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ORIGINAL RESEARCH

The Impact of Predictive Maintenance on the Performance of Industrial Enterprises

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Abstract
Optimizing maintenance and enhancing the performance of businesses are significant concerns in the modern industrial world. Predictive maintenance is emerging as an innovative approach to address these challenges, allowing companies to shift from corrective maintenance to preventive maintenance. Predictive maintenance relies on the use of advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) to collect and analyse real-time data from equipment. Through this predictive analysis, it becomes possible to identify early warning signals of failures, enabling the anticipation of potential issues and the proactive planning of maintenance interventions. In this study, we will thoroughly examine the impact of predictive maintenance on the performance of businesses. We will explore the benefits and opportunities it offers in terms of reducing downtime, optimizing maintenance costs, and enhancing productivity. We will also investigate the various technologies and methods used in the implementation of predictive maintenance, along with potential challenges and best practices for successful adoption. This research focuses on studying the application of predictive maintenance within a company using data science and machine learning methods. Predictive maintenance represents an innovative approach aimed at anticipating equipment failures by leveraging real-time collected data. Through the analysis of this data using sophisticated algorithms, it becomes possible to identify early signals of potential problems and implement preventive maintenance actions before breakdowns occur. This approach not only reduces unexpected downtime but also optimizes maintenance operations by avoiding unnecessary interventions and maximizing resource utilization. The ultimate goal is to improve equipment availability, optimize operational performance, and maximize the overall yield of the company.

Keywords Production · Predictive maintenance · Optimizing maintenance · Performance indicators · Artificial intelligence (AI) and machine learning (ML) · Data science

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Introduction

The performance and competitiveness of manufacturing companies depend on the reliability, availability, and productivity of their production facilities, with customers expecting the best products at the best prices with immediate availability. Success in manufacturing, and even survival, is increasingly challenging, requiring continuous development and improvement in how we produce goods. Meeting customer demands requires a high degree of flexibility, low-cost/low-volume manufacturing skills, and short delivery times. To ensure that the factory achieves the desired performance, the managers need effective monitoring of the maintenance process's performance. This can be achieved through the development and implementation of a framework for measuring the economic performance of the maintenance function within industrial organizations.

In the manufacturing industry, not staying at the forefront means a loss of opportunities and profits. Therefore, one way for a company to dominate the market is to reduce waste by using the lean approach in its operations to offer products at the lowest possible prices. In doing so, the company must also maintain its business and customer loyalty by producing high-quality and reliable products, where maintenance has proven to be a crucial business function [1]. It provides essential support to organizations by supporting their long-term profitability and contributing to the achievement of their business goals. There is significant interest among asset managers in assessing the impact of maintenance process outcomes on business objectives [2]. The most effective way to improve business performance is to have an efficient maintenance activity that contributes to cost reduction, productivity improvement, and the maintenance of the company's profile [3]. The effectiveness and efficiency of a maintenance system play a central role in the success and survival of the business [4]. Therefore, maintenance activities within a company must be monitored, controlled, and improved from time to time to produce an effective system. An appropriate and effective Maintenance Performance Measurement (MPM) is necessary to monitor maintenance activities and plan more successful improvements. Indeed, the results of maintenance performance measurement will indicate where the organization currently stands and where it is headed [5]. It serves as a guide to assess whether the organization is on track to achieve its goals or not.

The performance of maintenance-related functions has become a major management issue as companies increase their investments in equipment [6]. Justifying investment in maintenance and its significant costs, as well as the impact of downtime and failures on various aspects of the business, has made it necessary to measure its effectiveness and quality [7]. Maintenance performance indicators assess the effectiveness and efficiency of maintenance activities and provide a basis for improving efficiency, reducing costs, minimizing downtime, and eliminating waste [8].

The aim of this article is to demonstrate that performance indicators are not defined in isolation but should result from a thorough analysis of the interaction of the maintenance function with other organizational functions, especially with the production function. This is achieved by developing models used in the implementation of predictive maintenance using data science and machine learning methods, within a conceptual framework of the impact of predictive maintenance on the performance of industrial enterprises.

This article on predictive maintenance introduces several new perspectives that enrich both the field of research and industrial practices. The main contributions are as follows:

Integration of Advanced Technologies: The article highlights the significance of leveraging technologies such as the Internet of Things (IoT), artificial intelligence (AI), and machine learning in the implementation of predictive maintenance. This technological approach provides a new way of collecting and analysing real-time data, enabling precise failure anticipation.

Quantitative Performance Analysis: Through the application of precise metrics such as availability rate, OEE (Overall Equipment Effectiveness), and key performance indicators (KPIs), the study demonstrates how predictive maintenance can concretely enhance a company's operational performance. These quantitative analyses provide tangible evidence of the benefits of this approach.

Resource and Cost Optimization: The article emphasizes how predictive maintenance not only reduces unplanned downtime but also optimizes resource use. By avoiding unnecessary preventive maintenance interventions, this approach contributes to better cost and resource management.

Improvement in Product Quality: By minimizing production errors and equipment failures, predictive maintenance promotes an increase in the quality of manufactured products. This has direct implications for customer satisfaction and reduces costs related to manufacturing defects.

Impact on Maintenance Strategy: The article encourages companies to reconsider their maintenance strategies, advocating for a shift toward predictive maintenance, which is presented as an innovative and effective solution to contemporary industrial challenges.

Future Research Perspectives: By identifying application areas and emerging technologies that could further transform predictive maintenance, the article paves the way for future research. This includes exploring its use in various industrial sectors and integrating new analytical methodologies.

This research contributes to a deeper understanding of predictive maintenance, emphasizing its tangible benefits, practical applications, and potential to transform modern industrial operations.

Maintenance Definition

The definition of the term "maintenance" is well established in the literature. However, other terms related to maintenance, such as maintenance strategy, maintenance concepts, and maintenance approaches, are defined quite vaguely. These terms seem to vary among authors, making it sometimes challenging to understand the specific reference to which an author is alluding when using these terms. Therefore, it is crucial to specify the definitions of these terms adopted within the scope of this research.

According to the definition provided by Rastegari and Salonen [9], maintenance is "the combination of all technical, administrative, and managerial actions throughout the life cycle of an item, aimed at keeping it in a state where it can perform the required function or restoring it to that state." Maintenance, in its narrow sense, encompasses all activities related to maintaining a specific level of availability and reliability of the system and its components, as well as its ability to achieve a standard level of quality [10]. Maintenance also includes engineering decisions and associated actions necessary for optimizing the specified equipment capacity, where capacity is defined as the ability to perform a given function within a range of performance levels related to capacity, rate, quality, safety, and responsiveness [11].

According to Khairy et al. [12], the primary objective of maintenance is "the optimization of the total life cycle of assets," meaning maximizing the availability and reliability of assets and equipment to produce the desired quantity of products with the required quality specifications in a timely manner. This objective must be achieved cost-effectively and in compliance with environmental and safety regulations.

According to Swanson [13], to ensure the optimal operation of the factory, maintenance management must make conscious decisions regarding maintenance goals and strategies. Additionally, as noted by Pinjala et al. [14], effective maintenance doesn't simply result from an isolated determination of goals and strategies but rather stems from a derivation based on factors such as company policy, manufacturing policy, and other potentially conflicting demands and constraints within the company.

Maintenance objectives, as indicated by Anthony [15], are closely linked to achieving production goals. This includes the pursuit of high availability and required quality while respecting constraints related to the system's condition and safety. To meet these objectives, it is crucial to use resources efficiently, maintain equipment in good condition, achieve the intended lifespan, comply with safety standards, and simultaneously optimize energy usage and raw material consumption.

We summarize the maintenance objectives into five categories (as shown in Fig. 1): ensuring the functionality of the factory (availability, reliability, product quality, etc.); ensuring that the factory achieves its intended lifespan; guaranteeing the safety of the factory and the environment; ensuring the cost-effectiveness of maintenance and the efficient use of resources (energy and raw materials).

Types of Industrial Maintenance

Industrial maintenance encompasses a variety of strategies and approaches as shown by Fig. 2, designed to ensure the optimal performance and durability of machinery and equipment in industrial settings. These maintenance practices can

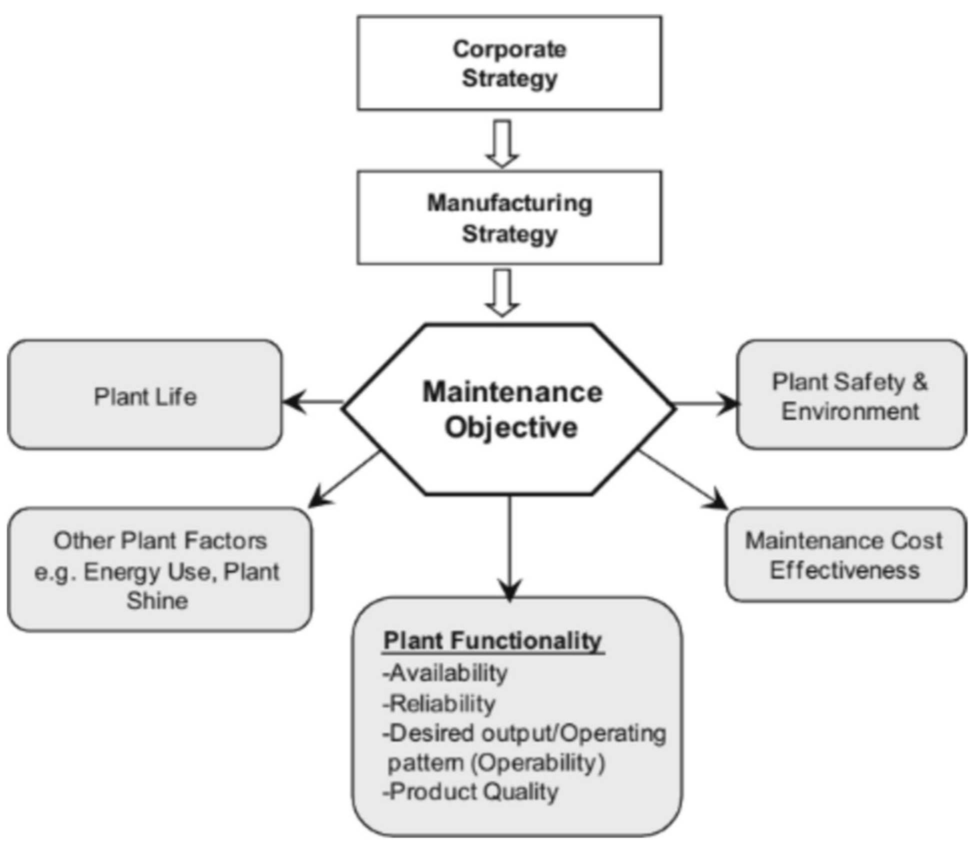


Fig. 1 A summary of maintenance objectives for a maintenance department

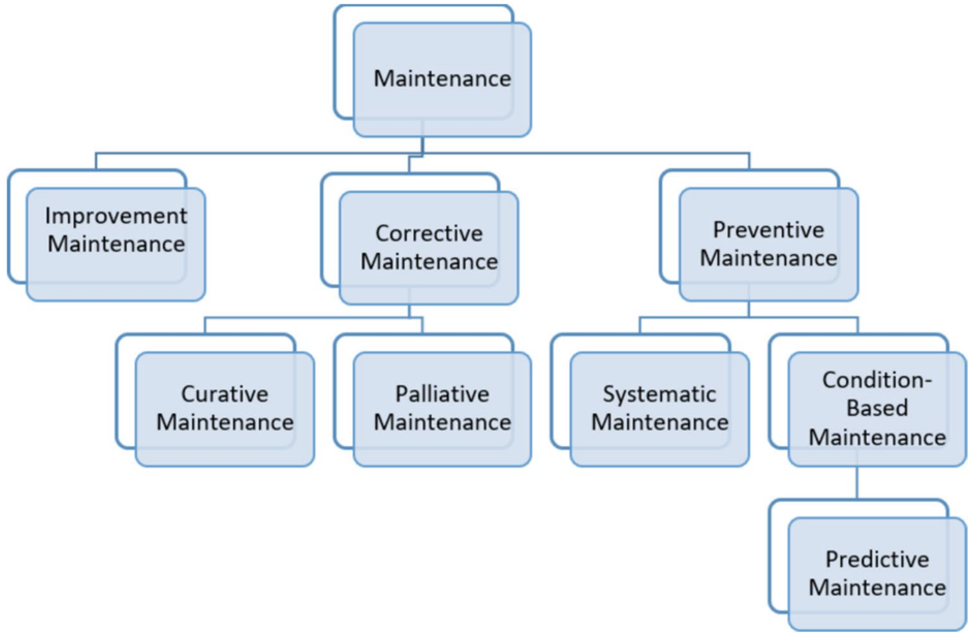


Fig. 2 Types of Industrial Maintenance

be broadly classified into four main types, each tailored to address specific operational needs and requirements.

Maintenance strategies play a crucial role in ensuring the reliability and longevity of industrial equipment and systems. Three primary approaches, preventive maintenance (PM), corrective maintenance (CM), and Improvement maintenance.

Improvement Maintenance: The improvement of capital goods involves a set of technical, administrative, and management measures aimed at enhancing the operational safety of an asset without altering its required function [16]. Modifications are made to the original design with the goal of increasing the lifespan of components, standardizing them, reducing energy consumption, improving maintainability, and more. Improvement maintenance is a mind-set that requires a critical observational ability and a creative attitude

Corrective Maintenance: Also known as "breakdown maintenance," involves addressing equipment failures and malfunctions after they occur [17]. It is a reactive approach aimed at restoring the equipment to its normal operating condition.

Preventive Maintenance: Proactive in nature, focuses on scheduled inspections, routine tasks, and repairs to prevent potential failures and breakdowns [16]. This type of maintenance is typically based on manufacturer recommendations or historical data.

Condition-Based Maintenance: Similar to predictive maintenance, condition-based maintenance places a heavier emphasis on real-time monitoring of equipment parameters and performance indicators [18]. It involves continuously tracking variables like vibration, temperature, and pressure to make maintenance decisions.

Strategically combining these maintenance types based on the specific needs and criticality of the equipment allows industries to optimize asset performance, minimize downtime, and reduce overall maintenance costs [16].

Predictive Maintenance: Relying on data analysis and condition monitoring, predictive maintenance predicts when equipment is likely to fail, allowing for timely intervention before a breakdown occurs [19]. It leverages technologies such as sensors and data analytics to assess the health and performance of assets.

In summary, the choice of an appropriate maintenance type depends on factors such as the criticality of the equipment, budget constraints, and operational priorities. Implementing a well-balanced maintenance strategy can significantly contribute to the efficiency, reliability, and profitability of industrial operations.

Optimizing Maintenance Performance Indicators Through Predictive Innovation

The integration of predictive maintenance into the calculation of maintenance performance indicators offers an innovative approach that revolutionizes how companies measure and optimize the efficiency of their maintenance activities. Through the use of advanced data science and machine learning methods, predictive maintenance positions itself as an innovative solution to anticipate equipment failures and positively impact key performance indicators in this specific domain.

The main reason for the increasing adoption of predictive maintenance in calculating maintenance performance indicators lies in its ability to proactively transform equipment management. By leveraging technologies such as the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML), this approach allows for the real-time collection and analysis of relevant data on equipment conditions. By identifying early signals of failure, predictive maintenance provides early visibility into asset conditions, enabling more efficient planning of maintenance activities.

This anticipation of failures directly impacts maintenance performance indicators, particularly in reducing unplanned downtime. By intervening strategically on at-risk equipment before major issues arise, companies minimize unplanned interruptions, thereby improving asset availability. This availability optimization translates directly into indicators such as operational reliability and the ability to meet contractual or production commitments.

Predictive maintenance also contributes to cost control, an essential aspect of performance indicators. By early identifying equipment requiring intervention, resources can be allocated more efficiently, avoiding the high costs associated with emergency repairs and unforeseen replacements. This proactive cost management has a positive impact on indicators such as the average maintenance cost per equipment or the overall maintenance cost.

In conclusion, the use of predictive maintenance in calculating maintenance performance indicators represents a major advancement in the sector. By adopting this innovative approach, companies can not only enhance the reliability of their equipment and reduce costs but also strengthen their competitive position through proactive and efficient asset management. Predictive maintenance becomes a centrepiece in the constant pursuit of optimal performance in the field of industrial maintenance.

Predictive Maintenance

Predictive maintenance employs advanced data analytics and condition-monitoring techniques to predict when maintenance should be performed on equipment. It entails the continuous collection of data related to the condition and performance of machinery. It a strategy that uses sensor data and analytics to optimize maintenance schedules, thereby reducing costs and enhancing competitiveness involving collaboration across multiple fields, including data processing, transmission, and analysis [20]. This approach minimizes downtime and mitigates the risk of unexpected failures.

