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FAKULTA STROJNÍ ZÁPADOČESKÉ UNIVERZITY V PLZNI

VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ

MM PRŮMYSLOVÉ SPEKTRUM

B·I·M ANALYSIS VISUALIZATION

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Optimizing Economic Efficiency in Industrial Maintenance Management: A Comprehensive Systematic Literature Review

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Abstract

In today's industrial factory, maintenance management goes beyond ensuring the continuous functionality of equipment; it plays a pivotal role in optimizing economic efficiency. This systematic literature review (SLR) examines the evolution of industrial maintenance management systems covering the period from 2015 to 2023. The studies, which were selected from 571 articles at the beginning, were reduced to 45 basic articles, especially considering maintenance, optimization and economic efficiency in the industrial field. Central research inquiries include the integration and application of Industry 4.0 tools within maintenance systems, optimization techniques employed to enhance economic efficiency, decision-making methodologies utilized in maintenance, and the distribution of research across sectors and machines. Our findings elucidate the profound impact of Industry 4.0 on maintenance management. Emphasis is placed on novel optimization strategies and decision-making techniques driving economic productivity. Additionally, a sectoral and machine-based analysis sheds light on areas of research concentration and potential gaps, offering insights for future exploration. The research provides valuable perspectives, serving as a cornerstone for academics and industry professionals interested in the intricate nexus between maintenance management, economic efficiency, and decision-making in the context of Industry 4.0. With a spotlight on current trends, methodologies, and potential avenues for further investigation, this review seeks to foster a deeper understanding and stimulate further innovation in the domain.

Key words : maintenance management, optimization, decision-making, Industry 4.0

Introduction

With the development of technology the fourth industrial revolution, sometimes referred to as Industry 4.0, has initiated a transformative movement marked by the harmonious integration of digital technologies, artificial intelligence (AI), sensors, machine learning (ML), and the Internet of Things (IoT) within different industrial applications. This rising growth indicates not just a technical transformation but also a reinvention of traditional industrial practices, bringing creative ways meant to boost efficiency, streamline operations, and improve decision-making processes. Maintenance and maintenance management systems are one of the most significantly impacted fields of this industrial revolution (Lee et al., 2020).

One of the crucial steps in the production process is maintenance. Ineffective and improper maintenance procedures have a detrimental impact on the efficiency of the production process as well as the final product's quality (Nasr et al., 2023). The goal of maintenance procedures is to successfully complete the manufacturing processes with the desired result. In terms of time, resources required, labour, technical tools, and spare parts, maintenance is a significant expense in the production process. The cost of maintenance workers, replacement parts, downtime, and production losses are some of the factors used to calculate maintenance costs. There are studies in the literature on the use of various optimization techniques to integrate Industry 4.0 technologies into maintenance management systems, automatically select the best maintenance policy, and provide economic efficiency in maintenance costs (Nacchia et al., 2021).

According to our systematic literature research, it has been shown that the use of AI especially use of ML techniques in mathematical models, may increase the cost efficiency of maintenance management systems (Nguyen et al., 2022). However, although these models have mostly been applied theoretically, there seems to be a lack of application in practice. Theoretically, studies have been conducted to economic efficiency of maintenance management system of different machines such as CNC machines (Adu-Amankwa et al., 2019), yoghurt machines (Simon et al., 2018), and fan motors (Chen et al., 2022), notably in sectors like automotive (Rahman et al., 2022), aerospace, medical products, and food. Despite the literature's emphasis on the importance of rotating equipment maintenance (Lee et al., 2020), it has been seen that no research has been done to improve the economic efficiency of the maintenance management system, particularly for compressed air systems that have rotary equipment as part of their system. In order to reveal the recent developments in maintenance management systems, the literature published in Scopus and the Web of Science in the last eight years has been systematically researched with our research questions. With our research questions, newly developed maintenance policies, the use of maintenance decision-making techniques, maintenance optimization and maintenance cost parameters were questioned. As a result of our research, optimization approaches applied for economic efficiency in maintenance management systems were discovered, and it was seen which sectors and machines could have the potential to work.

