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Autonomous Decision Support Based on Artificial Intelligence Techniques for Maintenance Processes

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Abstract

Through the recent digitalization of the industry and the use of technologies and ideas from Industry 4.0, maintenance tasks have altered. Companies are now able to develop knowledge about the production system's present and future health state by connecting to and talking with it, which enables more effective control over the machinery. Predictive maintenance is a technique whose objective is to minimize unscheduled downtimes and efficiently arrange maintenance tasks before faults and stoppages occur. Several Artificial Intelligence (AI) data analysis tools have been presented in recent decades to construct a prescriptive maintenance system that will aid with the autonomous choice in order to better assist this work. In order to comprehend how artificial intelligence algorithms are affecting maintenance policies and to analyze their implications in strategies, we investigate the state-of-the-art technologies in the prescriptive maintenance system in this study. The findings are compiled in a thorough database that offers illustrations of how to adopt maintenance policies based on descriptive, predictive, and prescriptive analytics using concepts and empirical evidence from the literature. The goal of this study, which is the first in-depth inquiry of these research subjects, is to provide a deeper understanding and awareness of current trends and major challenges while highlighting important aspects and barriers to the adoption of novel policies. *Keywords:* Intelligent maintenance system, artificial intelligence, prescriptive maintenance.

1. Introduction

Due to changes in the manufacturing production planning and control systems, the area of maintenance management has come under growing strain. Plant management has recently been faced with challenges to productivity and quality unprecedented in corporate history. The maintenance department is crucial to achieving higher levels of productivity and quality in order to continuously reduce costs and support a more dependable and long-lasting operation. New condition-monitoring technologies have since emerged, and they are anticipated to enhance maintenance procedures by lowering costs and enhancing the availability and dependability of the equipment. Since many of these technologies are still in their early stages of development, it is important to assess the projected benefit for the operation process at each stage of technical maturity and to create appropriate maintenance strategies that take these newly discovered insights into account. Although there are methods for aiding decision-making processes, most of them have the following drawbacks:

- Consider conventional preventive maintenance techniques.
- Use-case specific (unique difficulties) and not easily transferable to other problem categories.
- Currently used predictive maintenance techniques frequently overlook autonomous decision support. A key building block for creating intelligent cyber-physical maintenance systems that are capable of taking independent decision-supporting activities is artificial intelligence practice.

Future factories that integrate production planning and prescriptive maintenance will have maintenance plans that are more adaptable, customizable, and resilient.

2. Literature Review

Several studies on maintenance methods with a data analytics focus have been done in the last ten years. A substantial body of literature addresses issues, such as enhancing availability by forecasting the condition of equipment using historical and current data as well as expert knowledge. In their evaluation of a large body of research on prognostic-based decision support for condition-based monitoring, Bousdekis et al. [1] offered a useful way for efficiently identifying and choosing the best combinations of techniques, including data- driven approaches. A variety of Deep Learning-based techniques have been researched as alternatives to manual feature engineering. Convolutional Neural Networks, for instance, have been used to identify structural deterioration and detect defects in rotating machinery [2]. However, both approaches have been evaluated in simulated environments, which shows that Deep Learning is still in its infancy and requires further systematic research (e.g., standard datasets, insight into black box models, transferring models, imbalance in training data, etc.) before it can be applied in the field of prescriptive maintenance (PsM) [3]. Additionally, Wöstmann et al. [4] investigated how well-established predictive maintenance technologies may be applied to production systems while considering a number of requirements for a successful implementation. In the literature on maintenance, knowledge- based decision support strategies for PsM are a new trend. This area has not yet been thoroughly investigated. The process of finding, comprehending, and communicating maintenance data was covered by Karim et al. in their discussion of maintenance analytics [5]. A comprehensive strategy that incorporates modelling of data, knowledge, and context is required to design a maintenance analytic-based decision support solution [6]. PsM also refers to recent developments in enhancing self-organization and self-direction capabilities of cyber physical production systems (CPPS), which in theory aim at machine self-diagnosis and scheduled maintenance [7]. Condition-based maintenance or predictive maintenance

