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Maintenance strategy selection: a state of the art for practitioners

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Abstract

Purpose – In the face of a competitive industrial landscape, optimising maintenance strategies is critical for manufacturing companies striving to improve operational efficiency, safety and cost-effectiveness. Maintenance strategy selection (MSS) is crucial in mitigating downtime and enhancing system performance, where inadequate strategy selection can increase costs and risk. This paper investigates the current methodologies for selecting maintenance strategies, focusing on economic, technical and safety criteria that challenge decision-makers.

Design/methodology/approach – Through a systematic literature review (SLR), recent developments in maintenance strategies are explored, identifying key approaches such as preventive, predictive and condition-based maintenance alongside newer predictive models powered by machine learning and artificial intelligence (AI).

Findings – This study highlights the widespread use of MCDM methods – especially AHP, TOPSIS and DEMATEL – in supporting MSS, often enhanced with fuzzy or hybrid approaches. Traditional strategies like corrective and time-based maintenance remain common, but there is a growing shift towards data-driven approaches such as condition-based and predictive maintenance. Technical and economic criteria are the most frequently used, with safety and feasibility also playing key roles. Recent literature shows increased focus on environmental social and governance related factors like energy consumption and sustainability. The analysis reveals a trend from static decision models towards integrated, AI-supported frameworks, reflecting evolving industrial priorities.

Originality/value – This study provides a comprehensive overview of state of the art maintenance strategies, offering insights for industrial managers and researchers aiming to refine decision-making in maintenance management.

Keywords Systematic literature review, Maintenance strategy, Maintenance, MCDM, Decision criteria

Paper type Literature review

1. Introduction

In today's highly competitive industrial environment, the importance of effective maintenance strategies cannot be overstated. Manufacturing companies face continuous pressures to enhance plant performance across multiple dimensions, including cost efficiency, product quality, reliability and workplace safety. The selection and implementation of an appropriate maintenance strategy thus become pivotal factors not only in managing operational costs but also in achieving sustained competitive advantage and optimal overall performance (Bevilacqua and Braglia, 2000).

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Maintenance strategies significantly influence production processes by directly affecting machine availability and reliability. Optimal maintenance interventions minimise machine downtime, thereby ensuring smoother and more predictable production schedules. This synchronisation between maintenance and production functions results in enhanced product quality due to reduced variability in production processes, ultimately leading to higher customer satisfaction and stronger market competitiveness (Rakita *et al.*, 2024). Moreover, maintenance activities are intimately linked to safety management within industrial settings. An appropriate maintenance policy prevents equipment failures that could lead to accidents or hazardous incidents, safeguarding not only employee well-being but also the broader organisational reputation. Thus, a proactive maintenance approach contributes significantly to achieving high standards of workplace safety, regulatory compliance and corporate responsibility (He *et al.*, 2017).

From a financial perspective, maintenance costs can constitute up to 70% of total production expenditures, underscoring the strategic importance of maintenance in industrial management (Bevilacqua and Braglia, 2000). An optimised maintenance strategy contributes to reducing operational interruptions, lowering lifecycle costs of equipment and maximising asset productivity. Conversely, inappropriate strategy selection can exacerbate downtime frequency and duration, misallocate limited resources, escalate overall operational expenditures and increase risks of equipment breakdown, thereby negatively impacting overall organisational performance and profitability.

The complexity inherent in maintenance strategy selection (MSS) decision-making processes arises from the multidimensional nature of the criteria involved. Managers must navigate economic considerations alongside technical constraints, environmental impacts and safety implications, each carrying different weights and interdependencies (Abdulgader *et al.*, 2018). Furthermore, these criteria frequently involve subjective judgements and qualitative assessments that challenge objective quantification, complicating the selection and implementation of optimal strategies. To manage this complexity, multi-criteria decision-making (MCDM) methods have become instrumental, providing structured frameworks to systematically evaluate competing strategies based on diverse, often conflicting factors.

An emerging area of emphasis is the integration of maintenance management with broader business objectives. Modern perspectives advocate that maintenance should no longer be perceived solely as a cost centre but rather as a critical strategic lever capable of delivering measurable improvements across multiple performance metrics, including productivity, sustainability, profitability and long-term business resilience (Maletić *et al.*, 2015; Alsyouf *et al.*, 2020a, b). For instance, proactive and predictive maintenance approaches have demonstrated significant improvements in asset reliability, directly enhancing operational productivity by reducing unplanned stoppages and facilitating better utilisation of production capacity. Improved asset reliability also positively affects supply chain stability, enhancing responsiveness to customer demand fluctuations. Additionally, sustainable maintenance practices contribute to reduced energy consumption, waste minimisation and decreased environmental impact, aligning maintenance activities with corporate sustainability goals and improving brand image. Companies adopting integrated maintenance strategies report not only operational efficiencies but also improved innovation capabilities, increased workforce productivity, better financial performance through cost reductions and enhanced competitive positioning due to increased agility in adapting to technological advancements and industry trends (Maletić *et al.*, 2015; Alsyouf *et al.*, 2020a, b; Holgado *et al.*, 2020).

This paper aims to underscore the enduring significance and complexity of maintenance strategy decisions within contemporary manufacturing environments. By highlighting essential criteria influencing the decision-making process and examining the systemic impacts of strategy selection on organisational performance, this study provides insights into the intricate relationships between maintenance activities, production effectiveness and overall corporate success. Through a systematic review of recent literature, the paper intends to offer a comprehensive understanding of the maintenance strategies most frequently

adopted, the criteria prioritised in their selection and the decision-support methodologies applied to navigate these strategically vital choices. To facilitate reader comprehension of the subsequent sections, [Table 1](#) presents all abbreviations used throughout the paper in the order of their first appearance, from the abstract to the conclusions.

2. State of the art and motivation for the research

The maintenance of industrial plants is frequently acknowledged as fundamental; however, only a few companies effectively integrate it into their standard corporate decision-making processes.