The remainder of this article's sections are organised as follows: An introduction to maintenance, maintenance policy, and maintenance management systems is provided in Chapter 1. The systematic research methodology process for doing a literature review is presented in Chapter 2. In Chapter 3, answer of research questions is highlighted and the changing framework of maintenance by Industry 4.0 is discussed, along with a thorough study of the results. Final part, study's conclusion.

1 Theoretical Background

This section outlines (1.1) maintenance and maintenance policy, (1.2) maintenance management systems.

1.1 Maintenance and Maintenance Policy

A system or object has to be maintained in order to function properly or, if required, to be restored. Maintenance is described as a combination of technical and administrative operations. In addition, maintenance goals are broken down into four categories: guaranteeing system security, ensuring system lifespan, and ensuring human well-being. Maintenance is defined as all scheduled and unforeseen routine tasks performed on operational equipment in a production plant (Lee et al., 2020).

For the purpose of assuring continuing equipment maintenance and addressing related problems, maintenance planning is essential. The structuring of associated jobs and the choice of maintenance strategies form the foundation of this process. It is clear from the literature that maintenance strategies are also known as maintenance policies. The perceived significance of a piece of equipment shapes the maintenance policies that are organization-specific and direct the maintenance chores that go along with it. The structure used to schedule maintenance jobs, the maintenance decision-making platform, is supported or revitalized by these policies (Nasr et al., 2023). The identification, inspection, maintenance, replacement, and repair of equipment are essential tasks that fall under scheduled equipment maintenance. In the literature, there is no single maintenance policy accepted by everyone.Several categories of maintenance policies such as reactive, preventive, predictive, condition-based, time-based,realibity-center, total productivity have been established by various authors (Lee et al., 2020). This situation is explained in Tab. 1.

1.2 Maintenance Management Systems

In industrial companies, maintenance management systems are used to implement ideal maintenance policies and ensure optimum operation of equipment. For economic efficiency in maintenance, maintenance management systems should provide the necessary optimizations and the right maintenance policy selection should be made. Maintenance management systems (Passath & Mertens, 2019) started to be implemented as Failure Modes and Effects Analysis (FMEA) in the past and then continued as Computerised Maintenance Administration System (CMMS) with the development of computer and software technologies. In recent years, with the use of Industry 4.0 technologies, data analysis has been carried out, and with the formation of predictive models in maintenance, it has begun to be called intelligent maintenance, information-based maintenance and, decision-based maintenance management systems (Sharma & Govindaraju, 2020).

A systematic method called FMEA is used to recognise, assess, and rank probable failure modes in goods or processes (Prasad & Radhakrishna, 2019). A Risk Priority Number (RPN) is derived by evaluating the seriousness, frequency, and detectability of each failure mode. The RPN value (RPN=Severity×Occurrence×Detection) directs corrective efforts to reduce the greatest risks, thereby improving safety and dependability.

Tab. 1: Maintenance Policy (illustrated by Author).

Maintenance Policy	**Core Principles**	**Advantages**	**Disadvantages**
Reactive	Wait for a failure then repair	No planning needed, Simple approach	Unexpectec downtimes, High repair costs
Corrective (CM)	Repair the failed part	Addresses the root cause of failure	Can lead to unexpected downtimes
Preventive (PM)	Scheduled maintenance	Extends equipment lifespan, Reduces downtimes	Potential unnecessary maintenance activities
Condition-Based (CBM)	Maintenance based on equipment condition	Cost savings, Based on real condition	Requires condition monitoring systems
Time/use-based (TBM)	Maintenance based on time or usage	Predictable, Simple approach	Can overlook the actual condition of the equipment
Predictive (PdM)	Maintenance based on equipment condition predictions	Higher equipment uptime, Cost-effective	Requires predictive algorithms
Prognostic	Predict when equipment might fail	Provides advanced planning	Requires complex algorithms
Prescriptive	Suggests best maintenance actions based on predictions	Automated suggestion, Better decision support	Needs sufficient data and analysis
Reliability Centered (RCM)	Systematic approach to evaluate and define maintenance requirements	Improved system reliability and efficiency, Risk management	Requires significant upfront analysis and expertise
Business Centered (BCM)	Maintenance aligned with business goals	Positive impact on overall business performance	Requires more complex initial planning and analysis