(CbM/PdM) enhances condition monitoring by employing statistics, stochastics, simulation-based, data-analytics, and even machine learning algorithms, which allow making failure predictions. Prescriptive maintenance may therefore mature to its full potential, involving sophisticated techniques to foster and strengthen capacities for adaptation and optimization [8]. Not only can PsM forecast the system's future health condition, but it may also suggest autonomously timed judgments for maintenance chores (inspection, repair, and replacement) or action plans. As a result, PsM mandates the incorporation of a decision support system that prescribes and approves specific maintenance action plans that can be carried out automatically or manually. In this regard, PsM exemplifies the self-organization and self-direction capabilities of CPPS [9] while also keeping the operators informed by asking them to monitor the status from AR-based monitoring tools, check the available windows for maintenance planning, and choose whether to immediately call for augmented reality (AR) remote maintenance or schedule maintenance tasks for a later time [10]. PsM systems will eventually develop into autonomous digital orchestrators that schedule maintenance jobs in line with production plans, whereas in this application a human operator mediates and serves as a decision agent in a CbM/PdM environment [8]. While there has been a lot of study on techniques to integrate planning areas (such as production, maintenance, and quality) [11,12], novel maintenance strategies like PdM or PsM are typically lacking a global smart factory perspective and are not yet fully developed from a PPC standpoint. This connection would have a big impact on material planning, reducing waste from unanticipated tool failure/degradation [14], increasing energy efficiency [15], and minimizing the impact of remanufacturing on schedules [16]. The majority of research focuses on allocating suitable time frames for maintenance tasks [17]. For example, production scheduling and preventive maintenance have been combined in decision models to account for demand unpredictability [18]. Only a few models, meanwhile, focus on either CbM for resolving various job-shop scheduling issues [20] or on periodic maintenance [19] to record and use feedback data from the shop floor. Few research has recently begun to examine the relationship between PPC and PdM, for example, for job-shop scheduling based on degradation rates and projecting failure moments [21], but the promising relationship with PsM has not yet been examined. As a result, the discussion below identifies two holes that provide inspiration for the current research:

• PPC cannot afford to disregard the most recent advancements in data-driven maintenance strategies, such as PsM, which must be incorporated in real-world case studies from an application- and technology-focused standpoint. To this purpose, additional research is still needed on data interoperability, evaluation of potential production maintenance scenarios, and knowledge discovery and preservation.

•A factory's planning complexity and technological readiness level greatly influence the design decisions for an integrated PsM-PPC decision support system (and its successful implementation in an actual production environment) (concerning, e.g., available ICT infrastructure, data accessibility, availability, and quality as well as staff qualifications). Application studies are therefore required to evaluate and talk about the difficulties and technological problems resulting from actual use cases.

3. Study Aims

This study's objective is to provide the state-of-the-art in intelligent maintenance systems based on approaches that can influence maintenance policies, including descriptive, predictive, and prescriptive approaches, and to examine how these approaches may be applied to innovations. To do this, a review of recent publications in the literature was first required. This allowed the authors to pinpoint knowledge gaps and provide solutions for our goal of determining how descriptive, predictive, and prescriptive approaches are strengthening traditional maintenance practices. To the best of the authors' knowledge, there are currently no studies in the literature that explore the cutting-edge descriptive, predictive, and prescriptive methodology used in maintenance policies. Finally, by highlighting important characteristics and drawbacks for the adoption of novel policies based on descriptive, predictive, and prescriptive approach, the study offered in this paper aims to produce a deeper understanding and knowledge of current trends and significant challenges.

4. Knowledge-Based Maintenance Strategies

The greatest level of knowledge-based maintenance (KBM) in terms of complexity and maturity is known as prescriptive maintenance [22]. KBM presupposes that holistic assessment of production processes, as opposed to atomistic inspection of (all) influential components, results in competitive advantages for stabilizing maintenance operations and lowering unexpected costs [22, 23]. As a result, KBM focuses on examining maintenance as a non-isolated sub-domain of production systems, which in turn affects the development of organizational value [23]. Recent studies have revealed that the sub-domains of production planning, maintenance, and quality management interact strongly and collectively impact the attainment of the intended production performance, equipment availability, and product quality [24, 25]. Through careful examination of maintenance repercussions, system circumstances, organizational structure, and processes, KBM's primary goal is to build a general concept for optimizing maintenance processes [23]. The following categories can be used to classify current methods for fulfilling KBM objectives (see Fig. 1) [22]:

- Descriptive maintenance provides details on earlier maintenance procedures in response to the question "What happened?"
- Diagnostic maintenance examines cause-and-effect relationships, provides further technical information regarding previous maintenance operations, and provides an answer to the query "Why did that happen?"
- Predictive maintenance forecasts future events using historical maintenance data, possibly in real-time, to answer the question "What will happen when?" The terms "Smart Maintenance," "Data Driven Maintenance," and most recently "Maintenance 4.0" are also used to describe this.