The importance of maintenance concerning organisational performance is clearly articulated by [Swanson \(2001\)](#), who explores the relationship between maintenance strategies and business outcomes. Swanson highlights a notable gap in the literature regarding key performance metrics that organisations could effectively utilise to influence maintenance outcomes. The strategic significance of maintenance has been consistently

Table 1. Abbreviations

Full name	Abbreviation
Systematic Literature Review	SLR
Maintenance Strategy Selection	MSS
Multi Criteria Decision Making	MCDM
Analytic Hierarchy Process	AHP
Technique for Order Preference by Similarity to Ideal Solution	TOPSIS
Decision-making trial and evaluation laboratory	DEMATEL
Artificial Intelligence	AI
Corrective Maintenance	CM
Preventive Maintenance	PM
Remaining Useful Life	RUL
Time-Based Maintenance	TBM
Condition-Based Maintenance	CBM
Predictive Maintenance	PdM
Opportunistic Maintenance	OM
Total Productive Maintenance	TPM
Reliability Centred Maintenance	RCM
Total Quality Management	TQM
Autonomous Maintenance	AM
Outsourcing of the Maintenance	OuT
Fuzzy-MCDM	f-MCDM
Grey Relational Analysis	GRA
Analytical Network Process	ANP
ELimination Et Choix Traduisant la Réalité	ELECTRE
Visekriterijumsko kompromisno rangiranje	VIKOR
Complex Proportional Assessment	COPRAS
Functional Axiomatic Design	F-AD
Functional Requirements	FRs
Weighted Aggregated Sum Product Assessment	WASPAS
Decision-Making Grids	DMG
Failure Mode and Effects Analysis	FMEA
Failure Mode, Effects and Criticality Analysis	FMECA
Cumulative SUM	CUSUM
Discrete Event Simulation	DES
Mean Time Between Failures	MTBF
Mean Time To Repair	MTTR
Manufacturing Execution System	MES

recognised over time, as evidenced by sustained scholarly attention. Recent developments further confirm this ongoing interest, particularly through the studies by (Celen and Djurdjanovic, 2020; Yazdi, 2024). Celen and Djurdjanovic (2020) propose a decision-making framework that addresses uncertainties related to system degradation, aiming to optimise both maintenance scheduling and operational efficiency. Their model balances the trade-off between system reliability and cost efficiency by explicitly incorporating uncertainty into the decision-making process, thus highlighting the persistent challenges in managing uncertainties and the ongoing need for advanced decision-support tools. Similarly, Yazdi (2024) provides an extensive overview of contemporary maintenance strategies and optimisation methods, emphasising the importance of selecting suitable maintenance approaches to enhance system reliability and minimise costs. This review covers a variety of both traditional and contemporary optimisation techniques. Wu and Asadi (2024) also highlight the ongoing challenge of clearly defining optimal maintenance policies, confirming the complexity that still characterises this field. This complexity extends beyond traditional manufacturing contexts, as evidenced by research in other sectors such as mining, oil and gas, agriculture and food processing. For example, Afsharnia *et al.* (2015) demonstrate how appropriate management of tractor maintenance significantly enhances agricultural productivity and positively impacts local communities. In mining, Dayo-Olupona *et al.* (2023) extensively analyse predictive maintenance (PdM) strategies, underscoring the relevance of tailored maintenance policies for maximising productivity and minimising operational risks. Additionally, studies by (Afsharnia and Rohani, 2023; Afsharnia *et al.*, 2021) emphasise the critical role of machine availability in food processing industries, illustrating how effective maintenance strategies contribute to maximised operational performance. MSS remains a significant open issue in transportation as well, as confirmed by recent research from (Werbińska-Wojciechowska *et al.*, 2024; Ersöz *et al.*, 2022).

Jardine and Tsang (2005) emphasise the inherent complexities of maintenance decision-making, stressing the need for deeper exploration of optimal strategies tailored to different operational contexts. They identify a significant research gap in integrating maintenance policies with effective decision-support models – a gap that remains a prominent research focus, supported by subsequent studies by Lu *et al.* (2016), Ruschel *et al.* (2017), Pinciroli *et al.* (2023). Specifically, Lu *et al.* (2016) propose a combined model integrating quality improvement into preventive maintenance (PM) decision-making. Their approach identifies key adjustable process variables that impact product quality and equipment degradation, utilising quantitative process models and reliability assessments to derive optimal maintenance schedules. Ruschel *et al.* (2017) present a comprehensive framework summarising information flow across various decision-making domains, highlighting trends towards joint production system optimisation and enhanced predictive equipment capabilities. Pinciroli *et al.* (2023) further confirm persistent gaps, such as the lack of comprehensive decision-making models, limited integration of operational parameters and a need for advanced predictive maintenance tools. They advocate future research on robust decision-support frameworks that better address complexities and uncertainties in diverse operational environments to improve reliability and cost efficiency.

Furthermore, recent literature emphasises the critical role of variables and criteria within maintenance decision-making processes. For example, Ahmadian *et al.* (2023) investigate the internationalisation of automotive industry maintenance and repair systems, proposing a prioritisation model organised into multiple criteria such as cost, speed, capability and mission compatibility. The model identifies adoption capability as the highest-weighted factor, followed by speed, mission alignment and cost. Notably, supplier competence significantly affects cost, while employee competency and responsiveness influence speed. Flexibility and robust IT infrastructure are essential for mission compatibility, providing valuable insights into enhancing readiness for global expansion. Additionally, Saihi *et al.* (2023) identify and rank critical success factors for maintenance digital transformation initiatives using a hybrid Delphi and AHP approach. They highlight digital strategy, strategic alignment, top management

support and organisational change management as pivotal for successful digital maintenance implementation. Clearly, while strategic aspects have been extensively addressed, the practical implementation of maintenance decision-making processes remains complex and requires further exploration.

At the conclusion of this state-of-the-art review, it is evident that considerable scope remains for research and further investigation in the field of maintenance. In particular, this paper aims to address two specific research questions through a systematic literature review (SLR) methodology. The research questions are:

RQ0. Which maintenance strategies are most commonly adopted in industrial contexts?

RQ1. What are the principal methods to perform the MSS?

RQ2. What are the primary criteria utilised when selecting a maintenance strategy?

Addressing these questions will provide an understanding of current practices, methodologies and key criteria, offering insight into future research directions and industry innovation trends concerning maintenance policy selection.

3. Methodology

In the context of this research, a SLR was conducted to collect and analyse existing knowledge on maintenance strategies, decision-support methodologies and the criteria and parameters involved in decision-making. The SLR process followed a structured series of steps, beginning with the identification of relevant keywords and search strings. These were used to retrieve academic publications from major online databases – specifically, Elsevier and Web of Science.