In the early years of the industrial revolution, maintenance operated primarily in a reactive manner, addressing machine issues only when they rendered equipment inoperative. This reactive approach significantly impacted productivity, with machines remaining inactive during the repair process. To address this challenge, the concept of Preventive Maintenance [21] was introduced, involving scheduled maintenance to prevent extended periods of inefficiency. While PM addresses the issue of preventive damage, it has the drawback of conducting maintenance without considering the current state of the machines.

Recent technological advancements, particularly in sensors and the Internet of Things (IoT), now empower machines to continuously monitor their operations, detecting decreases in productivity or efficiency. These advancements have facilitated the gathering of crucial data related to the condition of machines and components, paving the way for the expansion of artificial intelligence models aimed at predicting failures. This field is referred to as Predictive Maintenance [22] and aims to determine the optimal time for maintenance.

Predictive Maintenance Overview

Predictive maintenance, as a proactive approach based on real-time data analysis, is transforming industrial practices across various sectors. It enables companies to enhance equipment reliability while optimizing operational costs. Many researches, reviews and surveys including case studies from diverse fields such as automotive, oil and gas, wind energy, and railways illustrate the tangible benefits of this technology, leveraging advanced algorithms like machine learning and artificial intelligence.

In our study, we also utilized these technologies to develop a more effective predictive model in a similar industrial context. By reinforcing our results with insights from these case studies, we aim to demonstrate the robustness of our approach while identifying areas for improvement. Our research is distinguished by its application in a specific production environment, where we evaluated the performance of various algorithms such as XGBoost, SVM, and KNN to optimize failure predictions and enhance overall system reliability.

Case Studies: Automotive Industry: A survey including case studies on an automotive manufacturer illustrates successful implementation of predictive maintenance using IoT sensors and machine learning algorithms along with fault detection for different subsystems using SVM, KNN, and random forests. This approach could lead to a significant reduction in unexpected downtime and an increase in equipment availability as recent advancements in machine learning have enhanced maintenance modelling, especially in the automotive industry, where predictive maintenance addresses safety and cost challenges [23].

Oil and Gas Industry: A review involving case studies in oil and Gas Industry focuses on the use of machine learning and artificial intelligence to address the challenges of processing large volumes of data, focusing on their application in upstream sectors. It highlights the benefits of machine learning and artificial intelligence in improving data processing efficiency, reducing maintenance costs, and managing large data storage [24].

Wind Energy: A review on the evolution of data-driven decision-making in the wind industry, from signal processing to artificial intelligence techniques with many case studies to discuss the current strengths and limitations of AI in wind energy. It shows that IoT is becoming increasingly used in the wind industry, with wind farms being able to be remotely controlled and maintained in real time, also indicates the transition from XGBoost to other transparent learners for explainable AI [25].

Rail Industry: In the railway industry, unexpected faults can disrupt service and pose safety risks, making timely maintenance crucial. A case study addresses the problem of traditional machine learning models, which are trained on batch data that are not effective for the enormous real-time data streams. Therefore it proposes a pipeline using online machine learning for real-time predictive maintenance of sensorized railway systems using KNN detector and one class SVM algorithms [26].

These papers combining case studies provide tangible evidence of the real impact of predictive maintenance on corporate performance across different industrial sectors. They validate the theoretical arguments presented in our study and demonstrate that the discussed algorithms and approaches can be successfully applied in real industrial environments. Additionally, the quantitative data from these examples underscore the financial and operational benefits companies can gain from adopting these strategies.

Literature Review on Predictive Maintenance

Predictive maintenance has emerged as a critical area of research, with significant advancements made over the past decade. From 2010 to today, the field has seen numerous contributions that have shaped its development and practical applications. Among these, [27] made a notable contribution by developing a statistical model tailored for scheduling imperfect predictive maintenance in multi-state systems. This approach utilized a Markov state diagram alongside the Universal Generating Function (UGF) to conduct robust reliability analyses, offering a powerful tool for optimizing maintenance planning under complex system conditions.

In the realm of decision-making under uncertainty, Khoury et al. [28] proposed two innovative maintenance policies that consider both cost and reliability as central criteria. These policies highlighted the critical importance of integrating diverse sources of information, enabling maintenance strategies to adapt dynamically to the gradual deterioration of systems. This research laid the groundwork for more sophisticated decision-support systems in predictive maintenance.

Machine learning has also been a game-changer in the field, as illustrated by Susto et al. [29], who introduced a methodology employing multiple classifiers to reduce downtime and maintenance costs. A central aspect of their work was the creation of "health factors," quantitative metrics designed to assess the operational status of equipment and its associated risks. This advancement bridged the gap between data-driven insights and actionable maintenance decisions.

Big data integration has further revolutionized predictive maintenance. Yan et al. [30] proposed a comprehensive framework for leveraging industrial big data to enhance maintenance strategies. Their work emphasized the structuring of multisource heterogeneous information while incorporating spatiotemporal characteristics, which significantly improved the prediction of the remaining useful life (RUL) of critical industrial components. This framework underscored the potential of big data in offering transparency and precision in production processes.

Aiming to address existing gaps in the literature, Khanh et al. [31] presented a holistic predictive maintenance framework that seamlessly combined data-driven prognostic techniques with advanced decision-making strategies. This framework demonstrated how integrating prognostic insights with real-time decision tools could provide a more cohesive and effective maintenance solution.

In a similar vein, [32] explored the application of advanced machine learning models, developing a predictive maintenance classification framework using an enhanced GA-XGBoost algorithm. By optimizing hyper parameters through genetic algorithms, their model achieved higher precision in predicting failures, offering valuable insights for maintaining key industrial equipment.

The field has also benefited greatly from several in-depth reviews that consolidate knowledge and provide strategic directions for future research. For example, Efthymiou et al. [33] proposed an integrated predictive maintenance platform structured around three key pillars: data acquisition and analysis, knowledge management, and sustainability. This framework provided a comprehensive approach to managing maintenance within industrial settings, emphasizing long-term operational efficiency.

Furthermore, Çınar et al. [34] reviewed the application of machine learning techniques in predictive maintenance, particularly within the context of Industry 4.0. They highlighted how advancements in machine learning algorithms have significantly enhanced the monitoring of equipment health, enabling proactive interventions and reducing unplanned downtimes. Additionally, Bouaicha et al. [35] offered a broad analysis of predictive maintenance evolution over the past two decades. Their work compared single-model and multi-model approaches in diagnostics and prognostics, providing a valuable perspective on the strengths and limitations of different methodologies.

Together, these studies and reviews underline the dynamic and interdisciplinary nature of predictive maintenance, showcasing its evolution from theoretical models to practical, data-driven applications that are transforming industries worldwide.

Comparison of Predictive, Reactive, and Preventive Maintenance

The comparison of different maintenance approaches, namely reactive maintenance, preventive maintenance, and predictive maintenance, has been the subject of numerous studies in the scientific literature. Each approach presents advantages and disadvantages, and their effectiveness varies depending on the operational context and performance objectives. Here is a comparison based on academic research and case studies.

Reactive Maintenance Reactive maintenance, also known as corrective maintenance, involves intervening only when equipment fails. This approach has the advantage of reducing short-term costs, as it does not require prior planning or continuous monitoring. However, it leads to many long-term disadvantages:

- Unplanned Downtime: Failures can cause sudden interruptions in production, resulting in significant financial losses.
- Repair Costs: Repairs can be more expensive, as they sometimes require emergency interventions or complete replacement of certain components.
- Safety Risks: Failures can pose risks to the safety of operators and installations.
- Pintelon and Parodi-Herz [36] showed that reactive maintenance is often associated with longer downtimes and decreased overall equipment performance.

Preventive Maintenance Preventive maintenance relies on a planned approach of regular interventions, regardless of the actual condition of the equipment. The aim is to perform interventions before failures occur, based on time or usage criteria. The main advantages include:

- Reduction of Unexpected Failures: By intervening before a failure occurs, some unplanned interruptions are avoided.
- Extended Equipment Lifespan: Planned maintenance often increases the lifespan of machines. However, preventive maintenance has several limitations:
- Unnecessary Interventions: Rigid planning can lead to interventions on machines in good condition, resulting in wasted time and resources.
- Higher Operational Costs: Regular maintenance planning results in more frequent intervention costs, even if the equipment does not necessarily need it.
- Garg and Deshmukh [37] indicate that preventive maintenance reduces sudden failures but at the cost of many unnecessary interventions.

Predictive Maintenance Predictive maintenance, which is the central focus of our article, relies on the use of real-time data to anticipate failures. Using technologies such as IoT and machine learning algorithms, predictive maintenance allows for the identification of warning signs of potential failures and intervention only when necessary. The advantages include:

- Cost Reduction: By limiting interventions to strictly necessary cases, predictive maintenance optimizes resource use and reduces operational costs.
- Minimization of Downtime: Failures are anticipated, significantly reducing unplanned interruptions.
- Resource Optimization: Unlike preventive maintenance, interventions are only carried out when specific signals indicate an imminent risk of failure. However, implementing predictive maintenance requires higher initial investments, particularly for installing IoT sensors and data analysis systems. This can be a barrier for some companies, especially smaller ones.
- Mobley [38] indicates that predictive maintenance can reduce maintenance costs by 12% to 18% compared to preventive maintenance while improving operational efficiency. Additionally, Jardine et al. [39] show that predictive maintenance can reduce downtime and increase equipment lifespan through continuous monitoring of machine conditions.

Comparative Synthesis

- Reactive Maintenance: Intervention after failure, low short-term cost but higher long-term due to downtime and unexpected repairs.
- Preventive Maintenance: Regularly planned interventions to prevent failures, with intermediate costs but potentially leading to unnecessary interventions.
- Predictive Maintenance: Intervention based on real-time data analysis to prevent failures before they occur, optimizing resources and costs, but requiring initial technology investment.

Recommendation of Predictive Maintenance The comparison between reactive, preventive, and predictive maintenance highlights the significant advantages that predictive maintenance can bring to a company. While reactive maintenance may seem economically beneficial in the short term, its hidden costs associated with sudden breakdowns, unplanned interruptions, and safety risks make it less sustainable in the long run. Similarly, although preventive maintenance can reduce certain failures, it often involves unnecessary interventions, leading to inefficiencies in resource utilization.

In contrast, predictive maintenance stands out as the most optimized and cost-effective strategy in the long term. Through the use of advanced technologies such as IoT, artificial intelligence, and machine learning, it enables real-time monitoring of equipment, proactive anticipation of failures, and reduction of operating costs. By minimizing unexpected downtimes, extending the lifespan of machines, and maximizing product quality, predictive maintenance offers superior return on investment and enhances a company's competitiveness in an increasingly demanding industrial environment.

We strongly recommend that companies, especially those operating in sectors where unexpected downtimes significantly affect productivity, invest in predictive maintenance solutions. This approach, while requiring initial investments in technological infrastructure, allows for optimal operational performance while ensuring long-term efficiency of production systems.

Predictive Maintenance Technologies: Practical Scenarios and Adoption Strategies

The implementation of predictive maintenance relies on several key technologies, including the Internet of Things, artificial intelligence, and machine learning. Each of these technologies plays a crucial role in optimizing maintenance operations.

Internet of Things (IoT)

Practical Scenarios:

- Continuous Equipment Monitoring: Installing IoT sensors on critical machines allows for real-time data collection on various parameters, such as temperature, vibrations, and pressure. For example, a sensor can detect imminent overheating, enabling a preventive intervention to avoid a breakdown.
- Equipment Status Dashboard: The collected data is integrated into a dashboard that provides an overview of machine status. This helps operators make informed decisions and reduce downtime.

Adoption Strategies:

- Gradual Implementation: Starting with pilot projects in specific production lines allows for the evaluation of IoT sensor effectiveness before large-scale deployment.
- Training and Awareness: Training sessions familiarize teams with new technologies and their usage.

Artificial Intelligence (AI)

Practical Scenarios:

- Predictive Failure Modelling: Using AI algorithms to analyse historical data enables the development of models capable of predicting failures, facilitating proactive planning of interventions.
- Optimization of Maintenance Strategies: AI can adjust maintenance schedules based on operational data, thereby reducing unexpected downtime.

Adoption Strategies:

- Design and Test Models: Create and test models to ensure their effectiveness.
- Performance Monitoring: Establish performance indicators to evaluate the effectiveness of AI models.

Machine Learning (ML)

Practical Scenarios:

- Anomaly Detection: Machine learning algorithms can detect abnormal behaviours in data, signalling imminent failures and allowing for quick intervention.
- Continuous Improvement of Models: Machine learning techniques refine maintenance recommendations based on new data, ensuring personalized interventions.

Adoption Strategies:

- Creating a Robust Database: Investing in relevant data collection ensures the accuracy of machine learning models.

The integration of IoT, AI, and machine learning in predictive maintenance has the potential to transform maintenance practices. By adopting these technologies strategically and developing tailored practical scenarios, it is possible to improve equipment availability, product quality, and operational efficiency. These advancements underscore the importance of predictive maintenance in optimizing industrial performance in the face of contemporary challenges.

The Integration of Machine Learning Techniques in Predictive Maintenance

In recent years, the incorporation of machine learning techniques into the field of predictive maintenance has revolutionized how industries manage their equipment and machinery. This paradigm shift has not only resulted in substantial cost savings but has also significantly reduced downtime, enhancing operational efficiency across various sectors. This article provides a comprehensive overview of key studies in this domain, shedding light on the pivotal role of machine learning in predictive maintenance.

The amalgamation of machine learning techniques with predictive maintenance practices has ushered in a new era of operational efficiency and cost-effectiveness. Studies by Hurtado et al. [40]; Peña et al. [41]; Geng and Wang [42]; Choi, et al. [43] collectively highlight the transformative power of machine learning in this domain. From substantial cost savings to real-time monitoring capabilities, these findings underscore the pivotal role of machine learning in shaping the future of maintenance practices across industries. As organizations continue to harness the potential of these technologies, the landscape of predictive maintenance is poised for even greater advancements.

Stages of Predictive Maintenance

Predictive maintenance is a proactive approach to equipment upkeep that leverages data analysis and machine learning techniques to anticipate potential failures before they occur. This process involves several key stages, each crucial for its successful implementation.

Data Collection and Acquisition: The first stage involves gathering relevant data from various sources, such as sensors, IoT devices, and historical records [44].

Data Pre-processing and Cleaning: Raw data often contains noise or inconsistencies that can affect the accuracy of predictive models. This stage focuses on cleaning and preparing the data for analysis, which may involve tasks like filtering out outliers, handling missing values, eliminating erroneous data and a feature selection process is applied to extract unnecessary features [45].

Feature Extraction and Selection: In this stage, relevant features or attributes are identified from the pre-processed data. These features serve as the basis for building predictive models. Feature selection helps reduce dimensionality and improve model performance [46].

Model Development: Machine learning algorithms are applied to the selected features to develop predictive models. Common techniques including classification and regression problems [40].

Model Training and Validation: Models are trained on historical data to learn patterns and relationships. The suggested predictive maintenance scheduling method is validated using a benchmarking dataset [47].

Deployment and Integration: Once validated, the predictive model is integrated into the company's maintenance workflow. In order to direct operational preventive actions, the system uses real-time sensor data to automatically identify probable error signals using machine learning algorithms, independent of human interaction [48].

Continuous Monitoring and Feedback Loop: Predictive maintenance is an iterative process. The model's performance is continuously monitored, and it may require periodic retraining with updated data to maintain its accuracy.

Alerts and Maintenance Actions: When the model predicts a potential issue, it generates alerts to notify maintenance teams. These alerts include information on the predicted failure, its likelihood, and recommended actions to take.

Maintenance Execution: Based on the alerts, maintenance teams can plan and execute the necessary actions. This can range from scheduling inspections to performing repairs or replacements.

Performance Evaluation and Optimization: After maintenance activities are completed, the effectiveness of the actions taken is evaluated. This feedback loop helps refine the predictive maintenance process and improve overall efficiency.

Predictive maintenance offers substantial benefits in terms of reducing downtime, optimizing resource utilization, and enhancing equipment reliability. Its effectiveness depends on the quality of data, choice of algorithms, and the integration of predictive models into the maintenance workflow.

Maintenance Performance Indicator Measurement Systems

Literature Review on Maintenance Performance Indicators

This section presents various performance measures and maintenance frameworks proposed in the literature. The different categories of measures highlight various areas of interest in maintenance performance, both in literature and in practice.

Performance measurement is a central principle of management, essential for managing the maintenance function, as with other manufacturing functions. Well-defined performance indicators have the potential to identify gaps between the current and desired situations, providing insights into progress toward resolving these gaps. Historically, maintenance decisions have relied on performance indicators as a guide [49]. These indicators, defined by Liyanage and Kumar [50], encompass measures including baselines and goals to facilitate predictive and diagnostic processes within a company. Their use extends to different organizational levels, contributing to decision-making and justifying actions aimed at improving the value of the business process. Well-defined performance indicators have the ability to identify performance gaps, track progress toward their resolution, and support the implementation of improvement initiatives [51].

Researchers have classified maintenance performance indicators into four main categories: maintenance outcomes (e.g., availability, failure frequency), maintenance productivity (e.g., workforce efficiency), operational relevance of maintenance (e.g., schedule compliance, work order rotation), and justification of maintenance costs (e.g., inventory turnover, maintenance cost per unit produced) [2].