- Prescriptive maintenance provides actionable advice for decision-making and enhances and/or optimizes upcoming maintenance operations to address the question of "How can we make it happen?" or, alternatively, "How can we control the occurrence of a given event?" It also refers to recent improvements made to the CPPS's self-organization capabilities, which ideally aim to facilitate planned maintenance and machine self- diagnosis.

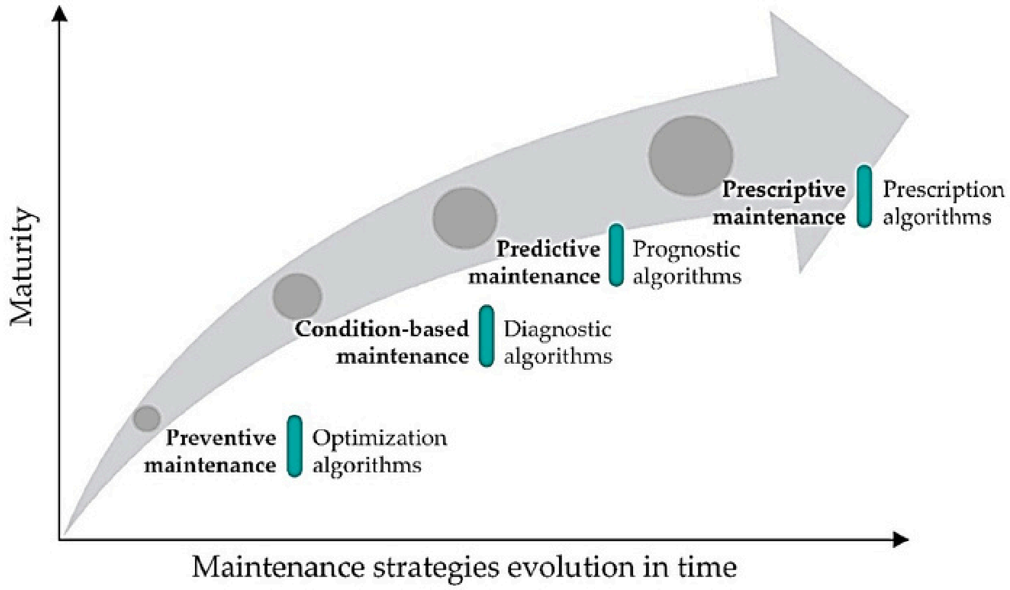

Fig. 1: Knowledge-Based Maintenance Strategies [22]

5. Artificial Intelligence in Maintenance

Because industrial maintenance tasks are inherently complicated, academics are increasingly turning away from more straightforward technological fixes in favor of more sophisticated strategies based on AI to address a variety of maintenance and evaluation difficulties. Artificial intelligence, often known as machine intelligence, refers to a machine's capacity for learning and problem-solving. It can serve as a catalyst for several advancements and cutting-edge technologies in the rail sector. Examples of areas where AI is used include pattern recognition, image processing, diagnostics, remote sensing, process planning and optimization, decision-making, and system control [26–28]. Machine learning (ML) offers powerful capabilities for adopting predictive maintenance and making significant financial savings. With AI-based predictive maintenance, availability can increase by up to 20% while inspection costs and yearly maintenance expenditures are reduced by up to 25% and 10%, respectively [29]. High uncertainty and numerous components that are frequently difficult for engineers to pinpoint directly are two characteristics that define maintenance challenges.