A specialised piece of software called a CMMS is created to support and improve the administration and monitoring of Operations & Maintenance (O&M) operations. By automating various logistics tasks, CMMS simplifies the tasks of management and maintenance personnel. Its features include keeping a historical record of these orders as well as creating, prioritising, and monitoring work orders according to equipment or component. CMMS can plan maintenance tasks, keep track of pertinent protocols, technical documents, and warranty situations for all components of the system. Additionally, CMMS offers real-time information, automates the development of work orders for preventative maintenance based on the calendar or run-time, and keeps tabs on both labour and capital expenses (Vilarinho et al., 2017).

2 Research Methodology

A procedure used to find, examine, and assess studies published within a certain study subject is called a systematic literature review. Using this technique, existing gaps in this field are found and potential research directions are highlighted. Preliminary studies are research studies that were included in the review. SLRs use an evidence-based methodology to summarise the body of knowledge in a certain field and offer a secondary assessment based on primary data. We used the SLR approach that Kitchenham (2004) and her team demonstrated in this work. First, the research begins by defining and clearly stating the research questions that the review aims to answer. Then, the scientific resources and research strategies used in scanning related articles are presented. Finally, the standards used in the selection of suitable articles are explained.

2.1 Research Objectives

This research aims to analyze and evaluate the research conducted in the last eight years on the improvement of maintenance management and increasing its economic efficiency in the industrial field. In addition to the literature review, the main purpose is to learn about the new maintenance policies and optimization techniques developed in maintenance management systems with the effect of Industry 4.0 technologies and to observe which techniques are used to decide on ideal maintenance policies. In addition, it is the discovery of areas where research is carried out in sectoral and machine-based areas and can be studied.

