is "critical." In practice, a situation may be considered critical if downtime losses exceed an agreed operational benchmark (for example, more than $5,000 per hour) or if a failure creates safety risks that surpass site-specific risk levels. Because these limits differ between organizations and sites, users of the framework should define criticality in line with their own cost structures, safety policies, and regulatory rules.

The framework also assumes that cost data—such as downtime losses, maintenance spending, and asset underuse costs—are available or can be estimated. In reality, this information may be incomplete or overlook hidden costs like productivity impacts, reputational risks, or unexpected safety penalties. To reduce this risk, it is recommended that practitioners apply expert judgment or sensitivity analysis when estimating costs to better reflect actual conditions and uncertainties.

After assessing criticality, the next step is to compare the potential downtime and asset utilization costs with the expected maintenance costs to identify the most cost-effective approach. If the failure is non-critical—such as a minor defect in auxiliary equipment—corrective maintenance may be the most practical and cost-effective approach. However, when failures result in major disruptions, such as halted transport, safety violations, or significant financial losses, preventive strategies become necessary. The choice among them depends on the cost dynamics and predictability of future operations.

When downtime and utilization costs are lower than maintenance costs, planned maintenance is recommended, particularly for safety-critical assets. This means that scheduled servicing is more cost-

Table 3
Summary of the literature review.

Author (s)	Maintenance strategy				Truck focus					Methodology					Real-world Case
	Corrective	Planned	Proactive	Predictive	Performance	Suspension	Engine	Transmission	Tire	M1	M2	M3	M4	M5	
Jardine et al. [38]			✓			✓							✓		✓
Knights and Boerner [72]	✓								✓			✓			✓
Samanta et al. [39]			✓		✓									✓	✓
Lhorente et al. [16]	✓	✓					✓				✓	✓			✓
Forbush [73]			✓				✓					✓			
Wang et al. [55]			✓				✓				✓				
Topal and Ramazan [18]		✓			✓						✓				
Moniri-Morad et al. [42]			✓		✓									✓	✓
Cheng [57]			✓	✓	✓						✓		✓		
Moniri-Morad et al. [43]			✓		✓									✓	✓
Secara et al. [44]			✓		✓								✓		
Kishorilal [32]		✓					✓					✓			
Phillips et al. [58]				✓			✓			✓					
de Toledo et al. [19]		✓			✓						✓	✓			✓
Silva et al. [59]				✓	✓					✓					✓
Said and Taghipour [23]		✓	✓		✓							✓			✓
Nikulin et al. [45]			✓		✓							✓			✓
Peralta et al. [46]			✓		✓							✓			
Said and Taghipour [22]		✓			✓						✓				✓
He et al. [60]				✓			✓						✓		
Ali and Frimpong [61]				✓		✓				✓					
Chaowasakoo et al. [24]		✓			✓						✓				✓
Kalra et al. [47]			✓		✓							✓			✓
Kudrevatykh et al. [56]			✓					✓				✓			
Doyen et al. [25]		✓					✓						✓		✓
Rahimdel and Mirzaei [26]		✓				✓				✓					
Angeles and Kumral [3]		✓			✓						✓				✓
Alla et al. [49]			✓		✓							✓			
Demyanov et al. [62]				✓	✓					✓					
Motahari et al. [50]			✓		✓						✓				✓
Nouri Qarahasanlou et al. [27]		✓			✓								✓		✓
Kudrevatykh et al. [63]				✓				✓		✓					✓
Kudrevatykh et al. [64]				✓				✓				✓			
Patil et al. [9]				✓	✓								✓		
Kahraman et al. [65]				✓	✓					✓					✓
Atmadyaya et al. [28]		✓					✓					✓			
Wibowo and Santosa [29]		✓							✓		✓				
Sarıgül [35]			✓		✓							✓			
Puzyrevskaya et al. [51]			✓		✓						✓				✓
Rau et al. [66]				✓			✓			✓					
Shakenov et al. [52]			✓						✓		✓				✓
Rahimdel [67]			✓						✓					✓	✓
Nouri Qarahasanlou et al. [34]			✓		✓								✓		✓
Stefaniak et al. [69]				✓	✓					✓					
Elbazi et al. [53]			✓		✓					✓			✓		
Silva et al. [17]		✓			✓							✓			✓
Rahmani et al. [33]			✓		✓							✓			✓
Canelón et al. [10]				✓			✓			✓					✓
Jardine [56]			✓			✓								✓	✓
Myrzabekov et al. [31]		✓			✓							✓			
Botyan et al. [30]		✓				✓						✓			

M1: AI-Driven & Intelligent Methods; **M2:** Optimization Models; **M3:** Statistical Methods; **M4:** Probabilistic Methods; **M5:** Stochastic Models;.