Additionally, due to developments in information technology (IT), the volume of digital data gathered from maintenance tasks has substantially expanded over the past few decades. These data can be mined for possible predictive and prescriptive knowledge utilizing AI techniques. It has been shown that AI can monitor systems, diagnosing faults, identifying acoustic emissions, and performing predictive maintenance [30–32]. Data accessibility and the application of machine learning algorithms to maintenance tasks have the potential to increase productivity and lower maintenance costs [33–35]. The machine learning approach can offer a way to gain the knowledge required to make predictions and judgments by learning from past or present data [36–39]. To diagnose the technical status of the systems and track them using the online mode (in real time), AI systems can be used. Furthermore, faulty system components can be found using an artificial intelligence system. Iterative training of the neural network's input data is possible in both supervised and unsupervised learning environments. Through supervised learning, predictions regarding the component's health status can be made in the future using previous or current data. On the other hand, in an unsupervised learning environment, the data collected is typically trained to confidently recognize and identify significant traits or trends related to component health and failure. The creation of intelligence systems for the early detection of flaws or mechanical issues prior to failure is the current area of research attention. This provides equipment remote diagnosis, real-time defect detection and diagnosis, and predictive maintenance. Additionally, artificial intelligence serves as the foundation for robotic systems that can help with assembly operations, maintenance, and repair works. In some system industries, AI can be used for predictive maintenance [40]. AI will also improve the reliability of the systems and reduce failure rates. Over time, data can be gathered from the measurements and used to train AI algorithms. Predictive models can be created using historical data trained to forecast system behavior in the future. Data mining and machine learning were used to apply predictive maintenance, according to Kalathas and Papoutsidakis [41]. The study's findings point to the suitability of using machine learning to achieve preventive maintenance. According to Famurewa et al. [42], maintenance analytics can improve e-maintenance and decision-making. Not many works have been reported on the development of predictive maintenance based on AI. As a result, this study's principal objective is to advance maintenance activities in the rail industry. The combination of AI and technology for predictive maintenance is shown in Figure (2). The image demonstrates how artificial intelligence can be used for proactive maintenance. Before a predictive model can be produced for making future predictions, an AI algorithm can be trained.

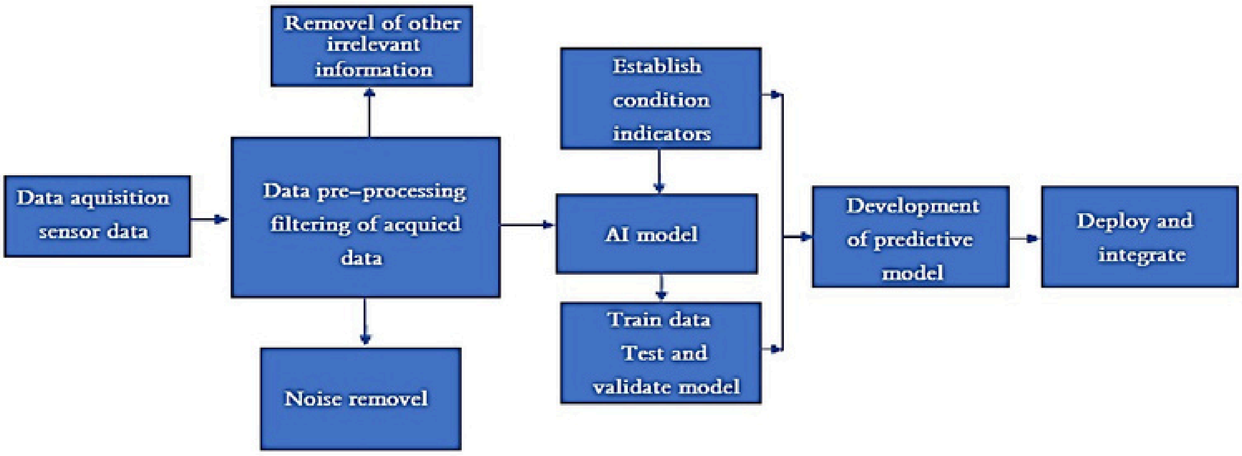

Fig. 2: Integration of AI and predictive maintenance technologies.