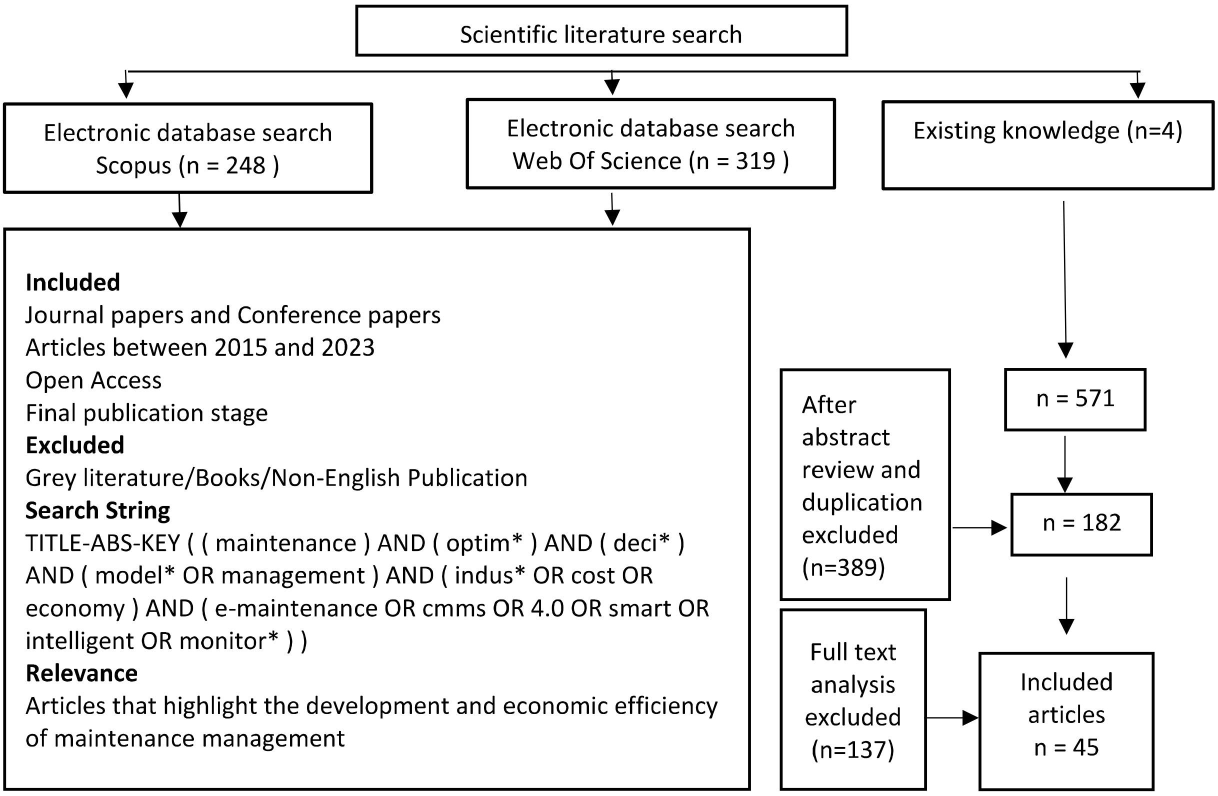

Fig. 1: Research Strategy (illustrated by Author).

2.2 Research Questions

Q1. Which parameters should be considered in order to ensure economic efficiency in maintenance management?

Q2. What developments have occurred in maintenance management systems that may have an impact on economic efficiency?

Q3. Which optimization and decision-making techniques are used for economic efficiency of maintenace management system?

Q4. In which field and with which methodology have the studies that will provide economic efficiency in maintenance management systems been carried out?

2.3 Research Strategy

Research data sources were searched on Scopus and WOS index. Keywords related to the subject were determined. Boolean operators "AND" and "OR" were used for keywords. Our research limit as title, abstract and keyword is "((maintenance) AND (optim*) AND (deci*) AND (model*OR management) AND (indus* OR cost OR economy) AND (e-maintenance OR cmms OR 4.0 OR smart OR intelligent OR monitor*))". It is explained in detail in the Fig. 1.

3 Results

In this section, a comprehensive analysis has been provided in light of findings from the literature, aiming to address the research questions posed.

3.1 Which parameters should be considered in order to ensure economic efficiency in maintenance management?

Tab. 2: Cost Category of Maintenance (Van Horenbeek et al., 2010; Zhang et al., 2018; Dmitriev & Novikov, 2019; Chen el al., 2022; de Lima Munguba et al., 2023)

Cost Category	Description	Calculation Methodology
Labor Costs	Direct costs for on-site workers and indirect costs for management and support staff.	(Hourly Rate) × (Hours Worked)
Material Costs	Includes expenses for spare parts, consumables, and other direct materials.	(Unit Cost) × (Quantity Used)
Tools and Equipment	Costs associated with purchasing, operating, and maintaining necessary tools and equipment.	(Purchase Price)+ (Operational Costs)
Contract Services	Expenditures related to external specialized maintenance services.	(Service Fee) × (Frequency)
Overhead	Indirect costs such as utilities, rental spaces, and administrative overheads.	(Fixed Costs) + (Variable Costs)
Inventory	Expenses linked to the storage and management of spare parts.	(Storage Cost) / (Item +Management Fee)
Downtime	Financial implications stemming from production losses due to equipment unavailability.	(Lost Production Value) / (Unit Time × Duration)
Training	Costs involved in updating the skills and knowledge of maintenance personnel.	(Training Fee + Materials Cost)
Documentation and Software	Expenses related to the maintenance of technical documentation and the acquisition or licensing of relevant software systems	(License Fee/Year + Update Costs)