The need for a holistic measurement of maintenance performance is widely recognized, evaluating the contribution of the maintenance function to manufacturing and business strategic goals [6]. However, challenges arise when quantifying and measuring inputs and outputs of the maintenance process, attributed to the complex relationship between maintenance and manufacturing.

Performance measures establish a crucial link between strategies and management action, thus supporting the implementation and execution of improvement initiatives [52]. They can also help maintenance managers' direct personnel and resources to specific areas of the production system that will impact manufacturing performance.

The literature explores a variety of approaches, frameworks, and models for Maintenance Performance Management (MPM). The (MPM) Maintenance Performance Management audit process stands out with a comprehensive assessment of maintenance system aspects, conducted through domain-specific questionnaires, such as the Performance Measurement Questionnaire (PMQ) by Dixon et al. [53].

Additionally, Overall Equipment Effectiveness (OEE) is advocated as a measurement method to assess system efficiency, providing a roadmap and priorities for improvement [54].

In response to strategic shifts and outsourcing growth, assessing asset performance becomes challenging. Dynamic stakeholder requirements, lack of integration, and a multitude of inputs/outputs pose challenges. Parida and Kumar [55] developed an integrated framework linking enterprise asset management measurement criteria across hierarchical levels, facilitating decision-making.

Concurrently, the literature suggests specific approaches to measuring maintenance performance. Lofsten [7] suggests aggregated measures such as the maintenance productivity index, evaluating the ratio of maintenance output to maintenance input. However, this approach has limitations, offering a narrow view of maintenance performance while facing the obvious challenge of quantifying various types of maintenance inputs.

Al-Najjar [56] proposes a model to describe and quantify the impact of maintenance on key competitiveness objectives related to production, quality, and costs. This model provides an assessment of the economic effectiveness of maintenance investments and facilitates strategic decisions regarding different improvement plans.

The literature identifies different maintenance measurement categories [57] use the time horizon to classify performance indicators into three levels: strategic, tactical, and operational. For example, Parida [58] introduce multicriteria hierarchical framework includes multicriteria indicators for each management level. Komonen [59] presents a hierarchical system of maintenance performance indicators, categorizing indicators into three main dimensions: OEE, production costs, and production quality.

Campbell and Reyes-Picknell [60] categorizes commonly used maintenance performance measures into three goal-based categories: equipment performance measures, cost performance measures, and process performance measures. The European standard for maintenance key performance indicators [51] suggests three main categories of indicators: economic, technical, and organizational.

Another frequently used classification is that of leading and lagging performance indicators, checking if tasks leading to results are performed and if the results have been achieved, respectively. Leading indicators, more crucial for avoiding unfavourable situations, are essential for managing the maintenance function's performance.

Research Methodologies

This study focuses on the impact of predictive maintenance on the performance of industrial enterprises, integrating this approach into the calculation of maintenance performance indicators. This integration revolutionizes how companies assess and optimize the efficiency of their maintenance activities. Through the use of advanced data science and machine learning methods, this innovative approach enables companies to enhance equipment reliability, reduce costs, and strengthen their competitiveness through proactive and efficient asset management.

In this comprehensive study, we will examine in detail the impact of predictive maintenance on the performance of businesses. We will explore the advantages it offers in terms of reducing downtime, optimizing maintenance costs, and improving productivity. We will also investigate the technologies and methods used in the implementation of predictive maintenance, addressing potential challenges and identifying best practices for successful adoption. The ultimate goal of this article is to demonstrate that performance indicators should not be defined in isolation but should result from a thorough analysis of the interaction between the maintenance function and other organizational functions within the company. This aims to enhance equipment availability, optimize operational performance, and maximize overall company performance.

During our research, we had the opportunity to delve into the exciting field of predictive maintenance. Often considered the future of industrial equipment management, predictive maintenance aims to anticipate machine failures before they occur. This innovative approach heavily relies on the intensive use of data and machine learning algorithms to establish robust predictive models.

Our methodology is based on four carefully defined major steps. Firstly, we dedicated considerable efforts to collecting a substantial amount of data necessary for the implementation of our data-driven predictive maintenance approach. These data form the foundation of our models, enabling machine learning algorithms to discern subtle patterns and make informed decisions.

The second step of our methodology involved data preprocessing, ensuring the validity of the applicability assumptions of our models through thorough data cleaning. This crucial step contributed to ensuring the best possible performance of our algorithms, thereby reinforcing the reliability of our predictions.

We then focused on prediction, not only determining whether a machine would fail but also anticipating the specific type of failure likely to occur. This proactive approach provides a significant advantage by enabling targeted maintenance planning and reducing unexpected downtimes.

The third step of our approach involves the development, use, and comparison of various machine learning-based models. This crucial step allowed us to select the most effective model, ensuring the efficient implementation of our predictive maintenance system.

Finally, the last step of our study involves calculating maintenance performance indicators and studying the impact of predictive maintenance on the performance of an industrial organization. We will explore the advantages and opportunities it offers in terms of reducing downtime, optimizing maintenance costs, and improving productivity.

Our work aligns with an innovative approach in the field of predictive maintenance, providing tangible perspectives to enhance the operational reliability of industrial equipment. Our rigorous methodology and promising results constitute a significant contribution to the evolution of predictive maintenance management.

The methodology of the study is based on the application of several machine learning algorithms in the context of predictive maintenance. Here is a detailed overview of the methodological approaches mentioned in the text:

- Logistic Regression: This model is used to predict the probability of a binary dependent variable (e.g., failure or no failure) occurring based on independent variables. Although simple, logistic regression serves as a baseline model due to its interpretability, allowing for performance comparisons with more complex models.
- K-nearest neighbours (K-NN): This algorithm classifies data based on its proximity to other already classified data points. The "K" parameter determines how many nearby neighbours are considered when assigning a class to a new data point. K-NN is particularly useful for datasets where spatial similarity or the distance between data points is a key factor.
- Support Vector Machine (SVM): This algorithm is used to create an optimal hyperplane in an N-dimensional space to separate data into two distinct classes. The goal is to maximize the margin between the two classes, ensuring clear classification of the data.
- Random Forest: A method based on ensemble learning. Multiple decision trees are independently constructed, each contributing to the final decision through a majority vote. This model is particularly robust for complex and noisy datasets.
- XGBoost: Based on gradient boosting, XGBoost is one of the most powerful methods for classification and regression problems. It builds many decision trees sequentially, with each new tree adjusted to correct the errors of the previous model. This iterative approach improves performance efficiently over time.

Methodological Clarification: Each algorithm was tested on real-time collected data to identify early failure signals. XGBoost, in particular, stands out for its ability to handle residual errors and iteratively improve predictions. The choice of these algorithms appears to have been driven by the need to balance predictive accuracy with algorithmic complexity while taking into account the specific characteristics of the available data.

Providing more detailed explanations on the criteria for model selection, how the data was split into training and testing sets, as well as the evaluation metrics used, would add clarity and depth to the methodological analysis.

Equipment, Operating Conditions and Dataset

The equipment used in this study is a manufacturing machine tool, commonly employed in industrial processes such as machining. This equipment is an integral part of an automated production environment, typical of advanced manufacturing systems (or smart manufacturing), where machine performance is monitored in real-time using integrated sensors. These machines collect a wide range of data, including temperature, rotational speed, and torque, enabling the prediction of failures and the optimization of productivity.

The operating conditions include an ambient air temperature maintained around 300 K with a standard deviation of 2 K, and a process temperature adjusted to +10 K relative to the air temperature. The machine operates at a rotational speed that fluctuates around 2860 rpm, with normally distributed noise. The average torque is 40 Nm, with a standard deviation of 10 Nm. Tool wear depends on the quality of the machined products and varies according to the L (low) Low-quality machined products, which may result in less tool wear, M (medium): Medium-quality products, leading to moderate tool wear, or H (high): High-quality machined products, which may cause more significant tool wear due to the required precision, variants, with an additional 2–5 minutes of tool wear depending on the quality.

The dataset used in this study includes 10,000 data points, each consisting of 14 features. It contains information such as air and process temperatures, rotational speed, torque, and tool wear. Each data point is associated with a label indicating whether a machine failure occurred and specifies one of five possible failure modes: tool wear, insufficient heat dissipation, power failure, overstrain, or random failure.

For example, tool wear failure (TWF) occurs after 200–240 minutes of use, while a failure due to poor heat dissipation (HDF) happens if the temperature difference between the air and process is less than 8.6 K and the rotational speed is below 1380 rpm. This data has allowed us to train machine-learning algorithms to accurately predict machine failures.

Data Processing, Predicting Machine Failures and Identifying Failure Types in the Manufacturing Industry

In the context of the manufacturing industry, proactive management of failures and breakdowns is crucial to maintaining smooth and efficient production. This section addresses three key aspects for optimizing maintenance in manufacturing: data processing, machine failure prediction, and failure type identification, highlighting their fundamental role in optimizing maintenance systems. First, data processing focuses on the collection, cleaning, and preparation of essential information for predictive analysis. Then, failure prediction examines the algorithms and methods used to anticipate machine failures before they occur, utilizing statistical models and machine learning techniques. Finally, failure type identification deals with methods to classify and diagnose failures, enabling targeted and efficient interventions. By integrating these three aspects, this section demonstrates how optimized data management and advanced prediction and diagnostic techniques can improve the reliability and productivity of production systems.

Data Processing

Data processing is the first essential step in implementing predictive maintenance models. This subsection explores the different methods used to collect, clean, and prepare data from industrial equipment. We will address data preprocessing techniques, including handling missing data, normalization, and noise reduction. Particular attention will be given to the tools and technologies used to ensure data quality and relevance, as clean and well-structured data are crucial for the effectiveness of predictive models.

In order to illustrate the impact of maintenance on business performance, our study focuses on analysing a dataset containing crucial information about equipment performance parameters in the manufacturing industry. This dataset encompasses the following elements:

- UDI (Unique Identifier): A unique code associated with each sample.
- Product ID (Product Identifier): The product identification linked to the equipment.
- Type: The equipment category.
- Air temperature [K]: The air temperature, measured in Kelvin.
- Process temperature [K]: The process temperature, measured in Kelvin.
- Rotational speed [tr/min]: The rotational speed, expressed in rotations per minute.
- Torque [Nm]: The torque, measured in Newton-meters.
- Tool wear [min]: Tool wear, calculated in minutes.
- Target: The target variable indicating whether a failure occurred or not.
- Failure Type: The nature of the failure, if applicable.
- The objective of this section is to leverage the available data to anticipate equipment failures, predict the occurrence of a breakdown. Through the application of machine learning techniques, our study will detail the various stages of implementing predictive maintenance. This includes data collection and processing, as well as

the establishment of a predictive model capable of learning from the information provided by the different columns, thereby predicting whether equipment is likely to experience a failure or not.

Outliers Inspection

The aim of this section is to verify if the dataset contains outliers, which can often mislead machine-learning algorithms. We start by examining a statistical report of the numerical features. To do this, we begin with the dataset description in Table 1.

Resampling with SMOTE

The result will be described using a pie chart (Fig. 3):

Resampling with SMOTE significantly contributes to the effective handling of imbalanced datasets by creating synthetic instances for the minority class, leading to enhanced performance and generalization of machine learning models.

Table 1 Analysing Numerical Features Statistically to Identify Outliers in the Dataset

	Air temperature	Process temperature	Rotational speed	Torque	Tool wear	Target
count	9973.000000	9973.000000	9973.000000	9973.000000	9973.000000	9973.000000
mean	300.003259	310.004031	1538.893212	39.978993	107.921087	0.033089
std	2.000548	1.483692	179.412171	9.966805	63.649152	0.178879
min	295.300000	305.700000	1168.000000	3.800000	0.000000	0.000000
25%	298.300000	308.800000	1423.000000	33.200000	53.000000	0.000000
50%	300.100000	310.100000	1503.000000	40.100000	108.000000	0.000000
75%	301.500000	311.100000	1612.000000	46.700000	162.000000	0.000000
max	304.500000	313.800000	2886.000000	76.600000	253.000000	1.000000

Figure 4 indicates that data augmentation proved successful, maintaining the feature distribution for faulty instances. Density peaks in the extreme areas of the distribution for rotational speed, torque, and tool wear indicate a correlation with failures. Outliers are not assigned to errors but rather to the inherently biased nature of the dataset. An examination of distributions related to failure causes affirms symmetry in rotational speed and torque, with a distinct separation in tool wear, in accordance with the objectives outlined in the task and dataset description section.

Analysing Potential Outliers in Rotational Speed and Torque

The potential existence of outliers in Rotational Speed and Torque may be suspected owing to the substantial gap between the maximum value and the third quartile. To support this observation, we meticulously analyse the situation using histograms as shown in Fig. 5 to enhance our comprehension of the distribution.

Study of PCA and Correlation Heatmap

PCA (Principal Component Analysis) is a technique used for reducing dimensionality in a multidimensional dataset, aiming to extract the most relevant features. The goal is to identify a linear combination of input variables that captures the highest variability within the data. By projecting the data into a new lower-dimensional space known as the "space of principal components," PCA reduces the number of dimensions. These principal components are eigenvectors associated with the eigenvalues of the data's covariance matrix. Simplifying the data structure, PCA facilitates analysis, visualization, and modelling while preserving the original data variability as much as possible as shown by Fig. 6.

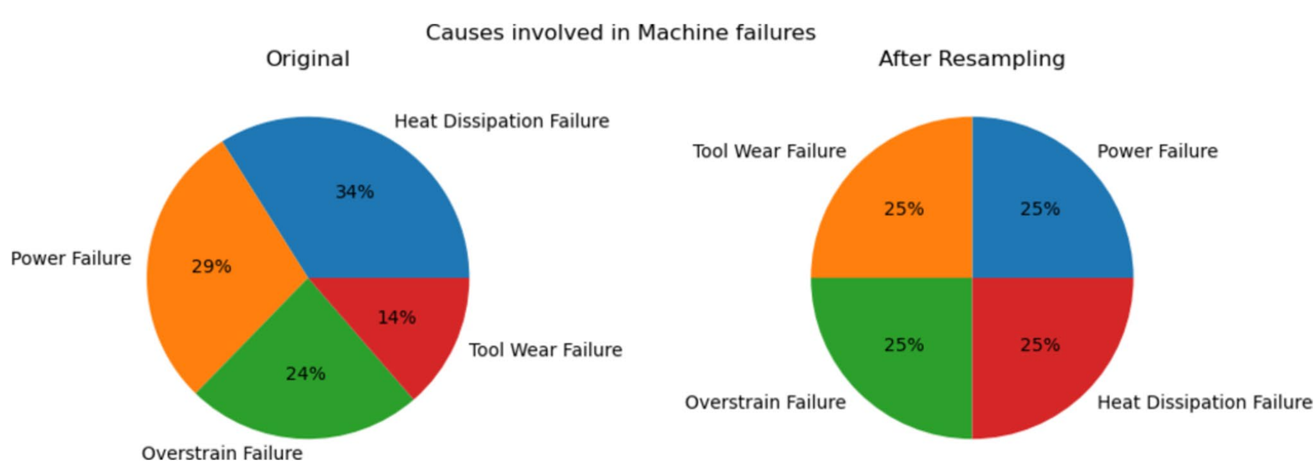


Fig. 3 The Causes Involved in Machine Failures Before and After Resampling

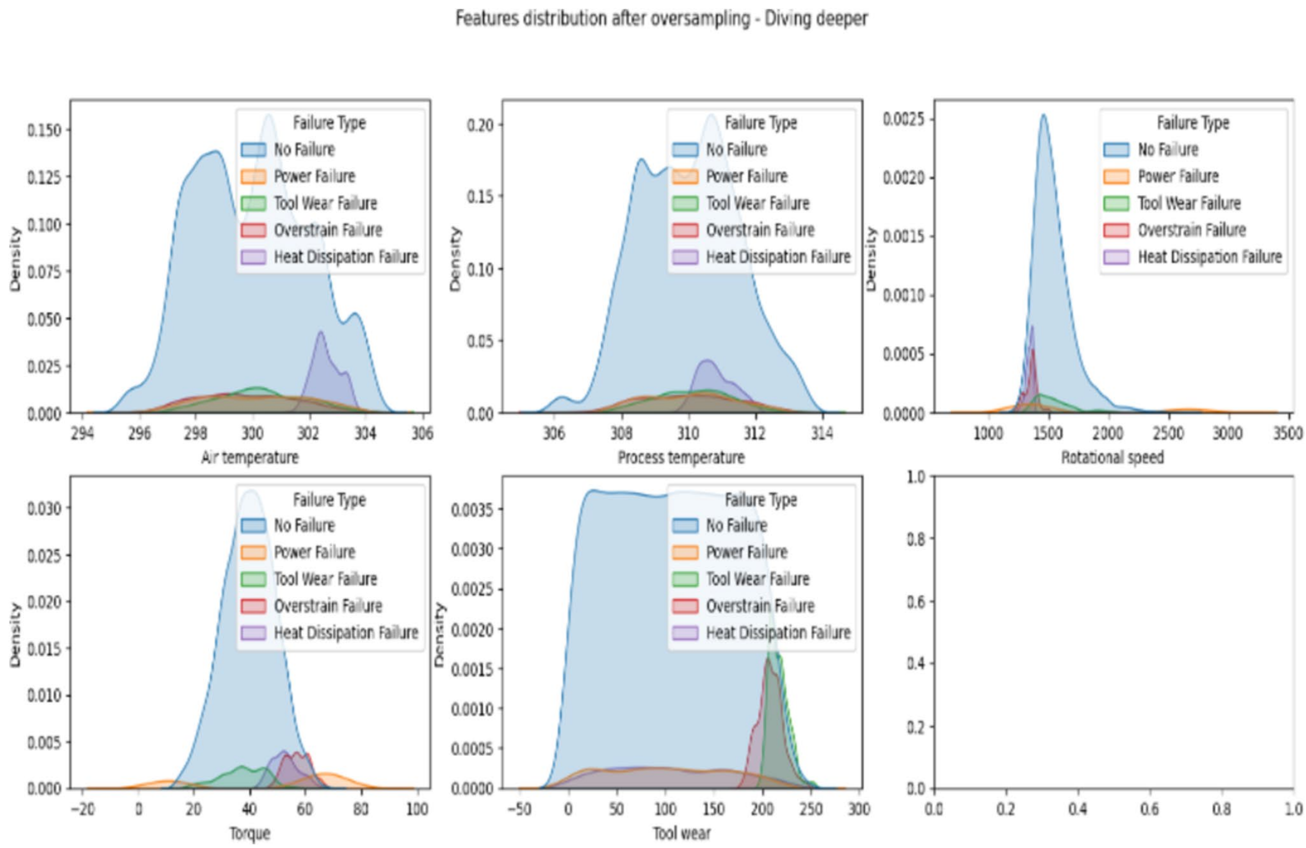


Fig. 4 Analysing the Correlation of Failure-Related Feature Distribution Following Oversampling with More Details

The projection onto this space with three axes reveals specific patterns: TWF (Tool Wear Failure) stands out as the most distinct failure class, predominantly dependent on PC3 (Tool Wear). PWF (Power Failure) occupies two extreme ranges along PC2 (Power) independently of the other components. The OSF (Overheating Failure) and HDF (Hardware Defect Failure) classes are less distinctly separated, yet notable differences exist; OSF is characterized by high Tool Wear and low power, while HDF is characterized by high temperature and low power.