The retrieved articles were then screened for relevance based on predefined inclusion and exclusion criteria, followed by a detailed content analysis. Papers were categorised according to their application areas, themes and contributions. This systematic approach ensured comprehensive coverage of the topic, minimised bias and provided a robust foundation for understanding the current state of research. The findings from the SLR were instrumental in identifying research gaps, emerging trends and future opportunities in the field of maintenance optimisation and decision-making support.

Following the definition of the research questions, the process of collecting articles for analysis commenced. This was carried out using two leading scientific databases: Scopus and Web of Science. The search process involved constructing a search string comprising relevant keywords aimed at retrieving articles aligned with the research focus. Developing the search string was an iterative process, as it was not immediately evident which keywords would yield the most relevant and high-quality results – those that were both.

The final search string, refined through multiple iterations, was as follows:

TITLE (“maintenance” AND (dss OR “decision support system” OR “decision-making” OR selection OR policy)) ABS (“maintenance strategy selection” OR mss OR dss OR “decision support system” OR (maintenance AND (selection OR decision OR policy))) AUTHKEY (“maintenance strateg*” OR “decision making” OR “maintenance decision-making” OR “maintenance strategy selection” OR “maintenance decision making” OR “maintenance policy”) AND (LIMIT-TO (PUBSTAGE, “final”)) AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “cp”) OR LIMIT-TO (DOCTYPE, “re”)) AND (LIMIT-TO (LANGUAGE, “English”))

Upon analysing the search string, several key aspects were identified:

- (1) The search was restricted to documents classified as “articles” and “conference papers.”
- (2) Only publications in the English language were considered.

- (3) The search was limited to titles, abstracts and author-selected keywords to ensure the retrieval of highly relevant papers rather than those broadly tagged by the platform.
- (4) No specific time range was initially set in the search string.

The search was conducted on 15 May 2024, yielding 566 articles from Scopus and 306 articles from Web of Science (WoS).

After obtaining the initial results, a screening process, also described in [Figure 1](#), was conducted using exclusion criteria to ensure that only the most relevant articles for addressing the research questions were analysed. The first step involved defining the time frame for the analysis. Following the approach of ([Patil et al., 2022](#)), a ten-year period (2012–2024) was selected. This decision was supported by an analysis using VOSviewer, which indicated that the majority of assigned keywords clustered within the past decade.

- (1) Of the 566 documents retrieved from Scopus, 448 were published after 2012.
- (2) Of the 306 documents retrieved from WoS, 277 were published after 2012.

The results from both databases were then merged, and duplicates were removed, resulting in a final dataset of 328 unique articles published after 2012.

Subsequently, articles were classified based on their field of application, with only those relevant to the industrial context being retained. This further refined the dataset, ensuring a focused analysis.

The final number of articles was determined by excluding those that were not directly relevant to the research questions or were inaccessible through institutional resources. Additionally, many articles were excluded because they focused on optimising a single maintenance strategy – such as refining maintenance intervals within preventive maintenance – using specific decision-making methods. However, SLR retrieved through the search string, such as ([Patil et al., 2021](#)), were deemed valuable. In particular, [Patil et al. \(2022\)](#) shared several key insights with this study and was therefore frequently referenced.

In conclusion, this systematic review includes 76 articles from the past decade that highlight decision-making criteria and methodologies for selecting maintenance strategies in the industrial context.

In the following chapters, the collected data will be analysed to address each of the research questions individually.

4. Bibliometric results

Before addressing the previously introduced research questions in detail, it is useful to present some bibliometric insights. These insights will assist the reader in identifying key aspects related to the topics analysed and discussed in this paper.

The 76 selected papers are distributed over the timeline as shown in [Figure 2](#).

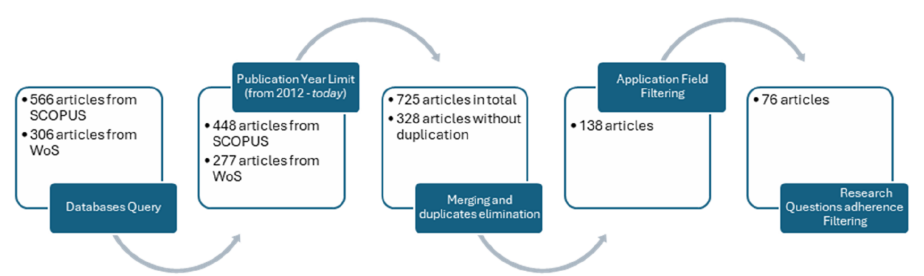


Figure 1. SLR filtering procedure

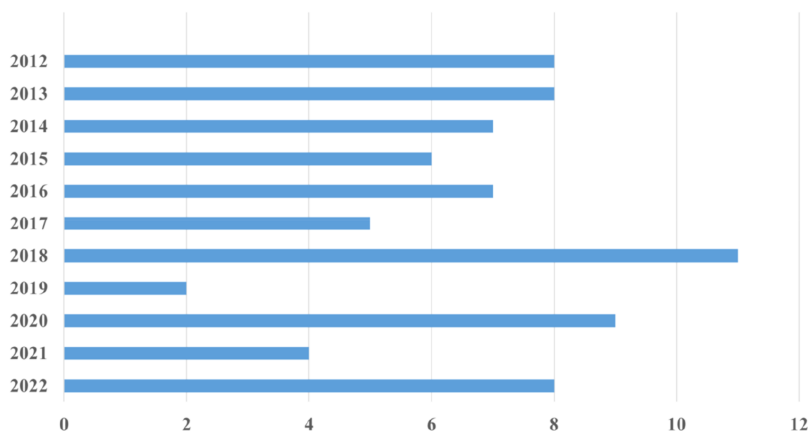


Figure 2. Time distribution of the selected papers

An analysis of the main keywords used in the selected papers was conducted. Before proceeding with the screening of results, the data obtained through the search string were examined. Specifically, VOSviewer® software was used to analyse the keywords and the nationalities of the authors of the articles retrieved from Scopus, highlighting the time periods during which these keywords were most frequently used (Figure 3).