Efficient maintenance management systems in industrial companies are an important factor for organizations aiming to extend the life of assets in the plant, minimize equipment downtime, and reduce costs. This multi-faceted domain ranges from cost-effectiveness, where the equilibrium between the expenses and benefits of maintenance activities is continually assessed to ensure value for money, to the adoption of lifecycle costing methodologies, providing a holistic perspective on total asset expenses throughout its operational span. The main goal of maintenance management is to constantly focus on the constantly accessible, reliable, quality, and efficient operation of assets. With Industry 4.0 capabilities at their disposal, maintenance procedures enable companies to proactively identify and prevent prospective equipment problems, thereby reducing downtime and related costs (Van Horenbeek et al., 2010). The complex interplay between routine (preventive) and sensitive (corrective) maintenance is continually evaluated with methodologies tailored to asset importance, historical performance, and failure trends. At the heart of these practices is the optimum use of resources. This encompasses the continuous training of staff to align with modern techniques and the efficient allocation of physical resources, like state-of-the-art tools, to guarantee uninterrupted operations. Industrial companies continue to provide meaningful outputs by regularly observing the goal of reducing maintenance costs, key performance indicators, and key metrics, and analyzing data (Zhang et al., 2018) (Tab. 2).

3.2 What developments have occurred in maintenance management systems that may have an impact on economic efficiency?

Maintenance management systems have experienced tremendous modification, particularly with the advent of Industry 4.0. Industry 4.0 capabilities, including augmented reality, autonomous robots, big data analysis, cloud computing, cyber security, IoT, and AI have started to be applied in maintenance management systems to improve economic efficiency (Teoh et al., 2021). Important developments in maintenance management systems the following;

Prescriptive Maintenance Policy: In recent years, especially with the inclusion of AI in maintenance policies, the concept of prescriptive maintenance has emerged as a more significant development than predictive maintenance. Prescriptive maintenance recommends specific steps to minimize equipment failure as well as predict when it may occur (Ansari et al., 2019).

Internet of Things: With IoT-enabled devices and connections to the system, physical assets can be monitored continuously in real time, and ensuring that up-to-date data is collected in the continuous management system. The IoT integration of the system gains importance at the point of performing dynamic data analysis, as constantly flowing data from the equipment to be maintained will vary (Lee et al., 2020).

Cloud Computing: The rise in the influence of maintenance management systems on operational effectiveness in the industrial sector and the reliance of decision-making processes on data have been aided by cloud computing. Cloud computing provides high-capacity data storage as well as infrastructure for advanced data mining, complex statistical analysis, time series forecasting, and ML methods, making maintenance data more accurate and useful (Lee et al., 2020).

Cybersecurity: Guard against possible intrusions that can cause expensive system failures or downtime (Lee et al., 2020).

Horizontal and Vertical System Integration: In order to ensure that all manufacturing equipment operates in harmony and effectively shares data, horizontal integration places a strong emphasis on fostering a cohesive environment across related processes or activities within an organization. Vertical integration, on the other hand, deals with lining up various hierarchical levels inside the business, from lower-level enterprise resource planning (ERP) systems to field devices on the factory floor (Ansari et al., 2019; Burduk et al., 2022).

Smart Maintenance Management System: Maintenance management systems called CMMS have started to be called Smart Maintenance Management System, Knowledge Base Maintenance Management System or Decision Support System in the literature with their integration into new technological developments. This model is shown in the Fig. 2. The system basically works as follows: Assets in the physical layer of the system are the key components where operations take place. The sensors and IoT devices on these assets continuously collect and record various types of data (maintenance records, machine data, fault data, task request data, quality data). This collected data is quickly transferred to a central database thanks to cloud computing technology. Here, the analysis of the collected raw data is carried out using methods such as data mining and ML. The meaningful information obtained as a result of this analysis is presented to users by concretizing it with data visualization tools. Deeply analyzed and visualized information is integrated into decision-support models to optimize maintenance. This integrated structure increases economic efficiency by allowing organizations to make more effective, rapid, and informed maintenance decisions (Guizzi et al., 2019; Meissner et al., 2021; Abadi et al., 2022).