In the context of visualization through a heatmap (Fig. 7), which provides a visual representation of the relationships between different variables within a dataset, observations further unfold. Notably, features associated with temperature and power exhibit strong correlations. Additionally, Tool Wear shows a notable correlation with our two targets, aligning with the findings of the PCA study. Finally, a weaker correlation is observed between torque and the two targets.

The Failure Prediction

Failure prediction plays a central role in establishing effective predictive maintenance. This section explores the methods used to anticipate failures before they occur, relying on both historical and real-time data. The goal is to improve equipment availability while reducing unexpected downtime. We will detail several machine learning algorithms used for failure prediction, with a focus on their accuracy and effectiveness in different industrial contexts.

The Prediction of Machine Failures

Failure prediction is at the heart of predictive maintenance strategies. This part of the section focuses on the various algorithmic approaches used to anticipate machine failures before they happen. We will examine statistical models and machine learning techniques, including classification algorithms, neural networks, and random forest methods. Emphasis will be placed on evaluating the performance of these models, their accuracy, and their ability to provide reliable predictions based on both historical and real-time data.

This section aims to identify the optimal classification model for predicting machine failures in a given dataset. Classification algorithms are integral to data exploration and employ supervised machine learning methods for predictions. The process entails using a dataset already categorized into classes ("labelled"), from which a classification

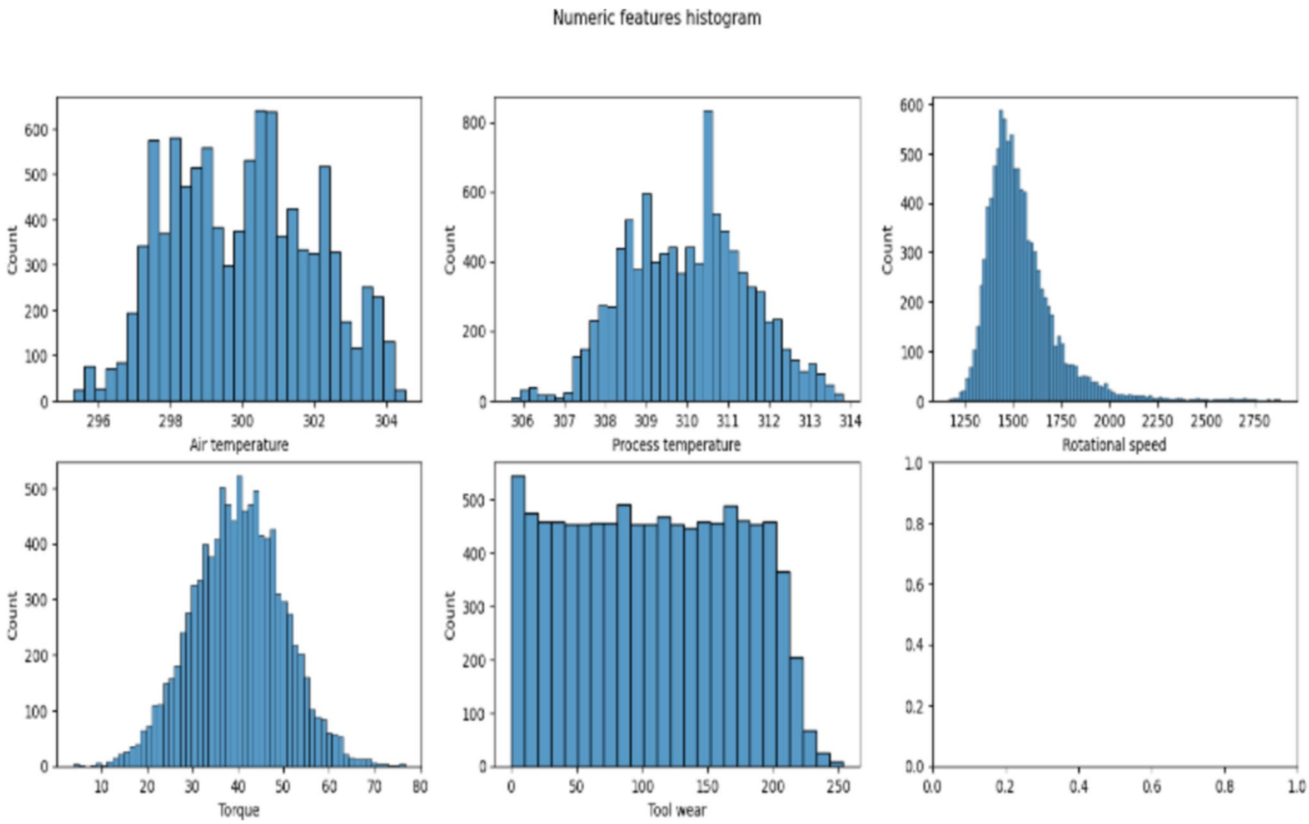


Fig. 5 Examining Rotation Speed and Torque with Histograms for Outlier Detection

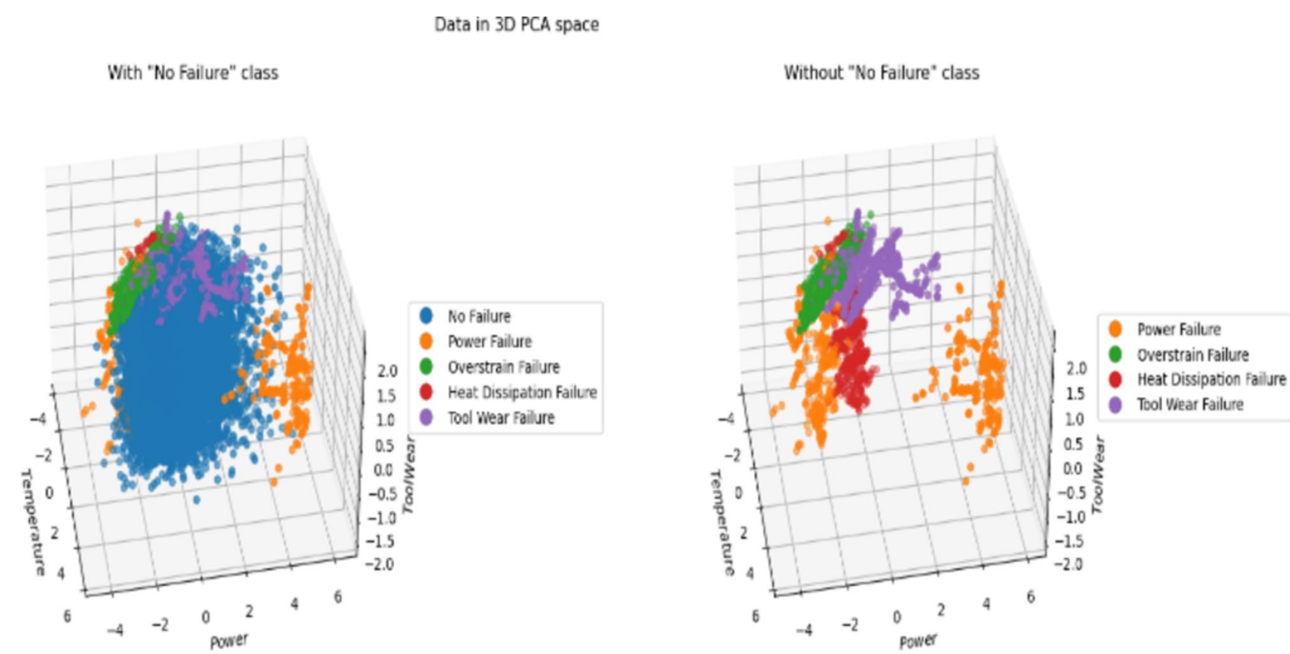


Fig. 6 Insights into the Separation of Failure Classes through Projection Analysis in the Principal Component Space

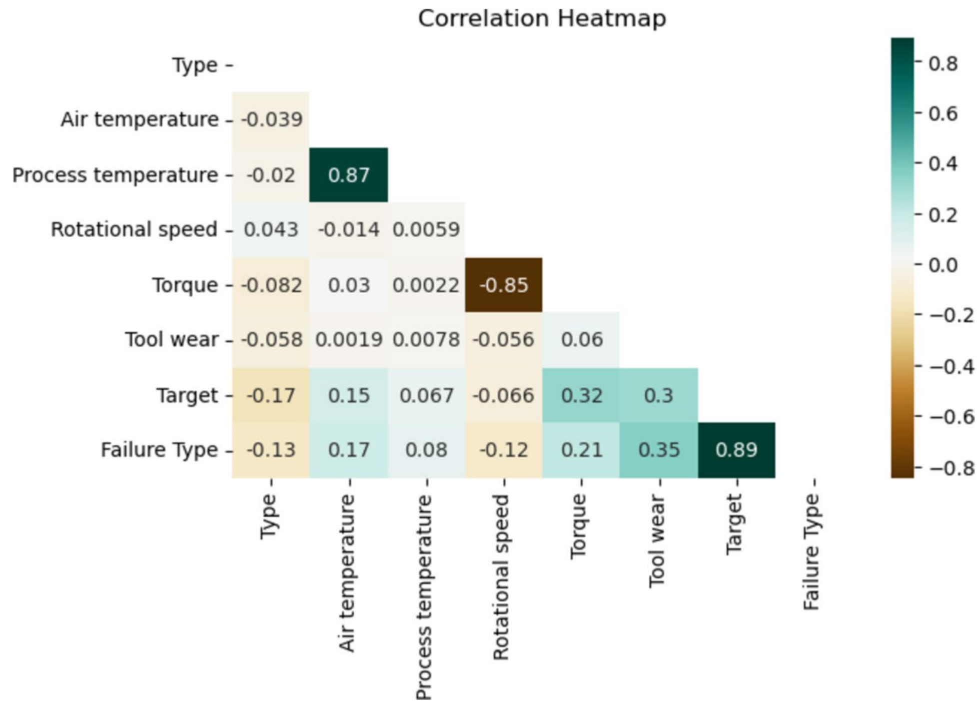


Fig. 7 Visual Analysis of Relationships between Features through Exploration of Correlations via Heatmap

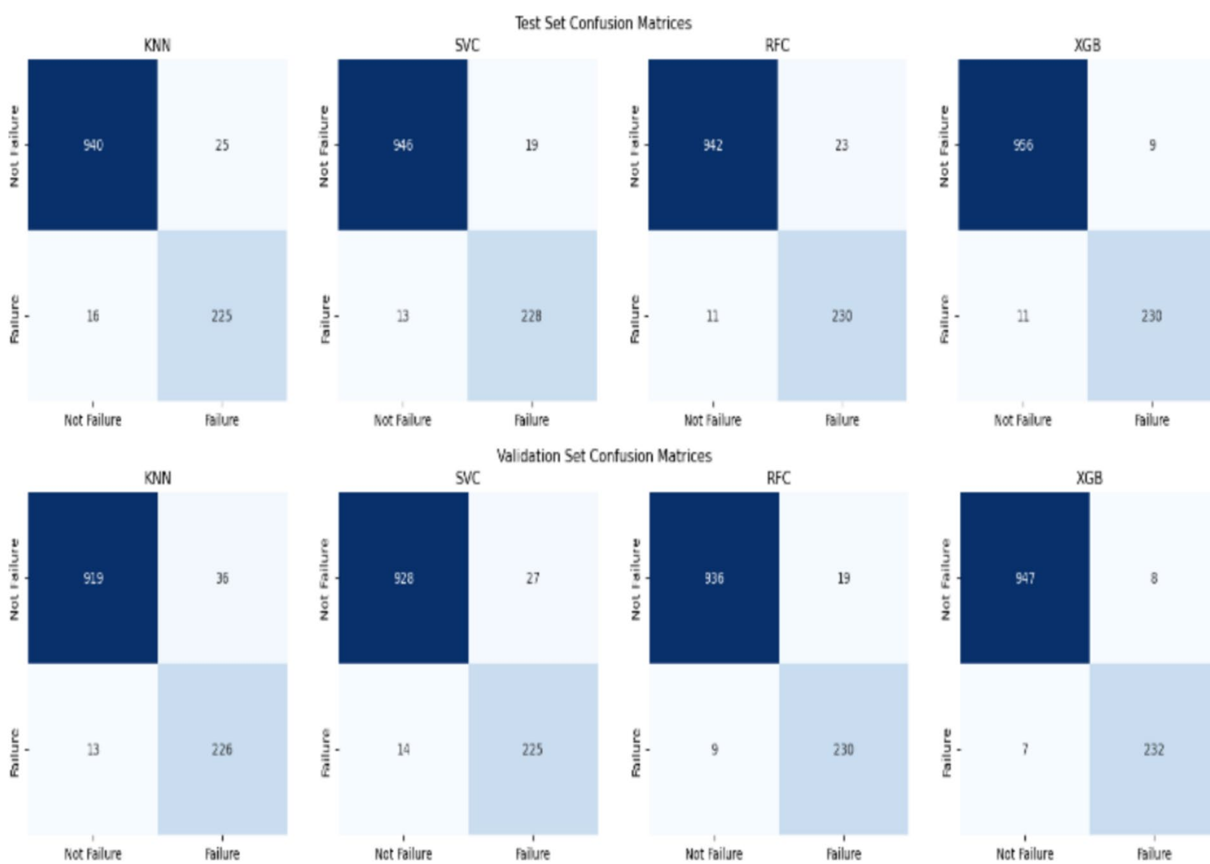


Fig. 8 Confusion Matrices and Insights from Metrics in the Comparative Evaluation of Model Performances and Parameter Tuning

model is developed. This model is subsequently applied to new, unlabelled data to assign them to the appropriate class. The initial dataset is typically divided into three groups: the training dataset, utilized to train the model; the validation dataset, employed to assess the model's fit on the training dataset while adjusting hyperparameters; and the test dataset, designed to evaluate the model (Fig. 8).

At the project's outset, a data scientist must perform this division using commonly accepted ratios. The following techniques have been applied in our project:

Logistic Regression: Evaluating the probability of a dependent variable based on independent variables. It serves as a reference model due to its simplicity and interpretability, acting as a starting point for comparing results with other models.

K-nearest neighbours (K-NN): An algorithm based on calculating the distance between elements in the dataset. Data is assigned to a certain class if it is close enough to other data in the same class. The parameter K determines the number of neighbouring data points considered when assigning classes.

Support Vector Machine: The goal is to find a hyperplane in an N-dimensional space that distinctly classifies data points while maximizing the margin distance, i.e., the distance between data points of the two classes.