The software was configured to map only keywords that appeared more than ten times across distinct articles. The results of this analysis are presented in Figure 3, offering valuable insights into the nature of the articles subsequently analysed. The size of each keyword block indicates the frequency of its occurrence, the colour represents the period during which the keyword was most commonly used, and the connecting lines illustrate the co-occurrence of keywords within the articles.

Key observations include the prominence of “Maintenance policy” as the most frequently used keyword, the increasing significance of “Predictive maintenance” in more recent

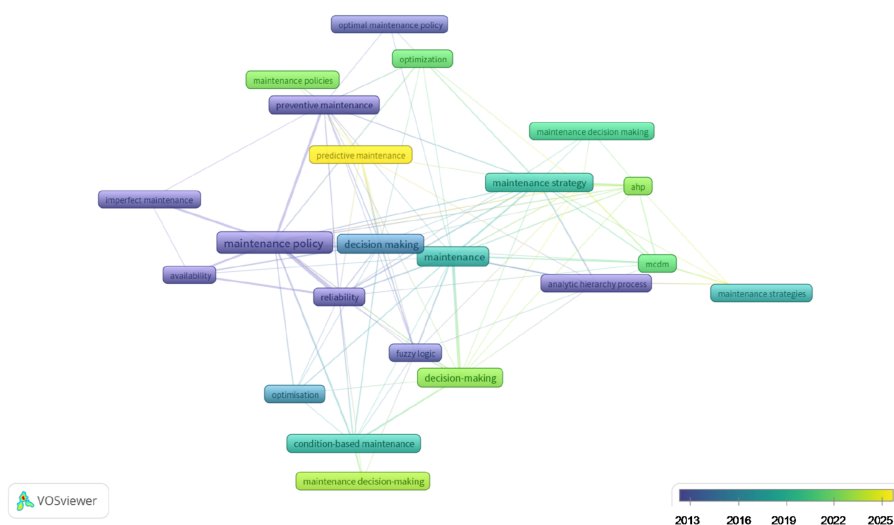


Figure 3. Keywords VOSViewer chart

publications and the emergence of decision-making as a relevant topic in related literature from 2015 onwards.

The analysed research originates from various countries worldwide, with a particularly strong representation from China, as evidenced in the VOSviewer® chart in Figure 4, which depicts the geographical distribution of the authors of the papers reviewed in this study.

Regarding the keyword chart, the size of each box for a country represents the number of contributions associated with that country – the larger the box, the greater the number of occurrences. As previously mentioned, China is the most prominent country in terms of the number of published papers in this research field, followed by the United States. Notably, the United States began contributing to this topic in 2014, whereas China’s significant involvement emerged later, around 2022.

5. Literature analysis

This section aims to comprehensively address the research questions formulated in the literature review, starting with RQ0 and concluding with RQ2. Each research question is introduced as a dedicated subsection to enhance readability and facilitate a clearer understanding for the reader.

5.1 RQ0: What are the most commonly considered maintenance strategies in the industrial context?

This research question was introduced to provide readers with a direct overview of the primary maintenance strategies discussed in international literature, while also offering insight into their evolution and adoption over time. Understanding these strategies is crucial for contextualising subsequent discussions on decision-making methodologies and criteria for selecting an appropriate maintenance policy.

Before presenting the results of the SLR regarding this aspect, a brief introduction to the principal maintenance policies identified in the selected literature is provided.

The first policy considered is corrective maintenance (CM), which involves actions taken only after a failure has occurred, with the objective of restoring an asset to an operational state (UNI EN 13306, 2018). This is the simplest and oldest maintenance strategy, often referred to

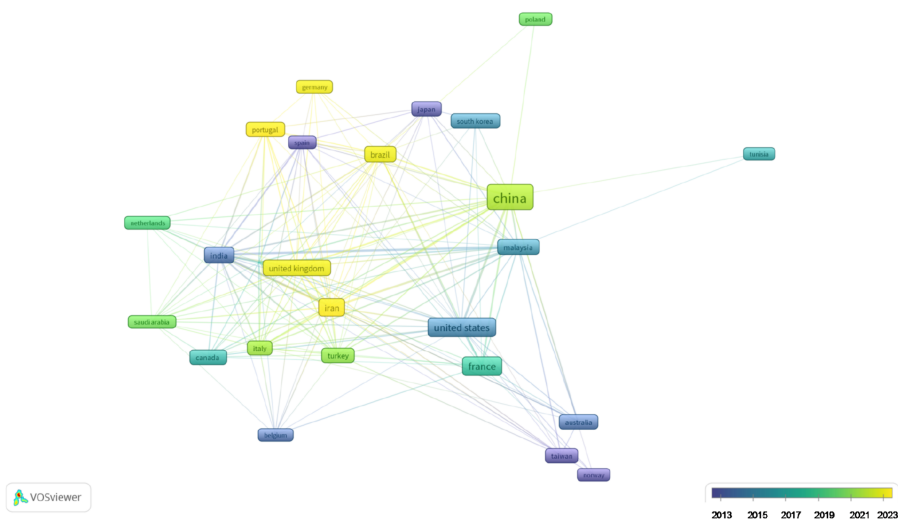


Figure 4. Chart of the country of origin for the selected papers

as a “run-to-failure” approach. CM is particularly suitable for non-critical and low-cost systems where failure mechanisms are difficult to predict, making preventive measures impractical. The strategy is cost-effective in contexts where failures do not cause severe disruptions or safety hazards. Corrective maintenance can be immediate, occurring directly after failure, or deferred, where the repair is planned at a later stage based on operational constraints or resource availability.