6. Predictive and Prescriptive ML Algorithms

Without making any presumptions, ML algorithms [43] can identify potential correlations between pieces of information [44]. Several supervised learning machine learning (ML) algorithms are now available that enable the creation of predictive models from historical data, each with specific benefits and drawbacks [45]. ML approaches are frequently used to diagnose faults in assets by spotting aberrant conditions. Most of the time, bad circumstances aren't immediately apparent; instead, they're shown by their symptoms, including increased vibration and rising temperature, which can be monitored by sensors. The performance of an ML model can be considerably impacted by the choice of an appropriate type of data that best represents the target fault. Mechanical, hydraulic, and electrical data are the three primary data kinds that are frequently utilized to identify system states, according to the literature. System mechanical data, including vibration, speed, and temperature, are important for fault diagnosis because they show the health of various system components. The most common mechanical data utilized for identifying a variety of issues is vibration [46]. In a digital twin, data analytics is essential (DT). Machine learning technology is described in this section as a potential key actor in the data analytics part of DT enabled PdM. A system or machine's health state can be understood and recognized through fault diagnostics (such as anomaly detection and faults categorization) based on historical and current condition monitoring data [47]. Manual diagnosis techniques took a long time and required a lot of expertise and experience. Artificial neural networks (ANN), support vector machines (SVM), and decision trees are examples of machine learning techniques that have opened the way for a higher level of automation in machine maintenance and a more precise problem diagnostic procedure [48]. Machine learning algorithms learn from labelled data with the goal of automatically identifying and categorizing faults. An algorithm would be used to identify problematic conditions and proactively predict future failures based on real-time condition monitoring data after being trained typically on past data. Deep learning, a branch of machine learning, differs from typical machine learning in that it doesn't rely on human input but instead uses a neural network to continuously study the data to increase prediction accuracy [49]. The pre-processing of raw data is necessary for traditional machine learning techniques like SVM and Random Forests before training and learning. Accordingly, data preprocessing and algorithm creation are the two processes involved in defect diagnosis utilizing conventional machine learning techniques. The number of data that has been collected has significantly risen because to developments in ICT and the Internet of Things (IoT), making it possible to use more precise problem diagnostic methods [50]. Traditional machine learning techniques, nevertheless, fall short when it comes to evaluating such large data sets with a diversity of data kinds (volume, velocity, variety, and veracity). Deep learning, a new advancement in machine learning, is built using hierarchical neural network topologies that can handle and process large amounts of data [51]. Through the elimination of pre-processing, feature extraction, and feature selection, this method streamlines and expedites the fault diagnostic prediction process. Importantly, this approach decreases human error in defect identification and does away with the necessity for signal processing knowledge [52].

7. Prescriptive Analytics for Maintenance

According to its definition, prescriptive analytics is a mathematical technique that uses computing to identify a collection of highly valuable activities or decisions. Decisions are made based on a wide range of goals, restrictions, and needs that help a certain sector work better [53]. Prescriptive analytics uses mathematical models to combine the usage of models, rules, and data with hybrid data and rules. It assists in resolving issues with Big Data, operational research, decision support systems, and optimization in the maintenance sector [54]. To make better decisions in prescriptive analytics, statistical and mathematical procedures are integrated with optimization techniques [55]. Prescriptive analytics explains, describes, and forecasts how to advise future courses of action. To accomplish the aim with better objectives, this improves the applications and company. The prediction result is connected to the decision alternative. Prescriptive analytics employs simulations and optimization to improve decision-making. The five main pillars of prescriptive analytics are represented in Fig. 3:

- Adaptive algorithms: As the volume, velocity, and diversity of data increase quickly, prescriptive analytics technology should be able to produce new protocols and automatically recalibrate all its built-in algorithms. To support the business process that is being handled continuously, this whole recalibration needs to be adaptive—dynamic and/or continuous.
- Integrated predictions and prescriptions: Predictive analytics' guaranteed promise is ensured by the prediction and prescription working together. The secret to wide adoption and retaining the benefits of prescriptive analytics is to integrate the two.

- **Hybrid data:** This type of data combines both structured and unstructured data. By using both structured and unstructured data, hybridized data enables the business to reach the optimal conclusion. The prescriptive analytics technology is transformational because it has the capacity to handle hybrid data. Nowadays, a lot of businesses work with structured data, which consists of numbers and categories.
- **Prescriptions and side effects:** Prescriptions suggest time-sensitive activities to improve the future using a variety of techniques.
- **Feedback mechanism:** Prescriptions are typically time-sensitive action plans that incorporate changes over a limited number of controllable influencers to foresee one or more anticipated issues (or to capitalize on one or more anticipated opportunities) [56].