Random Forest:

Using ensemble learning to solve complex problems. Simultaneous construction of many decision trees with equal importance. The selected class is the one chosen by the majority of the trees.

XGBoost: A machine learning library based on gradient boosting decision trees (GBDT). It uses an iterative boosting technique with shallow decision trees, each iteration using the error residuals of the previous model to fit the next model. The final prediction is a weighted sum of all tree predictions.

Table 2 In-depth Analysis of Validation and Test Scores for KNN, SVC, RFC, and XGB Algorithms

Validation scores:

	KNN	SVC	RFC	XGB
ACC	0.959	0.966	0.977	0.987
AUC	0.954	0.987	0.997	0.999
F1	0.902	0.916	0.943	0.969
F2	0.928	0.931	0.954	0.970

Test scores:

	KNN	SVC	RFC	XGB
ACC	0.966	0.973	0.972	0.983
AUC	0.954	0.992	0.997	0.998
F1	0.916	0.934	0.931	0.958
F2	0.927	0.941	0.945	0.956

Our Models

Table 2 demonstrates that all selected models exhibit similar performance on the validation set, except for KNN, which is slightly less effective. This similarity makes it challenging to determine superior performance based solely on these values. However, the results from the test set indicate that over fitting was avoided, as there was no significant drop in performance. To establish a clearer hierarchy among the models, we analyse confusion matrices and metrics on the test set. This reveals consistent patterns where metrics for a specific model are consistently either smaller or larger than those of the others.

The time required for parameter search is comparable for most models, except for KNN. Notably, KNN achieves the lowest performance, while XGB attains the highest. SVC and RFC fall in the middle, producing highly similar results.

Regarding parameters:

A literature-based grid search was conducted for each model, focusing on crucial parameters.

Grid search values were defined with consideration for computational cost and optimal values.

Optimal parameters for RFC and XGB are opposites: RFC prefers fewer estimators with deeper splits, while XGB favours more estimators with shallower splits. It's essential to note that although XGB performs best quantitatively, this may not hold true qualitatively. SVC and XGB lack clear interpretability, whereas RFC provides a comprehensive understanding of the algorithm's operation. For insights into significant feature contributions, we present feature importance using permutation importance in a bar chart in Fig. 9.

In conclusion, the chosen models function effectively in predicting machine failures. XGBoost emerges as the superior model, whereas KNN exhibits lower performance, despite its instantaneous response time. The decision between the two depends on the company's requirements: KNN for quicker application, XGBoost for enhanced accuracy.

The Prediction of Failure Type

Once failures are predicted, it is essential to identify their nature and type to implement appropriate corrective actions. This subsection addresses the methods used to classify and diagnose different types of failures in production systems. We will discuss failure signature analysis techniques, sensor-based approaches, and advanced diagnostic tools. The ability to correctly identify the type of failure not only improves response times but also enables more targeted and effective maintenance strategies.

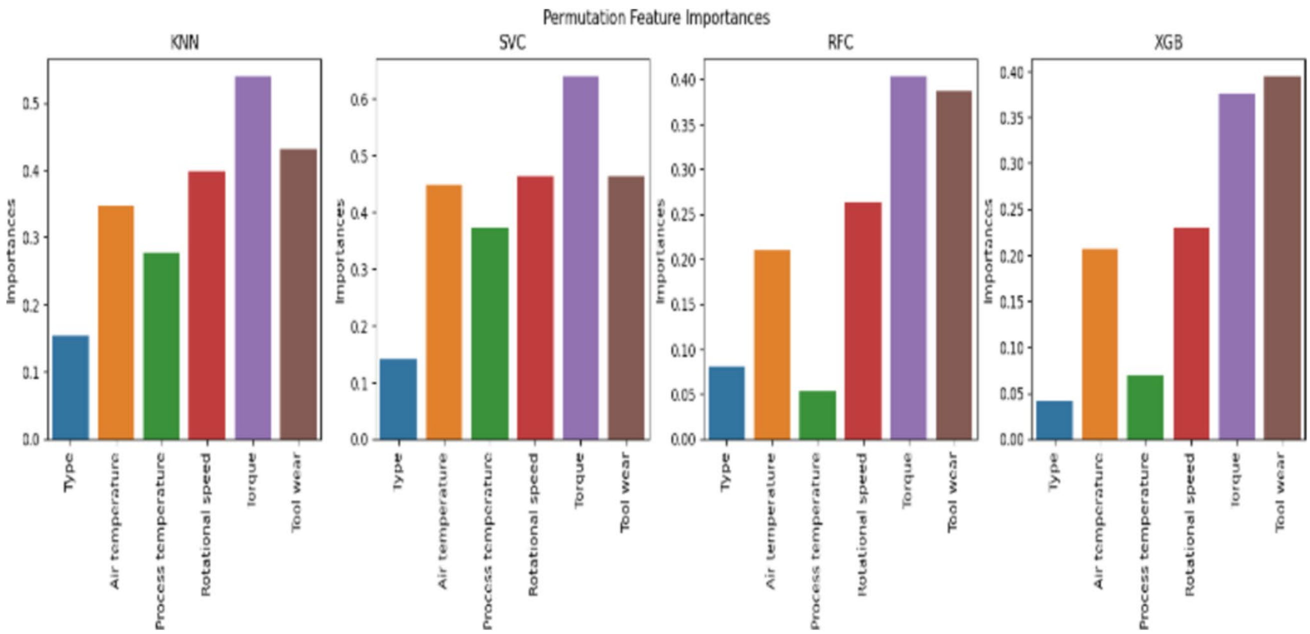


Fig. 9 Displaying Results of Feature Importance Analysis Using a Permutation Bar Chart

Multi-Class Task

We now proceed to the second task of this project, which involves predicting not only if a failure will occur but also the type of failure that will happen. Therefore, we are addressing multi-class classification problems, assuming that each sample is assigned to one and only one label. This assumption is verified during data pre-processing, where we eliminated all ambiguous observations belonging to more than one class.

For multi-class targets, when computing the values of AUC, F1, and F2 scores, we need to set the "average" parameter. We choose "average = weighted" to consider class imbalance: after data pre-processing, 80% of machines are functioning, and 20% fail.

Concerning the binary classification task, we opt for logistic regression as the reference model and seek models achieving higher values for the chosen metrics. Specifically, we adapt the models developed in the previous section for the multi-class case. While many classification algorithms (such as K-Nearest Neighbours, Random Forest, and XGBoost) naturally allow for the use of more than two classes, some (like Logistic Regression and Support Vector Machines) are inherently binary algorithms. However, these can be transformed into multi-class classifiers

Fig. 10 Confusion Matrix for Benchmark and Probability Analysis for a Multiclass Task in Logistic Regression Evaluation

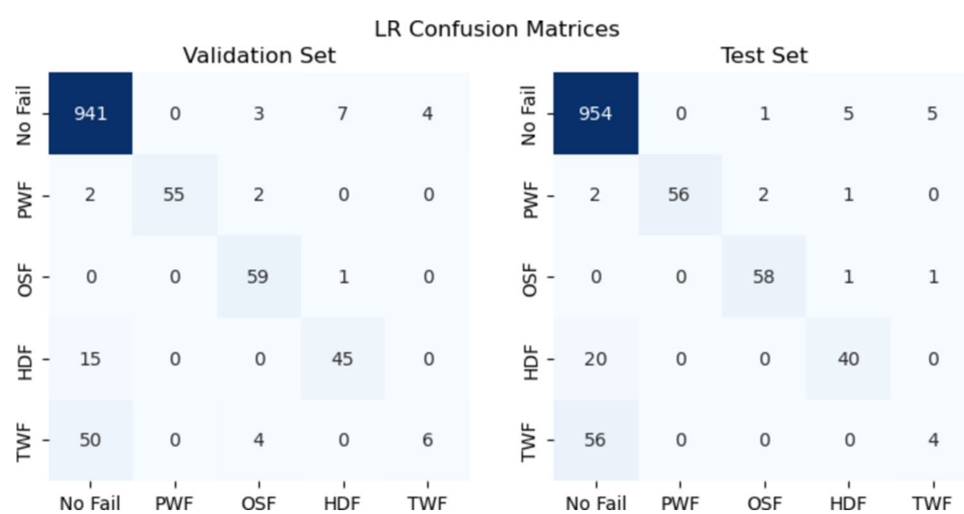


Table 3 Analyse des Résultats du Modèle: Comparaison des Métriques sur les Ensembles de Validation et de Test

```
Validation set metrics:
ACC     0.926
AUC     0.983
F1      0.909
F2      0.919
dtype: float64
Test set metrics:
ACC     0.922
AUC     0.982
F1      0.904
F2      0.914
dtype: float64
```

Table 4 Influence of Features on Failure Types via Logistic Regression Coefficient Analysis

	Type	Air temperature	Process temperature	Rotational speed	Torque	Tool wear
No Failure	1.920864	0.224090	2.866848	0.106442	0.059894	0.287084
Power Failure	0.697373	0.824558	0.982471	944.048373	2822.376842	0.744856
Tool Wear Failure	0.036806	0.215535	2.777322	0.108932	8.748803	406.189304
Overstrain Failure	0.636280	4314.687600	0.004253	0.000458	0.398540	0.711005
Heat Dissipation Failure	1.045501	1.337837	0.739732	0.225326	0.118551	749.948357

through various strategies. For our project, we decide to use the "One-vs-Rest" approach, involving training a single classifier per class, with the samples of that class as positive samples and all other samples as negative samples. We chose it because it is computationally more efficient than other types of approaches.

Logistic Regression Benchmark

First, let us examine the behaviour of logistic regression as indicated by Fig. 10, Tables 3 and 4:

In the Table 4, for each class, there are the odds ratios from the logistic regression that elucidate the contribution of each feature in predicting membership to a specific class. Upon comparing this table with the PCA scatter plot and the comments we made, it becomes evident that there is complete agreement on the features that most significantly influence the type of failure. For instance, examining the odds ratio values for PWF, it is apparent that rotational speed and torque play a pivotal role in predicting membership in this class. In the PCA analysis, we highlighted that PWF appears to depend solely on PC2, which represents the power derived from the product of rotational speed and torque. Similar considerations can be made for other classes.

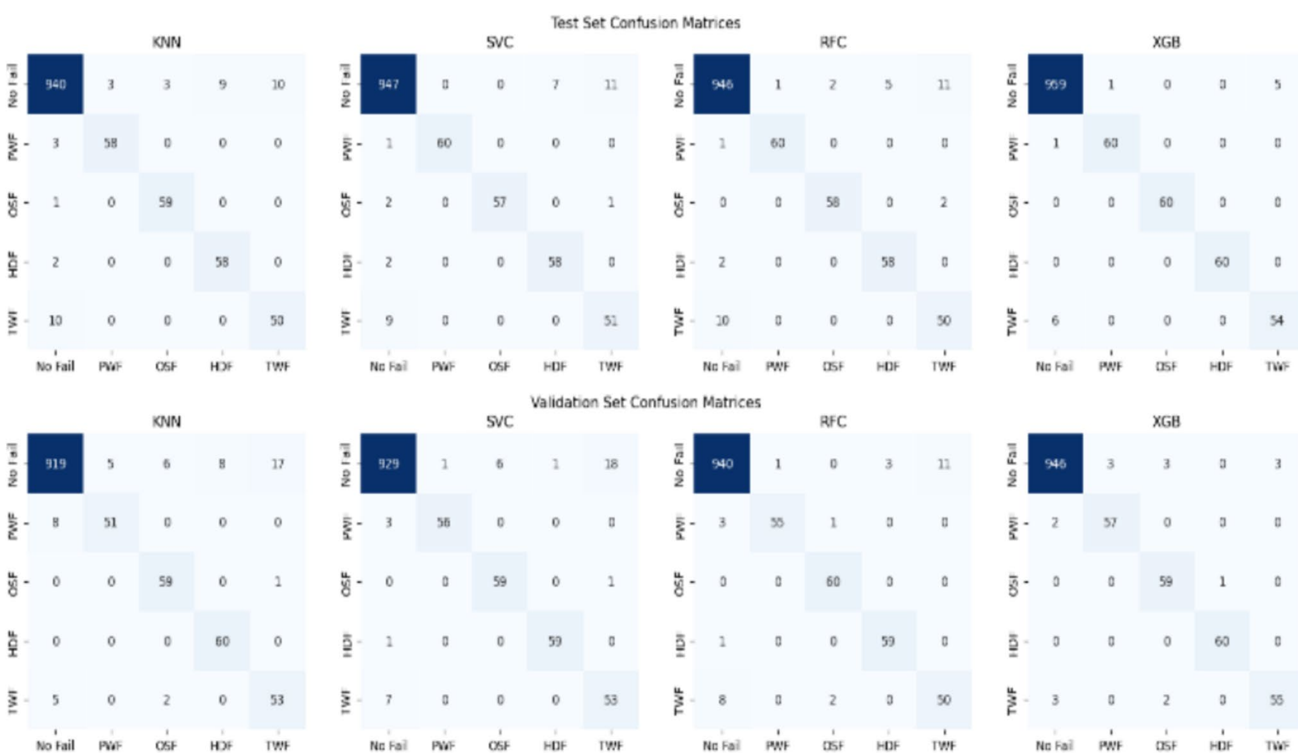


Fig. 11 Confusion Matrices and Insights from Metrics in the Comparative Analysis of Model Performances and Parameter Tuning

Table 5 Validation and Test Scores for the KNN, SVC, RFC, and XGB Models

Validation scores:

	KNN	SVC	RFC	XGB
ACC	0.956	0.968	0.975	0.986
AUC	0.956	0.993	0.998	0.999
F1	0.957	0.969	0.975	0.986
F2	0.957	0.968	0.975	0.986

Test scores:

	KNN	SVC	RFC	XGB
ACC	0.966	0.973	0.972	0.989
AUC	0.956	0.995	0.997	0.999
F1	0.966	0.973	0.972	0.989
F2	0.966	0.973	0.972	0.989

The Models

For each model, we initiate the Gridsearch for hyper parameter optimization, employing the weighted average F2 score as the metric to assess the model. Similar to the binary case, the Gridsearch is conducted on parameters that, according to the literature review, have been identified as crucial for each specific model. The grid search values were determined based on the literature, and multiple tests were conducted as shown by the following Fig. 11.

Comparing the obtained results in Table 5, it is observed that K-NN is the model with the weakest performance, and its accuracy is slightly lower than that of Logistic Regression. Despite this, we cannot exclude it a priori, as it still attains high values for the metrics and provides an immediate response. Thus, we can use it whenever we need to quickly assess the situation and then apply other models when we have more time.

All the other models outperform the benchmark, achieving high values for the chosen metrics in both the validation and test sets. The performances of SVC and RFC are very similar, and XGB outperforms them.

Examining the training phase, SVC and RFC take the same amount of time, while XGB takes over four times longer than them. Thus, since the improvement obtained with XGB is only 1.5%, one can choose which model to prefer based on their specific needs.

While the best parameters for multi-class K-NN and SVC are the same as for binary classification, for XGB and RFC, Gridsearch for both types of tasks returns different parameters. Additionally, when transitioning from the binary problem to the multi-class problem, the estimated training time remains the same for all models, except for XGB, which triples it.

To comprehend how the features contribute to the predictions, let us examine the permutation feature importance for each model.

Based on the preceding bar plots in Fig. 12, it is evident that the models assign greater importance to Torque, Tool Wear, and Rotational Speed, whereas the contribution of Type is very low. This corresponds with the observations made during the dataset exploration and is in line with the permutation feature importance for the binary task.