The second policy discussed is preventive maintenance (PM), which aims to assess and mitigate equipment degradation while reducing the likelihood of failure (UNI EN 13306: 2018). PM offers significant advantages over CM by proactively preventing damage from critical failures. However, in cases where the Remaining Useful Life (RUL) of a component is difficult to determine, PM may lead to unnecessary replacement of fully functional components, resulting in increased operational costs. PM can be categorised into various subtypes, including:

- (1) Time-based maintenance (TBM): Also referred to as cyclic maintenance, TBM involves performing maintenance at predefined time intervals or usage thresholds, regardless of the asset’s actual condition (UNI EN 13306, 2018). This method is widely used in industries where safety and regulatory compliance require scheduled maintenance activities. However, since it does not consider the real-time health of the equipment, it may lead to over-maintenance or unnecessary interventions.
- (2) Condition-based maintenance (CBM): CBM is a more advanced form of PM that relies on real-time monitoring to assess the physical condition of an asset, allowing maintenance to be carried out only when necessary (UNI EN 13306, 2018). Sensors and diagnostic tools continuously track key performance indicators (KPIs) such as vibration levels, temperature and pressure. This approach minimises downtime and reduces maintenance costs. However, the high cost of implementing sensor technology and data analysis platforms can be a limiting factor, particularly for smaller enterprises.
- (3) Predictive maintenance (PdM): PdM is an advanced type of condition-based maintenance that employs data analytics and predictive algorithms to forecast potential failures before they occur (UNI EN 13306, 2018). It utilises techniques such as machine learning, artificial intelligence and historical performance data to improve maintenance planning. Predictive models can be empirical, data-driven, model-based or based on physical simulations. Despite its advantages, PdM is not yet widely adopted as a mainstream alternative due to high implementation costs and the need for skilled personnel. Notably, PdM appeared in only 30% of the articles analysed in this systematic review, suggesting its gradual but still limited adoption in industrial practice.

The third policy examined is opportunistic maintenance (OM), a preventive strategy executed without prior scheduling but carried out in conjunction with other maintenance activities or triggered by specific events. OM is particularly effective in industries with complex production systems where downtime must be minimised. This strategy maximises machine availability by grouping maintenance tasks during scheduled shutdowns or when a failure in one component provides an opportunity to service others.

Beyond these traditional strategies, several managerial frameworks have emerged to enhance maintenance efficiency and integration with broader business goals. These include:

- (1) Total productive maintenance (TPM): A holistic approach that promotes autonomous maintenance by operators, reducing reliance on specialised technicians.
- (2) Reliability-centred maintenance (RCM): Focuses on optimising maintenance efforts based on the criticality and function of each component within a system.

- (3) Total quality management (TQM): Integrates maintenance into a company-wide quality improvement strategy.
- (4) Autonomous maintenance (AM): Typically embedded within TPM, allowing operators to perform basic maintenance tasks to prevent equipment failures.
- (5) Design-out maintenance (DOM): Aims to eliminate the need for maintenance altogether by improving system design.
- (6) Outsourced maintenance (OuT): Involves contracting third-party providers for maintenance services, often used to reduce internal labour costs and improve efficiency.

Table 2 presents a summary of the studies that have analysed and applied these maintenance strategies.

The bar chart of Figure 5 provides a quantitative analysis of how frequently different maintenance strategies are discussed in scientific literature on MSS. The distribution of strategies across the reviewed articles reveals key insights into prevailing industry practices and research focus.

CM and TBM emerge as the most frequently referenced strategies, appearing in 48 and 52 articles, respectively. This suggests that although industries strive for predictive and proactive approaches, many maintenance decisions are still guided by scheduled interventions or post-failure repairs. TBM remains a dominant approach due to its simplicity and ease of implementation, particularly in industries where real-time monitoring systems are not fully deployed. CBM is another widely discussed strategy, appearing in 38 articles. CBM enables maintenance actions based on real-time asset condition monitoring, reducing unnecessary interventions while preventing unexpected failures. Its high frequency suggests that industries increasingly integrate sensor technology and diagnostics into their maintenance plans. PdM, while still less cited than traditional approaches, has seen a rise in relevance, appearing in 14 articles. This increase can be attributed to advancements in machine learning, artificial intelligence and big data analytics, which are enhancing PdM’s ability to predict failures with higher accuracy. This trend aligns with the industry’s growing focus on Industry 4.0 and smart maintenance. Other approaches such as OM, RCM and TPM are referenced less frequently, each appearing in a small subset of the articles. These methodologies, though beneficial for specific applications, require higher levels of integration with operational strategies and are often used in highly complex systems where downtime is a critical concern. DOM and OuT, which aims to eliminate maintenance needs through improved system design, appears less frequently in recent literature. This suggests a shift in focus from modifying system design to optimising existing maintenance processes.

The analysis highlights a clear trend where preventive and condition-based strategies continue to dominate, while predictive methods are gaining attention as technological advancements make them more feasible. The shift towards data-driven and predictive approaches is evident but still in a transitional phase, as industries balance between traditional reliability-based strategies and modern AI-powered maintenance optimization. The reviewed literature highlights that while CM remains relevant, it is increasingly seen as a fallback strategy rather than a proactive approach. PM and its subcategories, particularly TBM and CBM, continue to be the dominant choices due to their straightforward implementation and effectiveness. PdM is experiencing a rise in adoption, fuelled by developments in data analytics, IoT and AI technologies, positioning it as a promising alternative. Meanwhile, managerial approaches such as RCM and TPM remain crucial for integrating maintenance strategies into broader organisational frameworks. The evolution of MSS reflects an industry-wide shift towards data-driven decision-making and reliability-focused methodologies aimed at optimising asset performance while controlling costs.