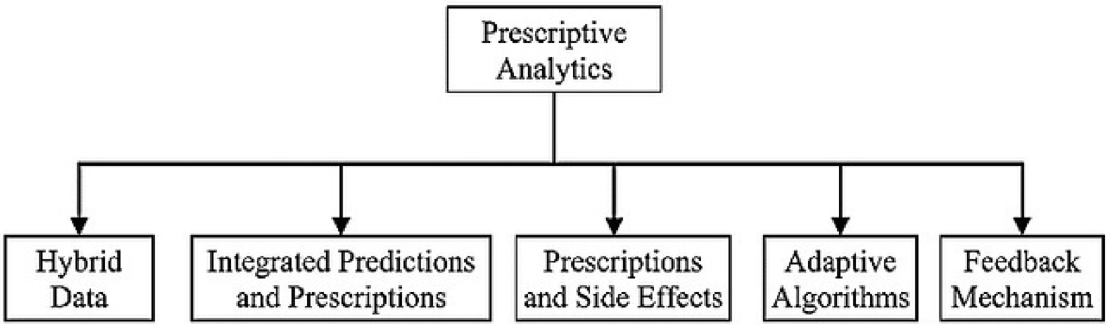

Fig. 3: Prescriptive analytics features.

In big data analytics, prescriptive analytics addresses what, when, and why of the forecast. Analytics are performed using operational research techniques that coordinate with the company and any applicable domain norms. As a result, the influence and its result can be recognized right away [57] compared to descriptive and predictive analytics.

8. Maintenance Decision Support Models

The most recent analysis of the literature suggests that most maintenance models in use are intended to help decision-making procedures. The intelligence of maintenance systems is increased by merging various data sources and knowledge assets and by using data-science techniques like exploratory data analysis or machine learning. This section presents several recently created maintenance decision support models (MDSM). A comprehensive and anticipatory approach was described by Glawar et al. [58] as being able to "identify maintenance critical conditions and predict failure moments and quality variations" for tooling machines. A degradation-based selective maintenance choice problem of a continuously monitored multicomponent system was addressed by Aghezzaf et al. [59]. A cost-effective collection of required maintenance procedures is discovered by modelling components as time-dependent stochastic processes. The study by Wang et al [60] also looked into "a cloud-based paradigm of predictive maintenance based on mobile agent to enable timely information acquisition, sharing and utilization for improved accuracy and reliability in fault diagnosis, remaining service life prediction, and maintenance scheduling." Arab et al [61] used real-time data from workstations, such as cycle times, buffer capacities, and mean time to repair of machines, to solve a dynamic maintenance scheduling problem for a multi-component production system. Additionally, Bärenfänger-Wojciechowski et al. [62] offered a reference integrated management method dubbed "smart maintenance" that incorporates essential maintenance knowledge assets, including people, sensors, data management, and help technologies. Abramovici et al. [63] developed the idea of "knowledge as a service," which facilitates knowledge allocation and the recommendation of potential fixes in line with failure reasons and the degree of similarity between prior failure descriptions recorded in a semantic knowledge base. Finally, Muchiri et al. [64] created a theoretical framework for assessing the effectiveness of maintenance interventions from a technical, management, and human standpoint. Mehairjan et al. [65] created a maintenance management maturity model based on five holistic dimensions, one of which was data quality, while Schumacher et al. [66] created an Industry 4.0 maturity model, which inferentially evaluated elements important for data-driven maintenance. These models produce useful results in prescriptive maintenance, but they have the following drawbacks:

- They consider the dynamics of maintenance processes (using time variables), but they do not entirely or partially consider learning and predicting how process-related parameters will behave over time.
- They are difficult to generalize to similar sets of problems since they are use-case-specific (a singular problem),
- They fail to appropriately use efficiency assessment methods and feedback loops to raise the caliber of maintenance planning.
- They employ well-established but dated process models for knowledge discovery and data analysis, which obviously call for improvement and extension for predictive analytics jobs.

9. Conclusion

This study reviews the state-of-the-art of intelligent maintenance systems using descriptive, predictive, and prescriptive approaches that might influence maintenance policies. It also discusses the implications of these approaches for innovations. AI will also improve the reliability of the systems and reduce failure rates. With AI-based predictive maintenance, availability can increase by up to 20% while inspection costs and yearly maintenance expenditures are reduced by up to 25% and 10%, respectively. The goal of machine learning algorithms is the automatic identification and classification of faults. To be more effective for autonomous decision support based on artificial intelligence techniques, maintenance decision support models need to put in more effort.

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