K-NN is the model that attributes more importance to Type, but unlike the binary case, we observe that for each model, the contribution of Type is almost negligible. We subsequently test the model on a new dataset, the one from which we removed the Type column. For K-NN and SVC,

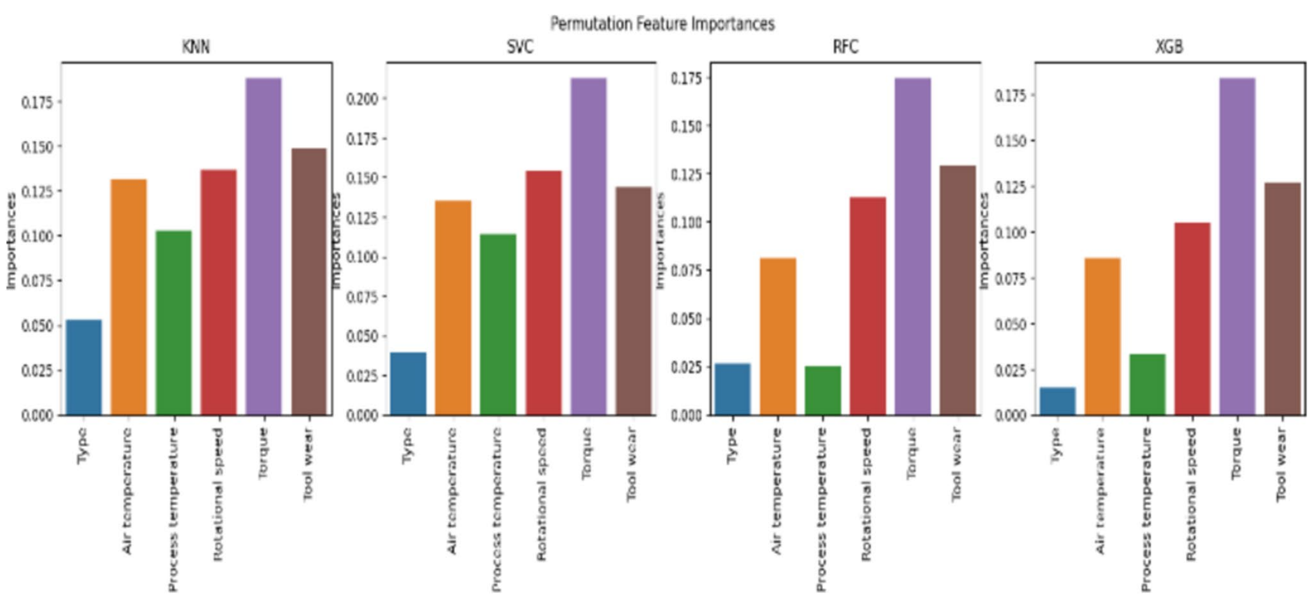
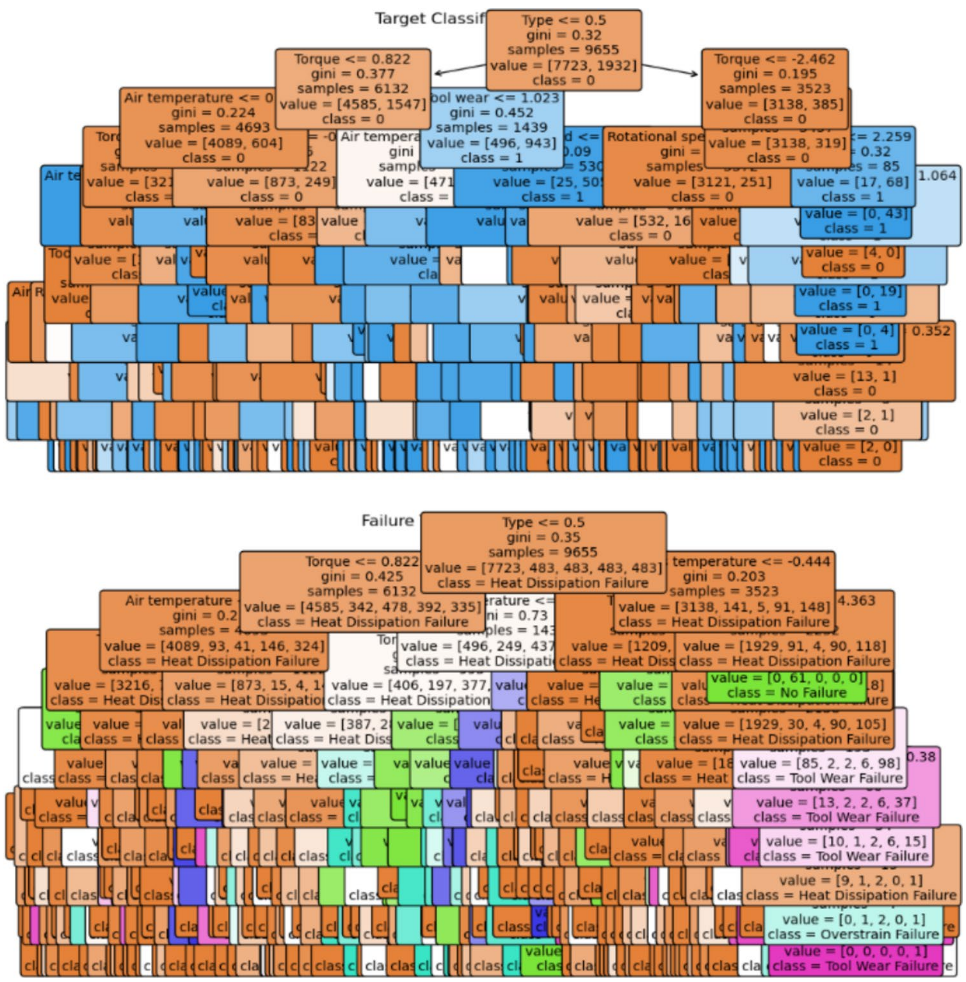


Fig. 12 Visualization of Feature Importance Analysis Results with a Permutation Bar Chart

Fig. 13 Analysis of Decision Paths of a Tree in the Random Forest for Both Tasks



there is a negligible improvement in the metric values, which were already very good. For RFC and XGB, we observe no change in the metric values.

As the training time for the different models is approximately equal in both cases, we leave it to the users to decide which dataset to use.

This section illustrates how an integrated approach to data processing, failure prediction, and failure type identification can transform maintenance management in the manufacturing industry. By optimizing these processes, companies can reduce unexpected downtime, improve equipment durability, and increase overall productivity.

Decision Paths

Here, we display the decision paths of one of the trees that constitute the random forest for both tasks, truncated at depth = 4, which is illustrated by Fig. 13. However, this depth is adequate to confirm that the trees need to be deep because the decision boundaries themselves are intricate and not indicative of over fitting. This is noticeable when examining the multi-class tree, where certain types of failure do not emerge until depth four. It is also evident in the binary classification tree when observing the progression of the Gini score along most paths.

An additional observation can be made that the Type feature serves as the root node in both plots and segregates the majority class (low quality) from the other two at the initial step. It only reappears one more time in the upper part of the trees and sporadically resurfaces at the lowest stages, where its impact is infrequent.

Analysis and Discussion of Results

In conclusion, following comprehensive analyses and the attainment of results, we can formulate conclusive observations about this work. The primary tasks involved predicting machine failure and determining the type of failure. Prior to constructing the models, we conducted data pre-processing to ensure model applicability and optimize performance.

Principal Component Analysis (PCA) unveiled that the majority of the variance is explained by the first three components, representing a combination of two temperatures, machine power (the product of rotational speed and torque), and tool wear. Contrary to initial assumptions that the type of machine affects the occurrence of failures, these features were found to contribute the most to predictions. Subsequently, we implemented predictive models to forecast machine failure and its type in a given dataset. For this purpose, we conducted a comparative study of different analytical approaches and several machine learning algorithms such as SVM (Support Vector Machine), RF (Random Forest), and KNN (K Nearest Neighbours) to choose the most efficient approach.

The selected models excel in both tasks, with XGBoost outperforming KNN. Notably, KNN provides an instantaneous response, while XGBoost requires more time, especially in the case of multi-class classification. The choice of the model depends on business requirements; for a quick application, KNN may be preferred, while precision considerations may lead to the use of XGBoost.

The Performance of Industrial Enterprises

Performance in industrial enterprises refers to a range of parameters and measures that together indicate how well a company performs within its field of expertise. It displays the capacity of the enterprise to meet its goals, making the most use of available resources and providing value to customers.

Importance of Performance in Industrial Companies

Performance plays a crucial role in the operation and success of Companies. It represents the efficiency and effectiveness with which a company utilizes its resources to produce goods or provide services. The importance of performance can be analysed on several levels:

Productivity: Performance is directly linked to the productivity of the company. Effective performance management optimizes the use of resources such as personnel, equipment, and raw materials. This results in increased production or services provided, which can have a significant impact on the financial results of the company.

Competitiveness: In a competitive environment, performance is a key differentiation factor. Companies that manage to improve their performance can reduce production costs, offer competitive prices, or enhance the quality of their products and services. This enables them to gain market share and position themselves advantageously compared to their competitors.

Profitability: Good performance directly contributes to the profitability of the company. By optimizing processes, reducing production costs, and increasing productivity, a company can generate higher margins. This improves profits and the long-term financial viability of the company.

Customer Satisfaction: Performance also influences customer satisfaction. By producing quality goods quickly and at competitive costs, a company can meet customer expectations. This fosters customer loyalty, generates positive recommendations, and strengthens the company's reputation.

Innovation and Growth: Performance improvement is often associated with innovation and company growth. By optimizing existing processes, identifying new improvement opportunities, and fostering a culture of innovation, a company can maintain its competitiveness and stimulate long-term growth.

In conclusion, performance is an essential element in business management. It optimizes resource utilization, improves productivity, enhances competitiveness, and ensures profitability. By paying particular attention to performance, businesses can position themselves advantageously in the market and achieve their short-term and long-term objectives.

The Impact of Maintenance on Industrial Companies

Maintenance is a crucial component of industrial operations, ensuring the effectiveness, dependability, and lifespan of machinery and equipment. It can have a significant impact on industrial companies, affecting multiple aspects of their operation, mainly:

Improvement of Equipment Availability

Maintenance plays a crucial role in enhancing the availability of equipment within companies. By ensuring regular preventive and corrective maintenance, businesses can minimize unexpected downtimes and major equipment failures. This optimizes asset utilization and reduces production disruptions.

Optimization of Maintenance Costs

Effective maintenance can contribute to cost optimization within companies. For instance, by conducting regular preventive maintenance, businesses can avoid major breakdowns that require expensive repairs or complete equipment replacement. Preventive maintenance is generally less costly than corrective maintenance as it identifies and resolves issues at an early stage, preventing them from escalating into major failures.

Increase in Productivity

Efficient equipment maintenance contributes to increased productivity within companies. When equipment is well-maintained, it operates optimally, reducing unplanned downtimes and production interruption.

Appropriate preventive maintenance helps avoid major breakdowns and failures that could lead to significant production delays. Furthermore, by ensuring equipment is properly maintained, companies can optimize energy efficiency and minimize waste, also contributing to increased productivity.

Improvement of Quality and Safety

Maintenance plays an essential role in enhancing product quality and operational safety within companies. By keeping equipment in good working condition, businesses can reduce the risks of technical failures that could result in quality defects or safety issues. Through regular preventive maintenance, companies can ensure that equipment operates in accordance with required standards and specifications, enhancing the production of higher-quality products.

Moreover, equipment maintenance helps prevent hazardous situations and reduces the risks of accidents. For example, by inspecting and repairing defective equipment or those showing signs of deterioration, companies can avoid incidents related to mechanical or electrical failures. Preventive maintenance may also include activities such as checking safety devices, installing protections, and training employees on safety best practices.

In summary, maintenance has a significant impact on business performance. By improving equipment availability, optimizing maintenance costs, increasing productivity, and enhancing quality and safety, maintenance contributes to improving operational efficiency, reducing downtimes, minimizing costs, and strengthening the competitiveness of the company.

Maintenance Performance and Evaluation

Performance measurement serves as a crucial management tool to assess the direction and pace of changes implemented by a company. It plays a pivotal role in enhancing progress toward becoming a more efficient organization.

Measuring maintenance performance enables the identification of factors contributing to poor performance and offers an opportunity to enhance the company's profitability. Moreover, performance measurement serves as a method for management to assess the state of its systems and make decisions regarding the maintenance policies adopted by the company.

Maintenance activities significantly impact operational costs, constituting approximately 30 percent of overall operational costs, particularly when a company employs automated production systems [37]. Several key performance measuring tools are employed in the industry, contingent on the adopted strategies.

Maintenance Performance Indicators

The maintenance performance framework outlined here elucidates key elements crucial in managing the maintenance function. These elements ensure the accurate identification of work aligned with defined objectives and its efficient execution for guaranteed outcomes in line with production performance requirements. Each step is, therefore, pivotal for the successful management of the maintenance function. Maintenance performance indicators, both predictive (upstream) and reactive (downstream), are pivotal for gauging the performance of the maintenance function.

For each element, the primary challenge is to pinpoint performance indicators that will determine if the element is well-managed. This raises the question of what makes a good performance indicator. Good indicators should support performance monitoring and control, aid in identifying performance gaps, foster learning and continuous improvement, support maintenance actions aimed at achieving goals, and focus maintenance resources on areas impacting production performance. However, delving into the analysis of various maintenance performance indicators is beyond the scope of this article. The indicators presented herein for each element are those frequently recurring in the literature. Of course, additional measures can be added as needed.

Upstream Maintenance Performance Indicators

Upstream maintenance performance indicators monitor whether tasks are executed effectively to achieve desired production outcomes. The maintenance process is addressed through the identification of work (based on maintenance goals and performance gaps), work planning, work scheduling, and work execution. Key performance indicators for each process are proposed to measure if the requirements of each process are met.

Downstream Maintenance Performance Indicators

The outcomes of the maintenance process can be summarized in terms of the reliability, availability, and operability of technical systems. These are the core elements that maintenance seeks to address and, therefore, provide measures of the success of the maintenance process. Since maintenance aims to achieve its goals at an optimal cost, it is imperative to measure the cost-effectiveness of maintenance activities.

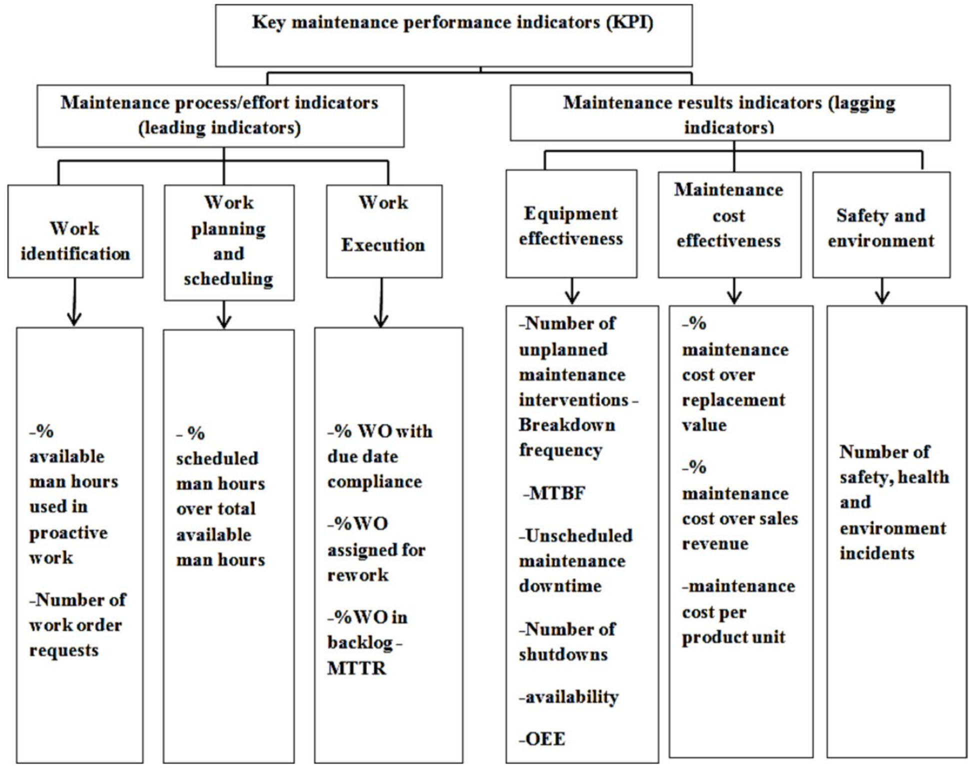


Fig. 14 Key Maintenance Performance Indicators

Downstream indicators are thus used to measure the results of maintenance in terms of equipment performance and maintenance cost. A summary of commonly used upstream and downstream maintenance indicators is presented in Fig. 14.

Measurement of Maintenance Performance Indicators

Maintenance Performance Measurement (MPM) is defined as "the multidisciplinary process of measuring and justifying the value created by maintenance investment and addressing the stakeholders' requirements from an overall business perspective" [61]. Parida and Kumar [4] discusses the significance of MPM, highlighting the following aspects:

- Enables companies to comprehend the value created by maintenance.
- Facilitates the reassessment and revision of maintenance policies and techniques.
- Justifies investments in new trends and techniques.
- Facilitates the adjustment of resource allocations and enhances the understanding of the effects of maintenance on functions, stakeholders, as well as health and safety.

Various categories of maintenance performance measures/indicators are identified in the literature. Kumar et al. [11] categorizes commonly used measures into three groups based on their focus: (1) equipment measures, (2) cost measures, and (3) process performance measures.

Performance measurement is a management tool that assesses the direction and speed of change within the company. It holds a crucial role in optimizing progress towards a high-performing organization. Evaluating maintenance performance identifies elements contributing to poor performance, providing an opportunity to enhance the company's profitability. Additionally, performance measurement is used to assess the state of management systems and make decisions related to the company's adopted maintenance policy.

Maintenance activities significantly impact operating costs, representing approximately 30% of these costs, especially when implementing automated production systems [37]. Various performance measurement tools are applied in the industry based on adopted strategies.

Mean Time Between Failures (MTBF) as its primary metric, measured per machine, where a higher figure is preferable. The second metric is the percentage of reactive maintenance (% Reactive), where a lower number is desirable. The global benchmark recommends a rate of 20% or less for reactive maintenance and 80% for preventive, improvement, or planned maintenance. The third metric is Mean Time to Repair (MTTR), where less severe and faster repairs are favourable. The fourth metric is Overall Equipment Efficiency (OEE), measured per machine or process, with a higher number being preferable. Enhancing overall equipment efficiency (OEE) is at the core of the maintenance strategy.