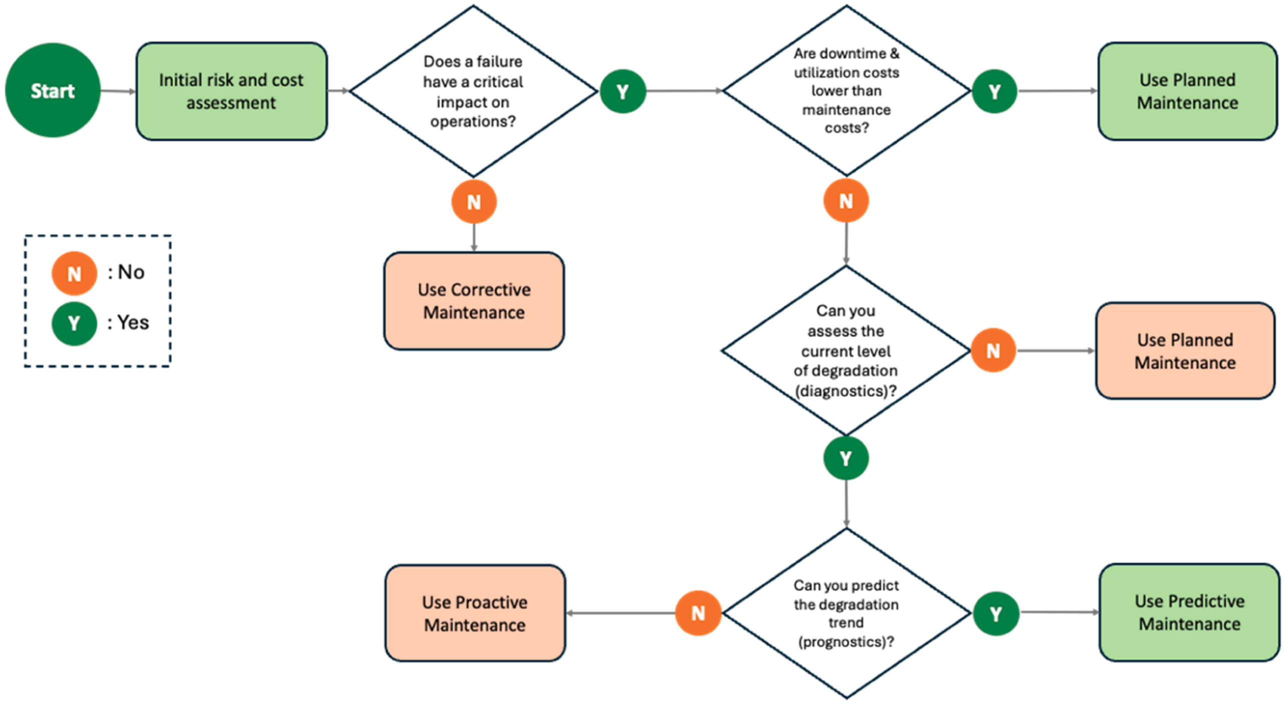

Fig. 13. Decision Tree for Maintenance Strategy Selection.

effective than unexpected repairs, and project delays are unlikely to justify extra spending if the asset can run to schedule with planned stops. It ensures reliability through scheduled servicing but does not consider actual degradation levels, which can lead to unnecessary maintenance and reduced equipment availability. If downtime and production losses exceed maintenance costs, preventive strategies must be further evaluated based on the predictability of future operating conditions. When future operational conditions (such as loading patterns or environmental stresses) are relatively stable, proactive maintenance—either CBM or RCM—is preferable. CBM uses real-time condition monitoring to trigger interventions, while RCM incorporates risk assessments and system criticality analysis to prioritize interventions.

However, when future operational conditions are dynamic and uncertain—due to factors like fluctuating loads, environmental variability, or dynamic utilization—predictive maintenance offers a better alternative. It extends beyond real-time diagnostics by forecasting the degradation over time, enabling maintenance teams to intervene at the optimal moment to minimize risks and operational costs. This approach requires more advanced prognostic capabilities, such as continuous sensor monitoring, predictive models, and a skilled workforce capable of interpreting complex analytics.

Finally, resource and expertise availability heavily influence strategy selection. Organizations lacking skilled personnel, real-time monitoring systems, or predictive analytics infrastructure are more likely to adopt planned or basic proactive strategies. In contrast, companies with mature data ecosystems and advanced analytics capabilities are better equipped to implement predictive strategies effectively.