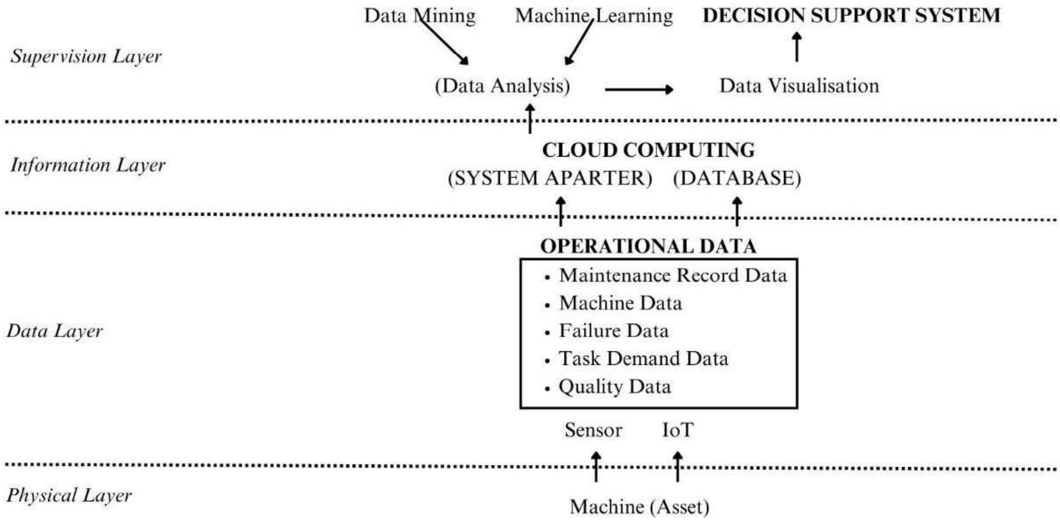

Fig. 2: Smart Maintenance Management System (illustrated by Author).

3.3 Which optimization and decision-making techniques are used for economic efficiency of maintenace management system ?

Optimization and decision-making techniques are essential to increasing the economic efficiency of maintenance management systems. Based on a blend of traditional operations research and modern computational methods, these techniques allow organizations to optimize resources, minimize downtime, and increase the economic efficiency of equipment (Van Horenbeek et al., 2010). Looking at the relevant literature, the optimization and decision techniques used in maintenance management are given below.

3.3.1 Prediction Methods

Statistics: In industrial maintenance applications, Statistical Quality Control (SQC) utilizes statistical techniques to identify premature equipment anomalies, guaranteeing efficient performance. On the other hand, the Support Vector Machine (SVM) approach operates as a supervised ML model designed for both classification and regression tasks. SVM assists in equipment failure prediction during maintenance, enabling quick and proactive action. On the other hand, the moving averages technique enables maintenance personnel to regularly assess the equipment's performance, enabling the early detection of potential flaws (Ansari et al., 2019).

Degradation Modeling: Thanks to deterioration models, we can better predict when equipment will fail. The Exponential Distortion Model is suitable for components that initially show rapid deterioration but then become stable. The logarithmic model is ideal for equipment that initially requires frequent maintenance but these needs decrease over time. The Weibull Distribution is used in reliability and life data analysis. When planning maintenance policies, Weibull analysis provides information about the life of the equipment, the possible timing of failures, and when maintenance interventions will be effective (Van Horenbeek et al., 2010) (Tab. 3).

Tab. 3: Degradation Models for Maintenance

Model / Distribution	Description	Calculation Methodology
Exponential Degradation	Assumes degradation is proportional to its current state.	$dD(t)/\mathrm{d}t = kD(t)$ $D(t)$: Degradation level at time t. Represents the accumulated wear or degradation of the component at a specific time point. k: Rate of degradation. This constant describes how fast the degradation occurs.
Logarithmic Degradation	Degradation rate decreases over time.	$D(t)=a+b\ln(t)$ *a: Represents the initial degradation when time is very close to zero*. b: Determines the rate of slowdown in degradation over time.
Weibull Distribution	Used in reliability; models various life behaviors.	$f(t;\lambda,k)=k\lambda(\lambda t)^{k-1}e^{-(\lambda t)k}$ t: Time. λ: Scale parameter. λ: Scale parameter