The performance of production equipment can be assessed through a widely recognized indicator, Overall

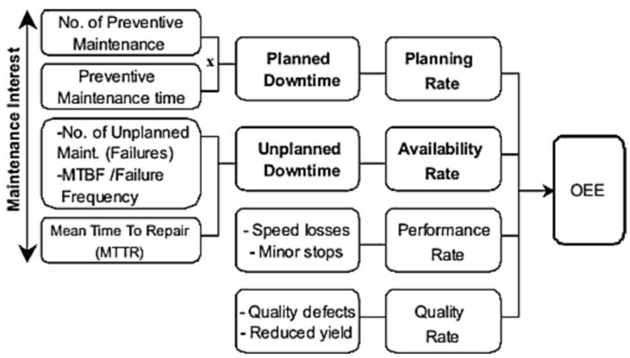


Fig. 15 Important maintenance performance indicators in the OEE metric

Equipment Effectiveness (OEE), and a variant of OEE known as Overall Production Efficiency (OPE) [62]. The OEE metric supports maintenance management by evaluating equipment availability and the planning rate, which are parameters linked respectively to planned and unplanned downtime. Among the crucial aspects that maintenance aims to monitor and control (see Fig. 15), we find the frequency of equipment failures (measured by MTBF and the number of unplanned maintenance interventions) as well as repair time. These two elements impact the unplanned equipment downtime. The maintenance planning rate is determined by the number of planned maintenance activities and the time devoted to preventive maintenance. Measuring these performance indicators within the framework of OEE assists maintenance management in analysing root causes to enhance equipment availability and reliability.

OEE, as an indicator, provides an understanding of the manufacturing zone's performance while identifying potential limitations [63]. It calculates the percentage of manufacturing process efficiency based on three factors: availability, operational yield, and quality [64]. This model, also known as Total Productive Maintenance, results from the multiplication of equipment availability (DE), production rate (TP), and quality rate (TQ). It is an effective and efficient model that uses Total Productive Maintenance implementation procedures to observe, analyse, and evaluate equipment efficiency and effectiveness. The goal is to maximize production by examining and eliminating losses associated with each component of the production process, optimizing the use of equipment, materials, personnel, and methods. The components of this model are calculated as follows:

The OEE takes into account three main factors contributing to the calculation of this key performance indicator through the formula (4):

Availability: This KPI measures the proportion of time during which the equipment is operational and available for production. It is calculated using the equation (1).

Performance: It measures the efficiency of the equipment or process in terms of production compared to its maximum potential output. It is calculated using the formula (2).

Quality: It assesses the compliance of the products or services produced by the equipment or process with established quality standards. (3) is the formula used to calculate this KPI.

$$EA = \frac{PPT - MDT}{PPT} \tag{1}$$

$$PR = \frac{STPU * UNPD}{NOT} \tag{2}$$

$$QR = \frac{TUP - DQ}{TUP} \tag{3}$$

$$OEE = EA * PR * QR \tag{4}$$

EA	Equipment Availability
PPT	Planned Production Time
MDT	Machine Down Time
PR	Production Rate
STPU	Standard Time Per Unit
UPND	Unit Produced Non Defective
NOT	Number Of Operating Time
QR	Quality Rate
TUP	Total Unit Produced
DQ	Defective Quantity
OEE	Overall Equipment Effectiveness/ Efficiency

To facilitate calculations, it is essential to compute these indicators:

- Gross Operating Time: The gross operating time is the total duration during which the system is supposed to be in operation, typically defined by the planned system opening time, minus the total downtime. It is calculated using the Eq. (9).
- Net Time: The net time is the gross operating time minus the total downtime due to unplanned failures or interruptions. It represents the effective time during which the system is operational and productive. It is calculated using the Eq. (10).
- Quality Rate: The quality rate is the ratio of the number of good pieces produced by a system to the total number of pieces manufactured. It measures the proportion of pieces that meet quality standards compared to the entire production. It is calculated using the Eq. (11).

- MTTR (Mean Time To Repair): MTTR is the average time needed to repair a breakdown. It is calculated by dividing the total downtime due to failures by the total number of stops using the Eq. (12).
- MTBF (Mean Time Between Failures): MTBF is the average time between failures of a system. It is calculated by dividing the total operating time by the total number of stops as shown in the Eq. (13).
- Efficiency Rate: The efficiency rate is the ratio of net operating time (actual operating time) to gross operating time. It measures the overall efficiency of the system, taking into account stops and failures. It is calculated using the Eq. (14).
- TRE (Total Rate of Return) is an indicator that measures the efficiency and intensity of use of investments made in a business. It evaluates the economic return on investments relative to the resources committed. The general formula for TRE (5) is as follows:

$$TRE = \frac{Useful\ Operating\ Time}{Total\ Time} * 100 \tag{5}$$

TRS (Overall Equipment Effectiveness): TRS is a widely used performance indicator in the industry to measure the overall efficiency of equipment, a production line, or a factory. (6) is the general formula to calculate TRS:

$$TRS = \frac{Useful\ Operating\ Time}{Required\ Time} * 100 \tag{6}$$

Performance Measurement

This section focuses extensively on the calculations and presentation of performance indicators before and after prediction, aiming to achieve our main objective: evaluating performance before and after prediction. Our methodological approach is structured around three key stages, each meticulously defined to ensure a comprehensive and precise analysis.

In the initial phase, we dedicated this step to data preprocessing and the creation of new functions. This process is essential to guarantee the quality and relevance of the data used in our subsequent analyses. Pre-processing optimizes the reliability of information, addresses missing values, and adjusts data based on the specific requirements of our study.

The second stage of our methodology involves a detailed analysis, including a series of in-depth calculations and the presentation of various performance indicators, both before and after prediction. This stage aims to provide a comprehensive view of changes, trends, and system performance, offering essential insights to assess the effectiveness of our predictive model.

Finally, the last phase of our study implements a judicious exploitation of the obtained results. Using the powerful tool that is Power BI, we will proceed with the visualization of maintenance KPIs, providing a clear and intuitive graphical representation of the data. Additionally, this step encompasses a thorough analysis of the impact of predictive maintenance on the overall performance of an industrial organization.

Throughout this in-depth exploration, we will seek to identify and understand the concrete benefits and opportunities generated by the implementation of predictive maintenance. This includes a significant reduction in downtime, optimization of maintenance costs, and overall improvement in productivity. By deploying a holistic approach, our study aims to provide strategic insights to guide decisions and actions aimed at maximizing the benefits of predictive maintenance within an industrial organization.

Performance Measurement Before Prediction

The 'Target' column will be of numeric type, and the 'Failure Type' column will be of string type in the DataFrame df.

```
df = pd.read_csv('predictive_maintenance.csv')
# Convertir les colonnes nécessaires en types de données appropriés
df['Target'] = pd.to_numeric(df['Target'], errors='coerce')
df['Failure Type'] = df['Failure Type'].astype(str)
```

Definition of two functions, generate_income and generate_cost, which generate income and cost values based on the type. Then, it applies these functions to the 'Type' column of the DataFrame to generate the corresponding income and cost values for each row. Finally, it displays our updated DataFrame.

```
# Définir la fonction de génération de revenu en fonction du type
def generer_revenu(type):
    if type =='L' :
        return np.random.uniform(1000, 3000)  # Générer un revenu entre 1000 et 5000 pour le type 'L'
    elif type == 'M':
        return np.random.uniform(2000, 4000)  # Générer un revenu entre 5000 et 10000 pour le type 'M'
    elif type == 'H':
        return np.random.uniform(6000, 9000)  # Générer un revenu entre 10000 et 20000 pour le type 'H'
    else:
        return 0  # Valeur par défaut si le type n'est pas reconnu

# Définir la fonction de génération de coût en fonction du type
def generer_cout(type):
    if type == 'L':
        return np.random.uniform(500, 2000)  # Générer un coût entre 500 et 2000 pour le type 'L'
    elif type == 'M':
        return np.random.uniform(1500, 5000)  # Générer un coût entre 2000 et 5000 pour le type 'M'
    elif type == 'H':
        return np.random.uniform(4000, 10000)  # Générer un coût entre 5000 et 10000 pour le type 'H'
    else:
        return 0  # Valeur par défaut si le type n'est pas reconnu

# Générer les valeurs de revenu et coût pour chaque ligne du dataframe
df['Revenu'] = df['Type'].apply(generer_revenu)
df['Coût'] = df['Type'].apply(generer_cout)

# Afficher le dataframe mis à jour
print(df)
```

Calculates and Displays Various Performance Indicators Before Prediction. Here are the Formulas Used for the KPIs

$$Availability\ Rate = \frac{Gross\ operating\ time}{Openingtime} \tag{7}$$

$$TRG = \frac{Useful\ operating\ time}{Openingtime} \tag{8}$$

$$Gross\ Time = Opening\ time - total\ stoppage\ time \tag{9}$$

$$Net\ Time = Gross\ time - Down\ time \tag{10}$$

Rate Performance

$$Quality\ Rate = \frac{Number\ of\ good\ pieces}{Number\ produced} \tag{11}$$

$$MTTR = \frac{Total\ stoppage\ time}{Number\ of\ stops} \tag{12}$$

$$MTBF = \frac{Total\ operating\ time}{Number\ of\ stops} \tag{13}$$

$$Efficiency\ Rate = \frac{Net\ Time}{Gross\ Time} \tag{14}$$

```python
# Calculer le temps de disponibilité avant la prédiction
total_system_uptime_failure = df['Target'].sum()
total_downtime_failure = df[df['Target'] != 0]['Target'].sum()
total_time_failure = total_system_uptime_failure + total_downtime_failure
# Calculer le taux de disponibilité des machines en panne après la prédiction
availability_rate_failure = total_system_uptime_failure / total_time_failure
print("Taux de disponibilité avant la prédiction :", availability_rate_failure)


# Définir les critères de filtrage pour exclure les enregistrements indésirables
filt_target = df['Target'] == 0  # Exclure les enregistrements avec Target égal à 0

# Appliquer le filtre pour exclure les enregistrements indésirables
df_filtered = df[filt_target]

# Calculer le revenu total et le coût total pour les enregistrements filtrés
total_revenue = df_filtered['Revenu'].sum()
total_cost = df_filtered['Coût'].sum()
# Calcul de l'indicateur de rendement
performance_indicator = (total_revenue - total_cost) / total_cost

# Affichage de l'indicateur de rendement
print("Indicateur de rendement :", performance_indicator)


# Calculer le taux de qualité avant la prédiction=nbre de pièce bonne/nbre de pièces réalisées
quality_rate = total_functional_products / (total_functional_products + total_defective_products)
print("Taux de qualité avant la prédiction :", quality_rate)
```

```python
# Calculer le temps total de fonctionnement en minutes
total_runtime = df['Timestamp'].max() - df['Timestamp'].min()
total_runtime = total_runtime.total_seconds() / 60

# Calculer le nombre total d'arrêts (défaillances)
total_failures = df[df['Target'] != 0]['Target'].sum()

# Calculer le MTBF avant la prédiction
mtbf = total_runtime / total_failures
print("MTBF avant la prédiction :", mtbf)

# Calculer le temps total d'arrêt en minutes
total_downtime = df[df['Target'] != 0]['Timestamp'].diff().sum().total_seconds() / 60

# Calculer le nombre total d'arrêts
num_failures = df[df['Target'] != 0]['Target'].sum()

# Calculer le MTTR avant la prédiction
mttr = total_downtime / num_failures
print("MTTR avant la prédiction :", mttr)
# Calculer le temps utile de fonctionnement en minutes
temps_utile_fonctionnement = total_runtime - total_downtime

# Calculer le temps d'ouverture en minutes (période totale de temps)
temps_ouverture = total_runtime
# Calculer le TRG avant la prédiction
trg = (temps_utile_fonctionnement / temps_ouverture)*100
print("TRG avant la prédiction :", trg)
# Calculer le temps brut de fonctionnement
```

Here are the obtained results:

```
Taux de disponibilité avant la prédiction : 0.5
Indicateur de rendement : 0.17419145888462442
Taux de qualité avant la prédiction : 0.5086211281216622
MTBF avant la prédiction : 768.8466076696166
MTTR avant la prédiction : 763.079681419469
TRG avant la prédiction : 0.7500750075007973
Temps brut : 260639.0
Temps net : 1954.987998800003
le taux d'efficacité :  0.0075007500750079725
```

Performance Measurement After Prediction We will use the newly predicted data.

```python
# Machines qui vont tomber en panne (prédiction de panne = 1)
machines_failure = X_test[y_pred_rf == 1]

# Machines qui ne vont pas tomber en panne (prédiction de panne = 0)
machines_no_failure = X_test[y_pred_rf == 0]

# Calculer le temps de disponibilité après la prédiction
total_system_uptime_after = machines_no_failure['Target'].sum()
availability_rate_after = total_system_uptime_after / total_time

print("Taux de disponibilité après la prédiction :", availability_rate_after)
```

Definition of two functions, generate_income and generate_cost, which generate income and cost values based on the type. Then, these functions are applied to the 'Type' column of the DataFrame to generate the corresponding income and cost values for each row. Finally, the updated DataFrame is displayed.

```python
import numpy as np

# Définir la fonction de génération de revenu en fonction du type
def generer_revenu(type):
    if type ==1 :
        return np.random.uniform(1000, 5000)  # Générer un revenu entre 1000 et 5000 pour le type 'L'
    elif type == 2:
        return np.random.uniform(5000, 10000)  # Générer un revenu entre 5000 et 10000 pour le type 'M'
    elif type == 3:
        return np.random.uniform(10000, 20000)  # Générer un revenu entre 10000 et 20000 pour le type 'H'
    else:
        return 0  # Valeur par défaut si le type n'est pas reconnu

# Définir la fonction de génération de coût en fonction du type
def generer_cout(type):
    if type == 1:
        return np.random.uniform(500, 2000)  # Générer un coût entre 500 et 2000 pour le type 'L'
    elif type == 2:
        return np.random.uniform(2000, 5000)  # Générer un coût entre 2000 et 5000 pour le type 'M'
    elif type == 3:
        return np.random.uniform(5000, 10000)  # Générer un coût entre 5000 et 10000 pour le type 'H'
    else:
        return 0  # Valeur par défaut si le type n'est pas reconnu

# Générer les valeurs de revenu et coût pour chaque ligne du dataframe
df['Revenu'] = df['Type'].apply(generer_revenu)
df['Coût'] = df['Type'].apply(generer_cout)

# Afficher le dataframe mis à jour
print(df)
```

```
            Coût          Revenu
0     1066.721860     2703.608594
1     2675.096205     7282.703906
2     1412.334541     4449.970530
3     1237.853230     1215.904445
4     3679.505369     3980.999489
..            ...             ...
962   2832.277674     6395.900136
963    559.668818     1648.605582
964   5321.886427    17307.561395
965   1163.435515     4644.672076
966   1890.818316     1951.812033
```

Calculates and Displays Various Performance Indicators After Prediction

```python
# Supposons que votre ensemble de données est stocké dans un DataFrame appelé "df"
# Assurez-vous que la colonne "TimeStamp" est de type datetime

# Tri du DataFrame par ordre croissant de la colonne "TimeStamp"
d_no_sorted = d_no_pred.sort_values('Timestamp')

# Récupération du premier et du dernier horodatage
first_timestamp = d_no_sorted['Timestamp'].iloc[0]
last_timestamp = d_no_sorted['Timestamp'].iloc[-1]

# Calcul de la durée totale d'exécution (total_runtime)
total_runtime = (last_timestamp - first_timestamp).total_seconds()  # En secondes

total_downtime = d_no_pred[d_no_pred['Target'] != 1]['Target'].sum()  # Exclure les enregistrements avec défaillance
# Calculer le temps de disponibilité du système (Total System Uptime)
total_system_uptime = total_runtime

# Calculer le temps total (Total Time)
total_time = total_runtime + total_downtime

# Calculer le taux de disponibilité
availability_rate = total_system_uptime / total_time

print("Taux de disponibilité après prédiction :", availability_rate)
# Appliquer le filtre pour exclure les enregistrements indésirables après la prédiction
filt_target = d_no_pred['Target'] == 0
df_filtered_pred = d_no_pred[filt_target]
```

```python
# Calculer le revenu total et le coût total pour les enregistrements filtrés après la prédiction
total_revenue_pred = df_filtered_pred['Revenu'].sum()
total_cost_pred = df_filtered_pred['Coût'].sum()
performance_indicator_pred = (total_revenue_pred - total_cost_pred) / total_cost_pred
print("Indicateur de rendement après la prédiction :", performance_indicator_pred)

# Calculer le taux de qualité après la prédiction
total_functional_products_pred = len(d_no_pred)
total_defective_products_pred = len(d_pred)
quality_rate_pred = total_functional_products_pred / (total_functional_products_pred + total_defective_products_pred)
print("Taux de qualité après la prédiction :", quality_rate_pred)
total_failures = d_pred[d_pred['Target'] == 1]['Target'].sum()
mtbf = total_runtime / total_failures
print("MTBF après prédiction :", mtbf)
```

```python
# Calculer le MTTR après la prédiction
total_downtime_pred = d_pred[d_pred['Target'] != 0]['Timestamp'].diff().sum().total_seconds() / 60
num_failures_pred = d_pred[d_pred['Target'] != 0]['Target'].sum()
mttr_pred = total_downtime_pred / num_failures_pred
print("MTTR après la prédiction :", mttr_pred)
# Calculer le TRG après la prédiction
temps_utile_fonctionnement_pred = total_runtime - total_downtime_pred
trg_pred = temps_utile_fonctionnement_pred / temps_ouverture
print("TRG après la prédiction :", trg_pred)
# Calculer le temps brut de fonctionnement après la prédiction
temps_brut_pred = total_runtime
print("Temps brut après la prédiction :", temps_brut_pred)

# Calculer le temps net de fonctionnement après la prédiction
temps_net_pred = temps_brut_pred - total_downtime_pred
print("Temps net après la prédiction :", temps_net_pred)
```

```python
# Calculer le taux d'efficacité après la prédiction
taux_efficacite_pred = temps_net_pred / temps_brut_pred
print("Taux d'efficacité après la prédiction :", taux_efficacite_pred)
```

```
Taux de disponibilité après prédiction : 1.0
Indicateur de rendement après la prédiction : 0.924853121784992
Taux de qualité après la prédiction : 0.8018242122719734
MTBF après prédiction : 65432.384937238494
MTTR après la prédiction : 1090.5397489539748
TRG après la prédiction : 0.95
Temps brut après la prédiction : 15638340.0
Temps net après la prédiction : 15377701.0
Taux d'efficacité après la prédiction : 0.9833333333333333
```

Here are the Obtained Results:

We used the 'tabulate' library to generate a table from the KPI data before and after prediction. Numeric values are then converted into colored character strings using the 'colored' function from the 'termcolor' library.