For example, in a large-scale mining operation, if a primary haul truck critical to material transport suffers downtime, the financial and production impacts can be severe. If the mining company possesses real-time monitoring systems but lacks advanced prognostic capabilities, implementing a proactive CBM strategy would be the most feasible and effective option. However, if predictive models capable of accounting for future operational variability and sufficient analytical expertise are available, adopting a full predictive maintenance approach would offer optimal results.

While the first decision tree (Fig. 13) focuses on selecting the appropriate maintenance strategy based on operational impact, cost considerations, and resource availability, the second decision tree (Fig. 14) refines the decision-making process by identifying the most suitable methodology based on the available data types. The effectiveness of a maintenance strategy depends significantly on data availability, as different methodologies require varying levels of historical and real-time information. The key data categories considered in this framework include:

- Operational Data: Usage patterns, fuel consumption, load factors, and cycle times, which help in assessing wear rates and operational efficiency.
- Environmental Data: Road conditions, temperature fluctuations, humidity, and external stressors that influence component degradation and failure risks.
- Maintenance and Failure Records: Historical logs of repair activities, replacement schedules, and past failure events, providing insights into failure trends and component lifespans.
- Condition Monitoring Data: Real-time sensor readings, such as vibration analysis, oil quality, thermal imaging, and pressure monitoring, enabling early detection of potential failures.
- Cost Data: Maintenance expenditures, including repair costs, downtime losses, and replacement investments, are essential for optimizing maintenance schedules while maintaining cost efficiency.

Once the maintenance strategy is selected, the next step is determining the most suitable methodology based on the available data types. Each strategy relies on different types and volumes of data, and aligning the methodology accordingly ensures accurate failure prediction, effective scheduling, and optimal resource use.

- Corrective Maintenance: If no data is available, maintenance occurs only after a failure happens without predictive modeling or scheduling tools. Decisions are reactive and based on immediate operational needs.
- Planned Maintenance: If only historical maintenance and failure records are available, statistical and probabilistic methods (e.g.,

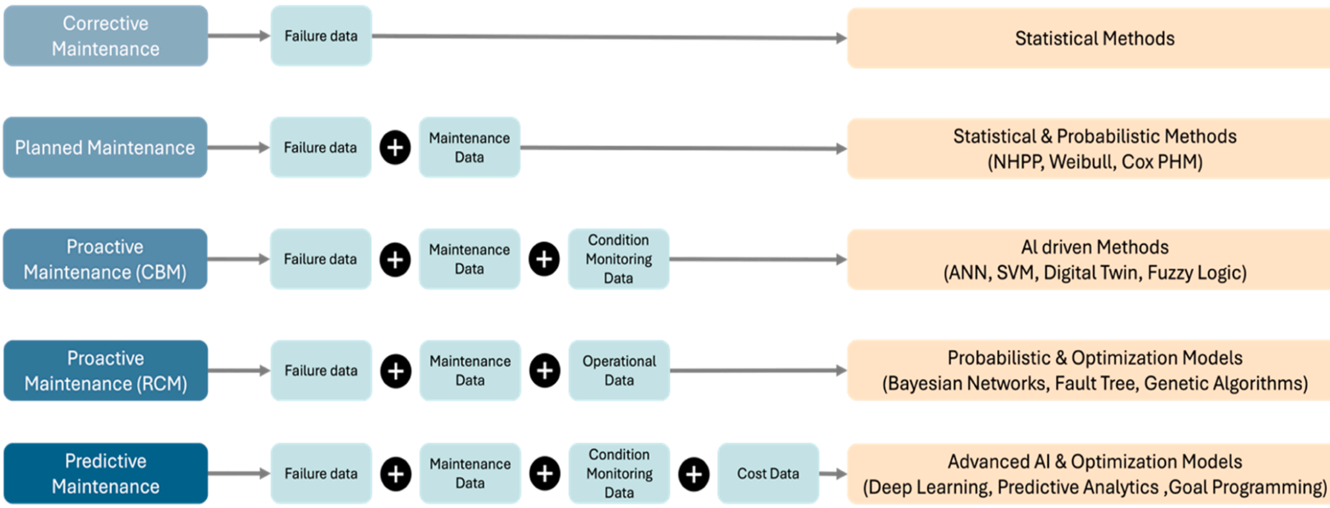

Fig. 14. Decision Tree for Strategy and Methodology Selection Based on Data Availability.

Non-Homogeneous Poisson Processes, Weibull Analysis, Cox Proportional Hazard Models) can be used. These methods help determine the optimal timing for scheduled maintenance without real-time monitoring.