Table 2. Maintenance policies applied by the international literature selected

Article name	PM					Managerial approach			Other approaches	International Journal of Quality & Reliability Management
	CM	CBM	TBM	PdM	OM	RCM	TPM	DOM		
Jiang <i>et al.</i> (2024)		X		x						
Dinh <i>et al.</i> (2024)		X		x						
Luo <i>et al.</i> (2024)		X				x				
Chang <i>et al.</i> (2023)		X			x					
Sellitto (2022)	X	X	x					X		
Mathew <i>et al.</i> (2020)	X	X	x							
Chopra <i>et al.</i> (2021)	X	X	x			x		X		
Avakh Darestani <i>et al.</i> (2020)	X	X	x							
Vrignat <i>et al.</i> (2022)										
Li <i>et al.</i> (2022)	X									
Feng and Li (2022)										
Bousdekis <i>et al.</i> (2021)										
Alsyouf <i>et al.</i> (2020a, b)										
Arjomandi <i>et al.</i> (2021)	X	X								
Yunusa-Kaltungo and Labib (2020)	X	X	x					x		
Hemmati <i>et al.</i> (2019)	X	X	x						SM	
Eseoghene Ighravwe and Oke (2020)	X	X								
Kurian <i>et al.</i> (2019)	X	X	x		x				RBM	
Golbasi and Turan (2020)	X									
Mohamed and Fahmy (2020)	X	X	x		x					
Martin <i>et al.</i> (2019)	X		x			x		X		
Urbani <i>et al.</i> (2020)					x					
Aghaee <i>et al.</i> (2020)	X		x			x				
Bahria <i>et al.</i> (2018)	X		x	x					AM	
Shafiee <i>et al.</i> (2019)	X	X	x			x				
Martinod <i>et al.</i> (2018)			x							
Hemmati <i>et al.</i> (2018)	X	X	x					X		
Seiti <i>et al.</i> (2018)	X	X	x					X		
Li <i>et al.</i> (2017)	X		x						OuT	
Cherkaoui <i>et al.</i> (2017)	X	X	x							
Ge <i>et al.</i> (2018)	X		x							
Ohta (2018)	X		x	x						
Farajiparvar and Mayorga (2018)	X	X	x							
Seecharan <i>et al.</i> (2018)	X	X	x					x		
Ge <i>et al.</i> (2017)	X	X	x	x						
Seiti <i>et al.</i> (2017)	X	X	x					X		
Alsyouf and Hamdan (2017)			x							
Oudjedi Damerdji and Nouredine (2017)	X		x							
Youssef Mahamoud <i>et al.</i> (2016)	X	X	x	x					OuT	
Xia <i>et al.</i> (2016)		X	x							
Kirubakaran and Ilangkumaran (2015a)	X	X	x	x						
Lazakis and Aykut (2015)	X		x	x						
Ali and Mobin (2016)	X	X	x							
Cherkaoui <i>et al.</i> (2016)		X	x							
Ali and Zadeh (2015)		X	x	x	x					
Shafiee (2015)										
Ding and Kamaruddin (2014a, b)	X	X	x					x		

(continued)

Table 2. Continued

Article name	PM					Managerial approach			Other approaches
	CM	CBM	TBM	PdM	OM	RCM	TPM	DOM	
Kirubakaran and Ilangkumaran (2015b)	X	X	x						
Emie Schutz (2014)			x						
Meddaoui and Bouami (2014)	X		x						
Ding <i>et al.</i> (2014)	X		x	x					AM
Zhang <i>et al.</i> (2013)	X		x		x				
Cao <i>et al.</i> (2013)	X		x						
Xie <i>et al.</i> (2013)	X	X	x	x					
Shahin <i>et al.</i> (2013)	X	X	x					x	
Thor <i>et al.</i> (2013)	X		x	x			X		AM
Clemente <i>et al.</i> (2013)								x	
Mariappan <i>et al.</i> (2013)	X		x						
Ding <i>et al.</i> (2012)	X		x	x				x	AM
Chan and Prakash (2012)	X	X	x						TQM
Majid Fouladgar <i>et al.</i> (2012)	X	X	x		x				
Tuan Huynh <i>et al.</i> (2012)	X		x	x					
Ilangkumaran and Kumanan (2012)		X	x	x		x			
Zaim <i>et al.</i> (2012)	X		x	x					
Lesage and Dehombreux (2012)									TQM

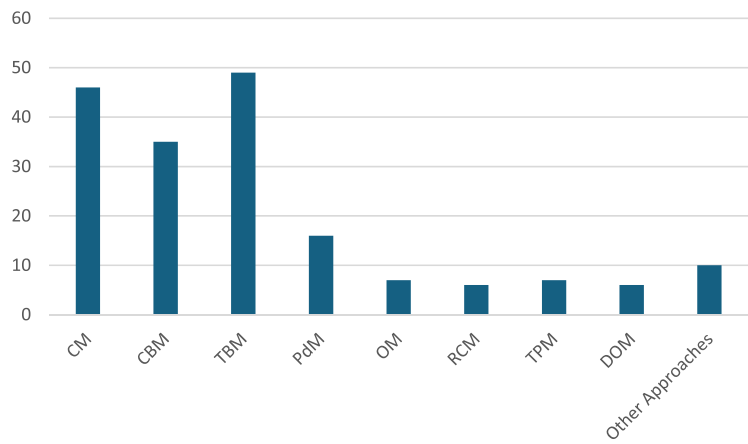


Figure 5. Occurrences of the maintenance policies in the analysed papers

At the end of this subsection, it becomes evident that answering research question RQ0 is relatively straightforward. The maintenance strategies applied in real-world cases largely align with those traditionally recognised. However, there is a noticeable shift within preventive maintenance strategies, transitioning from TBM to CBM first, and subsequently towards PdM. Moreover, managerial approaches appear to have lost some traction, particularly in research. In fact, over the last two years, no significant studies have focused on these types of policies. PdM emerges as the most promising strategy, primarily due to advancements in artificial intelligence and machine learning algorithms.

5.2 *RQ1: What are the principal methods to perform the maintenance strategy selection?*

To address this research question, this paper first examines the MCDM methods used in MSS, highlighting their distinct characteristics, advantages and limitations. Following this, an analysis of the literature available in the previously mentioned databases is conducted to identify the most frequently used methods in maintenance management research.

MCDM methods can generally be applied in two ways: crisp or fuzzy applications. When an MCDM method incorporates fuzzy logic, it is referred to as a fuzzy-MCDM (f-MCDM). If no fuzzy adaptation is applied, the standard MCDM approach is used. Additionally, grey relational analysis (GRA) has emerged as an alternative categorisation method for handling multi-criteria decision problems (Kuo, 2017).

Among the most widely used MCDM techniques, analytic hierarchy process (AHP) stands out. Developed by Saaty, AHP decomposes complex decision problems into hierarchical sub-problems, making them easier to analyse independently. Its key advantage is its structured and straightforward methodology, making it compatible with other approaches. However, AHP struggles with pairwise comparison consistency, which can introduce subjectivity and bias in judgment (Shaffiee, 2015). A more advanced version, the analytic network process (ANP), extends AHP by incorporating interdependencies between criteria and alternatives. While ANP provides a more comprehensive decision model, it is computationally intensive and complex to apply, requiring iterative processes to assign priorities effectively (Shaffiee, 2015).

Another commonly used MCDM method is TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). This method ranks alternatives based on their proximity to an ideal solution and distance from the worst-case scenario. TOPSIS is particularly useful for rapid decision-making in MSS due to its clarity and ease of use (Thor et al., 2013). However, it relies on Euclidean distance calculations, which may not effectively account for correlations between criteria, and the subjective assignment of criterion weights can affect the reliability of results.