By displaying the table in the Jupyter notebook using the 'display' function from the 'IPython.display' library, we obtain a clear and concise visualization of the KPIs before and after prediction. This allows us to easily compare performance and improvements made through predictive maintenance.

Visualizing KPIs before and after prediction helps us make informed decisions to optimize operations. It also enables effective communication of results to stakeholders and demonstrates the positive impact of predictive maintenance on overall business performance.

Métrique	Avant	Après
Taux de disponibilité	0.5	1
Indicateur de rendement	0.174191	0.924853
Taux de qualité	0.508621	0.801824
MTBF	768.847	65432.4
MTTR	763.08	1090.54
TRG	0.750075	0.953475
Temps brut	260639	1.56383e+07
Temps net	1954.99	1.53777e+07
Taux d'efficacité	0.00750075	0.983333

Here, we will save the predicted data and KPIs to import them into Power BI for visualization.

```python
# Créer une liste contenant les indicateurs et leurs valeurs
indicators_data = {
    'Taux de disponibilité': [availability_rate_failure],
    'Indicateur de rendement':[ performance_indicator],
    'Taux de qualité':[ quality_rate],
    'MTBF':[mtbf],
    'MTTR':[ mttr],
    'TRG':[ trg],
    'Temps brut':[ temps_brut],
    'Temps net': [temps_net],
    'Taux d\'efficacité':[taux_efficacite]
    }

# Créer un DataFrame à partir de la liste
# Créer un DataFrame à partir du dictionnaire
indicators_df = pd.DataFrame(indicators_data)

# Enregistrer le DataFrame dans un fichier CSV
indicators_df.to_csv('indicators_avant.csv', index=False)
```

```python
from tabulate import tabulate
from termcolor import colored
from IPython.display import display, HTML

# Créer une liste de listes contenant les résultats avant et après la prédiction
data = [
    ['Taux de disponibilité', availability_rate_failure, availability_rate],
    ['Indicateur de rendement', performance_indicator, performance_indicator_pred],
    ['Taux de qualité', quality_rate, quality_rate_pred],
    ['MTBF', mtbf, mtbf_pred],
    ['MTTR', mttr, mttr_pred],
    ['TRG', trg, trg_pred],
    ['Temps brut', temps_brut, temps_brut_pred],
    ['Temps net', temps_net, temps_net_pred],
    ['Taux d\'efficacité', taux_efficacite, taux_efficacite_pred]
]

# Définir les en-têtes de colonnes
headers = ['Métrique', 'Avant', 'Après']

# Convertir les valeurs numériques en chaînes de caractères colorées
data_formatted = [
    [row[0], colored(str(row[1]), 'green'), colored(str(row[2]), 'yellow')]
    for row in data
]

# Générer le tableau coloré au format HTML
table_html = tabulate(data_formatted, headers, tablefmt='html')

# Afficher le tableau
display(HTML(table_html))
```

Visualization of Performance Indicators Measured by Power BI Power BI is a data analysis and visualization platform that allows the creation of interactive and informative dashboards. When it comes to assessing Key Performance Indicators (KPIs) before and after a prediction, Power BI can be a valuable tool as shown by Fig. 16.

Before the prediction, Power BI was used to visualize and monitor relevant KPIs such as machine availability rate, performance indicator, quality rate, MTBF (Mean Time Between Failures), MTTR (Mean Time To Repair), TRG (Overall Equipment Effectiveness), gross operating time, etc. Power BI offers a range of customizable charts and visualizations to represent these metrics clearly and concisely.

After the prediction, we updated our dashboards with the new data and visualized changes in the KPIs. This allowed us to compare performance before and after the prediction and identify improvements or potential impacts.

Exploitation of Results The effectiveness of predictive maintenance on the company's performance is clearly highlighted by comparative metrics before and after the implementation of prediction. The provided results show a substantial improvement in performance following the implementation of predictive maintenance, quantified through several Key Performance Indicators (KPIs). Here is how these results were measured and explained in detail.

A high availability rate means that predictive maintenance interventions have successfully reduced unexpected failures, thereby maximizing equipment availability. The increase in the availability rate from 0.5 to 1 indicates that the machines are now available almost continuously. This KPI is crucial as it shows that predictive maintenance has virtually eliminated unexpected downtime, thus increasing the overall productivity of the company.

The performance KPI, which rose from 0.174191 to 0.924853, measures the efficiency with which the equipment operates compared to its theoretical maximum capacity. This significant increase demonstrates process optimization through the reduction of unexpected interruptions and better monitoring of machine health.

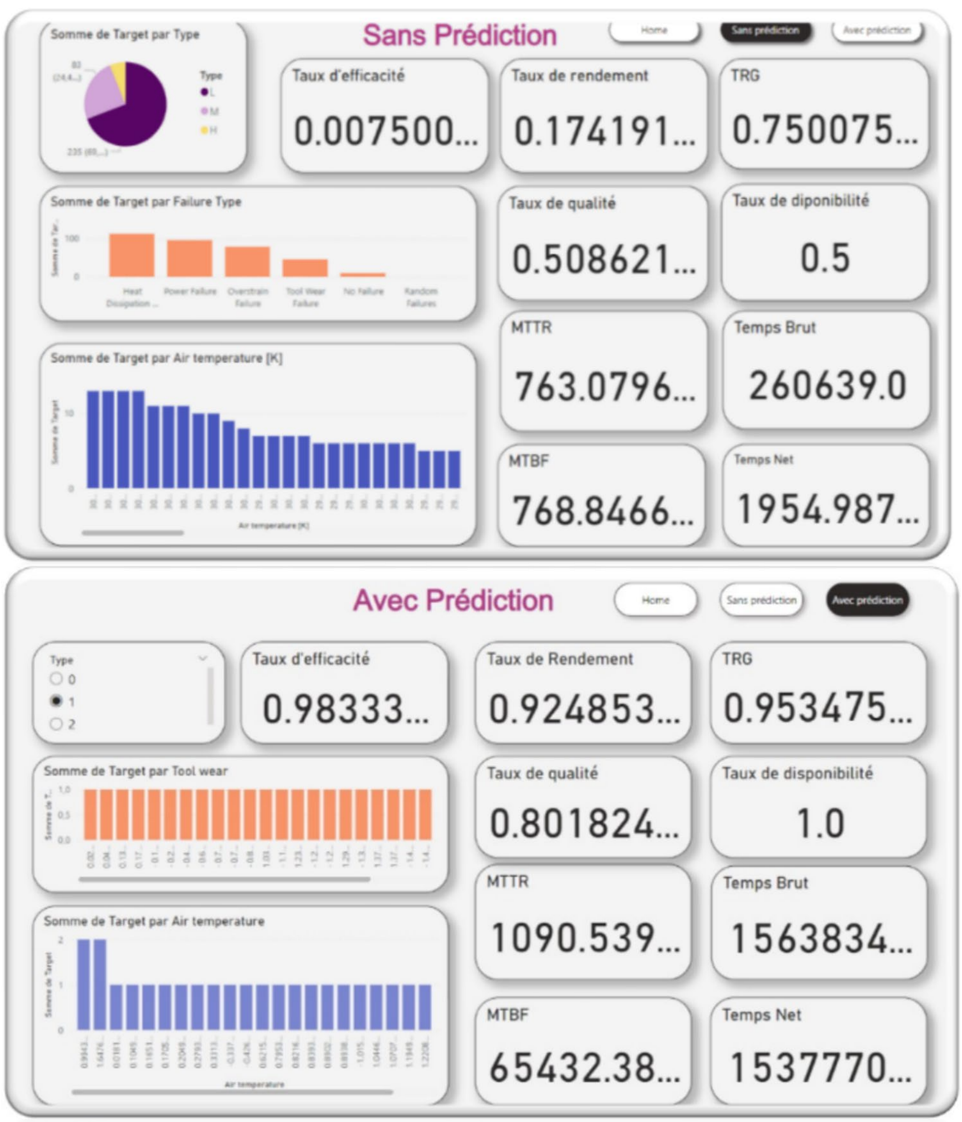


Fig. 16 The performance indicators measured before and after the prediction

The improvement in the quality rate, from 0.508621 to 0.801824, reflects an increase in the proportion of products that meet quality standards. This KPI is essential because it directly affects customer satisfaction and reduces costs associated with defective products.

The MTBF has soared from 768.847 to 65,432.4, meaning that the average time between failures is now significantly longer. This KPI demonstrates the effectiveness of predictive maintenance in preventing failures, contributing to a reduction in unexpected downtime.

MTTR has increased from 763.08 to 1,090.54, which means that the time required to repair a machine after a failure has decreased. This KPI is important as it reflects the speed and efficiency of maintenance interventions after a breakdown.

The TRG (Overall Equipment Effectiveness OEE), which has increased from 0.750075 to 0.95, represents a comprehensive measure of equipment efficiency. This KPI is an essential indicator as it takes into account availability, performance, and quality, demonstrating an improvement in all these dimensions following the implementation of predictive maintenance.

Finally, the increase in the efficiency rate from 0.00750075 to 0.983333 is one of the most impressive measures. This KPI shows that the maintenance process has been dramatically optimized, minimizing unplanned downtime and maximizing the utilization of operating time.

These quantitative metrics indicate that predictive maintenance has significantly improved the overall performance of the company through well-defined KPIs. Gains in availability, performance, quality, MTBF, MTTR, OEE, and efficiency rate reflect an optimized maintenance system that reduces unplanned downtime and costs while increasing productivity and customer satisfaction.

These results clearly demonstrate the positive impact of predictive maintenance on the company's performance. By anticipating potential failures and taking proactive measures to prevent them, we have been able to improve machine availability, product quality, operational efficiency, and overall company performance. These improvements contribute to greater profitability, increased customer satisfaction, and enhanced competitiveness in the market.

Potential Limitations of the Study

Dependence on Quality Data: The performance of predictive maintenance algorithms heavily relies on the quality and quantity of collected data. This could limit the effectiveness of predictions in environments where data is incomplete or poorly structured.

Specific Industrial Context: Although the study focuses on a particular case of maintenance within a company, the results may not be directly applicable to other sectors or to equipment with significantly different configurations.

Necessary Technical Infrastructure: Implementing predictive maintenance requires investments in advanced technologies such as IoT and AI, which could pose obstacles in low-budget industrial contexts or those with limited technological infrastructure.

Limited Data: The analyses are based on data from specific case studies or simulations. Access to broader databases from various industries could enrich and deepen the analysis.

Lack of In-Depth Comparison with Other Maintenance Strategies: While predictive maintenance has been generally compared to reactive and preventive maintenance, a more detailed and empirical comparison could have been further explored.

However, these limitations do not affect the validity of the conclusions drawn within the scope of the study. We thus open the door to future research that could expand the analysis to different industrial sectors, evaluate the organizational and economic impact of such a transition, or explore alternative methods for data collection and processing. That said, the results obtained in this study remain a robust demonstration of the effectiveness of predictive maintenance in the studied industrial environment.

Future Research Directions

To enhance the contribution of this article to the field of predictive maintenance, several future research avenues can be considered. Here are some suggestions to deepen current work and explore new paths:

Evolution of Predictive Maintenance with Emerging Technologies

- Predictive Maintenance and Advanced AI: Integrating artificial intelligence, particularly deep learning and unsupervised learning techniques, could further improve prediction capabilities. It would be interesting to explore the application of these technologies in more complex, multi-component systems.
- Edge Computing and Predictive Maintenance: With the advent of Edge Computing, it becomes possible to process data locally, near the machines, thus reducing latency and communication costs. Combining Edge Computing with IoT for predictive maintenance represents a promising research avenue, especially for remote or large-scale industrial environments.
- Digital Twins: Integrating digital twins with predictive maintenance systems could enable real-time simulation

of machine behaviour and more accurately anticipate failures. This approach deserves increased attention in future research.

Predictive Maintenance in Other Industrial Sectors

- Industry 4.0 and Non-Manufacturing Sectors: Although predictive maintenance is widely used in manufacturing industries, its application in other sectors such as healthcare, smart farming, and smart cities is still underexplored. Studying these areas could open new opportunities for predictive maintenance.
- Renewable Energy: The renewable energy sector, such as wind and solar, could benefit from predictive maintenance techniques. For example, future research could focus on applying these techniques to optimize maintenance for solar panels or wind farms to improve their lifespan and reduce costs.

Cybersecurity and Predictive Maintenance

- Protecting Predictive Maintenance Systems from Cyberattacks: As systems become more interconnected through IoT, they become more vulnerable to cyber-attacks. Research could be conducted to develop solutions that secure collected data and predictive maintenance algorithms while ensuring the confidentiality and integrity of industrial data.

Predictive Maintenance and Sustainable Development

- Reducing Environmental Footprint: It would be interesting to develop predictive maintenance models that not only reduce costs and downtime but also contribute to lowering the industry's carbon footprint. For instance, research could evaluate how predictive maintenance minimizes energy or raw material consumption.
- Recycling and Reusing Equipment: Studying the impact of predictive maintenance on equipment lifespan and its potential for recycling or reuse could be a key research area in an increasingly circular economy-focused industrial context.

Improving Prediction Algorithms

- Automating Model Selection: Future research could aim to automate the selection of the most suitable predictive maintenance algorithms based on equipment type and usage conditions, leveraging techniques like AutoML (automated machine learning).
- Self-Learning Algorithms: Developing algorithms capable of continuously and autonomously learning from real-time data to improve their predictive accuracy would be a major advancement. These algorithms could adjust their models as new data becomes available.

By exploring these research avenues, it will be possible to expand the impact of predictive maintenance into new sectors while continuing to innovate to enhance the performance and safety of industrial systems.

Conclusion

During this study, we observed the crucial importance of predictive maintenance on the performance of a system or process. Predictive maintenance plays a vital role in maximizing equipment availability and efficiency, directly resulting in a significant improvement in overall performance.

By using measures such as availability rate, TRG (Overall Equipment Effectiveness), net operating time, and efficiency rate, we were able to assess the impact of predictive maintenance on operational performance.

A high availability rate, achieved through proactive and preventive maintenance, ensures that the system is available to operate according to production needs. This reduces unplanned downtime and increases useful operating time, resulting in an improvement in TRG.

Net operating time, which is the effective time during which the system is operational, is greatly influenced by predictive maintenance. By reducing downtime caused by failures and implementing effective maintenance strategies, one can significantly increase net time, allowing for more optimal use of resources.

Furthermore, predictive maintenance contributes to improving the quality rate by minimizing production failures and errors. By conducting regular maintenance, ensuring prompt repairs during failures, and closely monitoring equipment, one can reduce quality issues and increase the proportion of parts compliant with standards.

In conclusion, the study underscored the crucial importance of predictive maintenance in enhancing the performance of a system or process. By investing in appropriate maintenance strategies, focusing on equipment availability, reducing downtime, and optimizing quality, organizations can achieve superior operational performance and meet production goals more efficiently.

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Data Availability Data is available from the corresponding author upon request.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

Research Involving Human and/or Animals This research does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent Informed consent was obtained from all individual participants included in this research.

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