- Proactive Maintenance:
  - CBM: With access to real-time condition monitoring data (e.g., sensor data on vibration, oil quality, or pressure), AI-driven methods can analyze sensor data to detect early failure indicators and trigger interventions only when necessary.
  - RCM: If historical failure data and operational data (e.g., component reliability, failure modes, risk analysis) are available, probabilistic and optimization models can assess risk, prioritize critical components, and allocate resources effectively based on failure modes and system reliability.
- Predictive Maintenance: If both failure data and condition monitoring data are accessible, predictive models can forecast degradation trends, enabling proactive interventions before failures occur. If cost data is also available, optimization models can further enhance decision-making by balancing reliability goals with cost efficiency.

For instance, if a mining company selects Planned Maintenance but lacks real-time condition monitoring, it would rely on historical failure records and use statistical models to determine optimal servicing schedules. If the same operation deploys real-time sensors for oil viscosity and engine temperature, it can adopt CBM or predictive models to detect deviations from normal behavior, reducing unnecessary interventions and improving.

4. Conclusions

This study introduced a comprehensive evaluation framework to systematically classify, compare, and assess maintenance strategies for mining truck operations. Through a Systematic Literature Review, the application of a Frame of References approach, key research trends, dominant methodologies, and knowledge gaps were identified. The framework is supported by a two-level decision-support model that helps strategy managers choose the most suitable maintenance approach by weighing operational impact, downtime costs, data needs, and available resources.

The analysis highlights a clear industry shift toward proactive and predictive maintenance strategies. CBM emerged as the most extensively studied proactive approach due to its real-time diagnostic capabilities that to helps to plan maintenance more effectively. RCM has received comparatively less attention despite its structured risk-based prioritization framework. Predictive maintenance, driven by advances in AI and IoT technologies, has gained significant traction, enabling companies to anticipate failures more accurately under varying operational conditions. In contrast, corrective maintenance remains the least studied, reflecting the industry's move away from reactive, failure-driven practices. Although planned maintenance is still widely implemented, its inherent limitations, such as unnecessary interventions and lack of real-time adaptability, have accelerated the transition toward more data-driven, reliability-based strategies.

To put these insights into practice, a two-level decision-support model was proposed. The first decision tree assists in selecting an appropriate maintenance strategy by considering the criticality of failures, cost trade-offs between downtime and maintenance activities, and the available diagnostic and prognostic capabilities. In particular, the distinction between planned, proactive, and predictive approaches is clarified based on the variability of future operating conditions and the level of expertise and technology infrastructure available. The second decision tree further refines the methodology selection based on the types of data accessible, ensuring that analytical methods, whether statistical, probabilistic, optimization-based, or AI-driven, are aligned with the organization's technological maturity and operational priorities.

Despite these contributions, there are still barriers to using advanced maintenance in real operations. Many mining sites face poor data quality, rely on single sensors, and lack the infrastructure for real-time monitoring. Multi-sensor fusion is a promising fix because it combines signals from different sensors to provide a more comprehensive and robust understanding of equipment health. But this also introduces specific challenges, notably sensor noise and data heterogeneity. To mitigate these problems, advanced signal processing techniques such as filtering, smoothing, and outlier detection are essential to cleanse raw data and enhance signal quality before analysis. Additionally, sensor calibration protocols and redundancy in sensor deployment further improve data reliability and make multi-sensor fusion more practical. Another area that deserves more research is how project-specific deadlines or contract requirements might affect maintenance choices, since these factors can influence the trade-offs between cost, reliability, and schedule performance.

While the proposed evaluation framework provides structured guidance for selecting maintenance strategies, it has certain limitations. Specifically, project deadlines and contractual constraints, such as production targets, delivery schedules, and penalties for downtime, are not directly captured in the current literature-based model. During preliminary validation with a mining company, practitioners highlighted that the framework effectively maps operational constraints, data availability, and technological readiness to suitable maintenance strategies. However, they emphasized that real-world maintenance decisions are also strongly influenced by contractual obligations, project schedules, and site-specific resource availability. Incorporating these practical constraints in future iterations of the framework would enhance its relevance and enable more informed, context-sensitive maintenance planning in operational mining environments.

Future work should test this framework in real mining operations and develop models that can adapt to diverse operational environments and handle large, mixed data sets to improve failure forecasting accuracy. More research is also needed to connect maintenance planning with inventory management, especially for perishable materials, to support sustainable maintenance practices and to adapt strategies for different site conditions and contract terms. By addressing these technological and operational barriers, the mining industry can move toward smarter maintenance solutions that reduce unexpected failures and costs, increase equipment availability, and ensure sustainable operational performance.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Scholar GPT in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Malihe Goli: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Behzad Ghodrati:** Writing – review & editing, Methodology, Conceptualization. **Nick Eleftheroglou:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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