Machine Learning: ML has started to be used in industrial factories as an optimization techniques in maintenance with the integration of Industry 4.0 tools into systems. In particular, subcategories of ML such as supervised and unsupervised learning are used in the automation of maintenance processes, early detection of faults, and real-time monitoring of equipment status. Dynamic Bayesian Networks (DBN), on the other hand, are used to predict the future state of equipment in complex systems and time-varying relationships (Nacchia et al., 2021). When several parameters need to be examined at once in multivariate industrial systems, this is extremely helpful. A growing number of maintenance applications employ artificial neural networks (ANN) to swiftly analyse massive data volumes and resolve non-linear issues. ANNs are renowned for their capacity to recognize trends in equipment deterioration and precisely forecast maintenance requirements. Combining these technical methods provides an industrial maintenance strategy that is proactive and predictive, decreasing downtime, lowering operating costs, and prolonging equipment life (Ansari et al., 2019). According to the literature, these strategies may significantly reduce costs and boost manufacturing efficiency when used appropriately.

Markov Chain: Markov Chains are mathematical constructs used to describe random processes in which the next state of a particular system depends only on its current state. This principle of "memorylessness" implies that when predicting a future state, past states do not need to be considered. Discrete Time Markov Chains are employed in situations where time progresses at defined intervals, such as hourly or daily. Specifically, the probabilities of transitioning between various states at certain time steps are analyzed with this type of chain, much like weather forecasts. On the other hand, Continuous Time Markov Chains are used to model scenarios where time progresses uninterruptedly. A typical application might be modeling the likelihood of an industrial machine malfunctioning within a certain period of time (de Lima Munguba et al., 2023).

3.3.2 Decision-making Methods

The decision-making methods used in maintenance are detailed in Tab. 4.

Tab. 4: Decision-making Methods for Maintenance

Method	Description
Linear Programming	Both the objective function and the constraints are linear. It is often used for issues such as allocation of maintenance resources maintenance planning or cost optimization (Nacchia et al., 2021).
Non-linear Programming	The objective function or at least one of the constraints is non-linear. It is used when the performance of the equipment or the probability of failure changes non-linearly over time (Manzini et al., 2015).
Stochastic Dynamic	Determines optimal decisions under uncertainty (Vilarinho et al., 2017)
Semi-Markov Decision Process	A Markov process considering time distributions. It allows us to predict how long equipment will remain in a given state and how long it will take to transition to the next state (Ansari et al., 2019).
Partially Observable Markov	Addresses decisions in Markov processes where states aren't directly observable (Ansari et al., 2019).
IF-THEN	Rule-based method that checks a condition's truthiness (Ansari et al., 2019).
Event Condition Action	Checks event, then tests a condition before acting (Chen et al., 2022)
Decision Trees	Flowchart-like structures for decisions/tests (Nacchia et al., 2021)
Multi-Criteria Decision Analysis	Decision-making with multiple, often conflicting, criteria. The most appropriate maintenance strategy is determined by summing the evaluations and weightings made according to the criteria (Simon et al., 2018)
Neural Networks	Systems for forecasting and pattern recognition (Nguyen et al., 2022)
Fuzzy Logic	Logic system reasoning in degrees of truthiness (Simon et al., 2018)
Genetic Algorithms	It is used when making maintenance decisions where uncertainty and complexity are high (Zhang et al., 2018)
Bayesian Networks	Graphical models using Bayesian inference (Galar et al., 2012)
Analytic Hierarchy Process (AHP)	Decision-making tool that breaks down a complex problem into a hierarchy (Bumblauskas et al., 2017)

3.4 In which field and with which methodology have the studies that will provide economic efficiency in maintenance management systems been carried out?