ELECTRE (ELimination Et Choix Traduisant la REalité), a family of methods based on pairwise comparisons, is particularly beneficial when decision-makers need to evaluate multiple criteria simultaneously (Gonçalves et al., 2014). Its ability to disregard insignificant differences through discrimination thresholds makes it robust, but it requires extensive data and careful weight assignment, making it less practical in cases of uncertainty or limited information.

The VIKOR (Visekriterijumsko Kompromisno Rangiranje) method seeks a compromise solution that maximises group utility while minimising individual regret. It is particularly useful when conflicting criteria must be balanced, but its reliability heavily depends on the definition of best and worst reference values, which can introduce variability (Thakkar, 2021).

COPRAS (Complex Proportional Assessment), introduced by Zavadskas et al. (2007), identifies the best alternative based on a proportional evaluation relative to an ideal solution. It is effective even with incomplete data, though its mathematical approximations may sometimes lead to inconsistencies.

DEMATEL (Decision-Making Trial and Evaluation Laboratory) is another widely used method, particularly when analysing causal relationships between factors influencing maintenance decisions. It excels in identifying key drivers within complex decision environments but lacks hierarchical structuring and prioritisation capabilities, making it unsuitable for ranking alternatives (Thakkar, 2021).

A refined method known as F-AD (Fuzzy-Axiomatic Design) extends the original axiomatic design (AD) framework (Park, 2007). It applies fuzzy logic to the classical independence axiom (which ensures that functional requirements remain independent) and the information axiom (which prioritises minimal information use to reduce uncertainty). This hybrid approach is particularly useful in complex decision-making scenarios requiring a balance between flexibility and structured evaluation.

WASPAS (Weighted Aggregated Sum Product Assessment), an approach that combines the Weighted Sum Model and Weighted Product Method, offers high classification accuracy

with low computational demand (Alinezhad *et al.*, 2019). However, inconsistencies in results can sometimes arise.

Decision-making grids (DMG) that are a fundamental matrix-based approach for evaluating maintenance strategy alternatives based on weighted criteria (Thakkar, 2021).

It is worth noting that often the MCDM techniques are also used in combination with several decision-support tools are commonly used in maintenance management. In particular, these tools are called to identify, preliminary what are the critical units or systems, and based on this identification an MCDM, generally is applied. These include (1) failure mode and effects analysis (FMEA) and failure mode, effects and criticality analysis (FMECA): Used for systematically evaluating failure risks and prioritising maintenance interventions; (2) control charts, i.e. statistical tools, such as Shewhart charts and CUSUM control charts, to monitor system performance over time; simulation tools, i.e. methods like discrete event simulation (DES) and Monte Carlo simulation are used to model maintenance scenarios, assess system reliability and optimise intervention schedules.

Ultimately, the effectiveness of each method depends on the specific context and complexity of the maintenance decision. In practice, hybrid approaches combining multiple methods are frequently used to overcome the limitations of individual techniques. The growing integration of AI and big data analytics in maintenance decision-making suggests that fuzzy-based, hybrid MCDM techniques will play an increasingly significant role in MSS research and industrial applications.

After summarising the main MCDM methods, we now proceed to analyse their prevalence and consistency in the literature within the field of maintenance management. The following Table 3 presents a classification of all the papers analysed in this study, grouping them based on the techniques previously introduced. Notably also the papers that deal with the MSS but without the use of a MCDM method is also reported and classified as “NO MCDM”.

The methods used in the literature from 2012 up today are several as clear from the previous list, but it is possible to identify what are the main used as it will be clear from the following Figure 6.

The prevalence of the methods used are in favour of the MCDM ones, while the other methods used to support the decision making in maintenance management are just in almost 30% of the research sources analysed as it is clear from Figure 7.

Several key insights emerge regarding research focus and methodological shifts over time. In the early period (2012–2016), there was an initial adoption and diversification of several MCDM. Between 2012 and 2016, there was a steady presence of MCDM applications in maintenance decision-making. Studies during this period were primarily focused on traditional methods, including AHP, ANP and TOPSIS. The consistency of research activity during this time suggests a foundational phase, where researchers were experimenting with various decision-support frameworks for maintenance policy selection. Afterwards there was a growth and peak activity (2017–2020) that was characterised by an expansion of fuzzy and hybrid approaches. A noticeable increase in research output occurs between 2017 and 2020, reaching its peak in 2018. This period marks a transition from crisp MCDM models to fuzzy and hybrid decision-making approaches. Studies incorporating Fuzzy-AHP (F-AHP), Fuzzy-TOPSIS and DEMATEL became more prevalent, indicating an increasing recognition of uncertainty and subjectivity in maintenance decision-making. Additionally, hybrid approaches (such as the combination of AHP with GRA, WASPAS and VIKOR) were introduced to improve ranking accuracy and robustness. This shift aligns with the rise of Industry 4.0 concepts, which emphasised data-driven decision-making. In the last five years, we assisted to a phase of decline and recent trends (2021–Present), in which there was a lower research volume that is probably due to a shift towards AI-driven models of prediction as demonstrated in the previous research question results. In fact, after 2020, there is a significant decline in the number of publications focusing on MCDM for MSS. This could be attributed to two primary factors: shift in research focus from traditional MCDM-based decision frameworks to AI-driven predictive maintenance models and the maturity of many MCDM

Table 3. List of papers about the MCDM applied in the maintenance management field