Research aiming to increase economic efficiency in maintenance management systems is carried out in different sectors using many methodologies. This section will review the various studies found based on our SLR and provide an overview of the areas they target and the methodologies they use for optimal maintenance management. Combining Genetic Algorithms with ML algorithms such as Decision Trees and Random Forests , (Teoh et al., 2021) the study is particularly focused on the manufacturing industry and the production equipment used therein (e.g., die casting machines, laser cutting machines, and plasma cutting). This methodology aims to optimize three performance measures of time, energy and cost for more economically efficient maintenance management systems. CNN algorithms (Zhou et al., 2023), a sub-branch of ML, and Monte carlo decision technique were used for optimization in maintenance with deep learning. In the maintenance decision support system application (Rosati et al., 2023) on robotic machines in production, Python software was supported by the RF algorithm, and an Azure program was used for ML. Markov decision processes (de Lima Munguba et al., 2023) were used to model the optimal maintenance policy on refrigeration systems, and a reinforcement learning (RL) algorithm was used to develop an optimal maintenance policy. In the study to optimize the operation and maintenance of wind turbines (Saleh et al., 2023), RL algorithms are used as the basis, in addition, other mathematical and computational methods such as genetic algorithms, neural networks, and Petri nets are also used in this optimization process. In the study for the maintenance optimization of production lines (Paraschos et al., 2023), a model that combines dynamic programming and RL methods is proposed. While dynamic programming is used to solve optimization problems mathematically, RL is used to optimize decision-making processes. In order to reduce the maintenance costs of the water bottling production line (Nasr et al., 2023), a mathematical model has been developed with data mining and optimization techniques, and this model aims to minimize the expected total cost per unit time. Another study on production machinery (Abidi et al., 2022) in the manufacturing industry used ML techniques such as Hidden Markov Models and the Weibull-SAX framework for predictive maintenance planning. A blockchain-based system and a hybrid ML approach have also been developed for secure information sharing. According to Arena et al. (2022) statistical methods such as stochastic process models, probability density functions and Sequential Monte Carlo (SMC) were used in the research on Remaining Useful Life estimation. In the study on turbofan motors (Chen et al., 2022), ML techniques such as ANNs and Random Forests are used to optimize maintenance schedules and reduce costs. Analytical, simulation and meta-heuristic approaches are discussed for the maintenance management optimization of the hydroelectric power plant (Nasrfard et al., 2022). While dealing with stochastic and dynamic systems, multi-criteria decision-making methods are used for maintenance decisions. Genetic Algorithm was used in a maintenance optimization for fully mechanized equipment for the mining industry (Cao et al., 2021). Failure rates of equipment are modeled with Weibull distribution (He et al., 2018), this distribution is used in industrial failure analysis. Weibull parameters (scale and shape parameters) of the equipment were determined and maintenance decisions were made based on these failure rates. In summary, research on optimizing maintenance management systems spans multiple industries and employs a diverse array of methodologies, ranging from ML (Cho et al., 2018) and genetic algorithms to analytical and statistical approaches, all aimed at enhancing economic efficiency and operational effectiveness.

Conclusion

The systematic literature review examines in depth the economic efficiency of maintenance management systems in industrial companies between 2015 and 2023. It shows new developments, areas of new research and research gaps in maintenance management through the use of optimization and decision-making techniques. While creating our research, first of all, 571 publications were found according to selected keywords. Among these publications, 45 important studies were selected according to our research methodology. While addressing our research questions, we first identified the primary cost factors in maintenance as labor, materials, tools, contracted services, overhead, inventory, downtime, training, documentation, and software costs. We have seen that Industry 4.0 technology is integrated into maintenance management systems to ensure savings in economic parameters in maintenance. As we have seen from our results recently, with the rise of prescriptive maintenance, there has been an increase in the popularity of smart maintenance management systems supported by data analytics and ML techniques. However, despite the growing role of ML in maintenance management, we observed a lack of studies on the effectiveness of theoretical optimization models in practice. In our sectoral and machine-specific reviews, we identified studies in areas such as laser cutting, CNC, food machinery, and fan motors. Yet, despite the emphasis on rotary machines, there are no studies on compressed air systems. This assessment illustrates the current situation and suggests possible future research avenues. It will be an important reference source for academics and industrial sector professionals interested in optimization and decision-making techniques in maintenance management within the scope of Industry 4.0 technologies. Future research should consider addressing gaps to advance research in the field. Focusing on currently used maintenance management systems and new methods evolving with Industry 4.0, this review aims to inspire further innovation and understanding at the intersection of maintenance management, economic efficiency and Industry 4.0.

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