Author	Application field	Methodologies
Sellitto (2022)	Chemical Industry	NO MCDM
Soltanali <i>et al.</i> (2023)	Agricultural Industry	DEMATEL
Mathew <i>et al.</i> (2020)	System	F-AHP; TOPSIS
Chopra <i>et al.</i> (2021)	System	Fuzzy-Vikor
Arjomandi <i>et al.</i> (2021)	Petrochemical Industry	DEMATEL; ANP; VIKOR
Yunusa-Kaltungo and Labib (2020)	Cement Production	DMG
Hemmati <i>et al.</i> (2019)	Chemical Industry	F-AHP; TOPSIS
Ardil (2024)	System	TOPSIS
Eseoghene Ighravwe and Oke (2020)	Rolling Mill	F-AHP; WASPAS
Kurian <i>et al.</i> (2019)	Production cement	ANP
Golbasi and Turan (2020)	System	NO MCDM
Mohamed and Fahmy (2020)	Petrochemical Industry	AHP
Martin <i>et al.</i> (2019)	Iron Industry	AHP; WSM
Urbani <i>et al.</i> (2020)	System	NO MCDM
Aghaei <i>et al.</i> (2020)	Petrochemical Industry	F-Delphy; F-DEMATEL
Bahria <i>et al.</i> (2018)	Production System	NO MCDM
Shafiee <i>et al.</i> (2019)	System	ANP
Shahin <i>et al.</i> (2018)	Iron Industry	DMG
Martinod <i>et al.</i> (2018)	Transportation System	NO MCDM
Hemmati <i>et al.</i> (2018)	Chemical Industry	Fuzzy-AHP
Seiti <i>et al.</i> (2018)	Rolling Mill	FAD
Viswanath Dhanisetty <i>et al.</i> (2018)	Aerospace	NO MCDM
Li <i>et al.</i> (2017)	Healthcare	NO MCDM
Cherkaoui <i>et al.</i> (2017)	System	NO MCDM
Ge <i>et al.</i> (2018)	Aerospace	DMG
Ohta (2018)	Production System	AHP; Fuzzy-AHP
Farajiparvar and Mayorga (2018)	Automotive Industry	AHP; F-AHP
Seecharan <i>et al.</i> (2018)	Production System	NO MCDM
Ge <i>et al.</i> (2017)	System	AHP
Seiti <i>et al.</i> (2017)	Iron Industry	AHP
Alsyouf and Hamdan (2017)	Electronic Industry	WCCM
Youssef Mahamoud <i>et al.</i> (2016)	System	AHP
Xia <i>et al.</i> (2016)	Defense Industry	AHP; TOPSIS
Kirubakaran and Ilangkumaran (2015a)	System	Fuzzy-AHP; GRA-TOPSIS
Lazakis and Aykut (2015)	Industry naval	AHP; FST; TOPSIS
Cherkaoui <i>et al.</i> (2016)	System	NO MCDM
Ding and Kamaruddin (2014a, b)	Electronic Industry	fuzzy-TOPSIS
Djebala <i>et al.</i> (2015)	Energy Production	NO MCDM
Kirubakaran and Ilangkumaran (2015b)	Paper Industry	ANP; TOPSIS
Gonçalves <i>et al.</i> (2014)	System	ELECTRE
Meddaoui and Bouami (2014)	System	AHP
Ding <i>et al.</i> (2014)	Agricultural Industry	TOPSIS
Faccio <i>et al.</i> (2014)	Iron Industry	NO MCDM
Savsar (2013)	Production System	NO MCDM
Zhang <i>et al.</i> (2013)	System	NO MCDM
Xie <i>et al.</i> (2013)	Electronic Industry	F-AHP
Shahin <i>et al.</i> (2013)	Iron Industry	DMG
Thor <i>et al.</i> (2013)	Electronic Industry	TOPSIS
Clemente <i>et al.</i> (2013)	System	DSS
Mariappan <i>et al.</i> (2013)	Production System	Integrated Graphical Model
Ding <i>et al.</i> (2012)	Electronic Industry	NO MCDM
Chan and Prakash (2012)	Production System	Fuzzy-MCDM
Majid Fouladgar <i>et al.</i> (2012)	Mining Industry	F-AHP; COPRAS
Tuan Huynh <i>et al.</i> (2012)	System	NO MCDM
Ilangkumaran and Kumanan (2012)	Agricultural Industry	F-AHP; VIKOR
Zaim <i>et al.</i> (2012)	Printing	AHP, ANP
Lesage and Dehombreux (2012)	Production System	NO MCDM

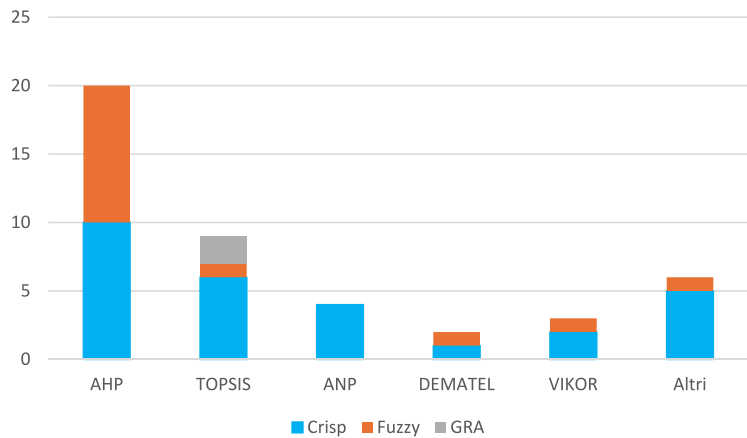


Figure 6. Occurrences of MCDM in the scientific literature analysed

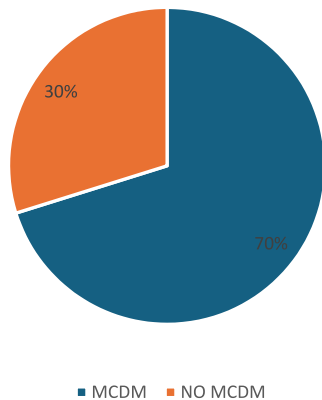


Figure 7. Occurrence of papers that uses MCDM and no-MCDM methods

applications, leading to a reduction in exploratory studies. In the most recent years (2022–2024), fewer studies have been published on decision-making methodologies in maintenance management, but those that remain focus on more advanced models, such as DEMATEL, probabilistic models and hybrid methodologies. This suggests that research has moved towards more integrated, automated and real-time decision-making solutions, reducing reliance on classical MCDM approaches.

The overall trend highlights a paradigm shift in MSS, transitioning from static decision-support frameworks to dynamic, real-time and data-driven methodologies.

Consequently, the answer to RQ1 can be summarised as follows:

- (1) AHP is the most commonly used decision-making method, appearing in 20 instances, evenly split between classic (crisp) AHP (10 occurrences) and fuzzy-AHP (F-AHP) (10 occurrences) (see Figure 6). Notably, the use of the fuzzy version has been increasing over time, peaking in 2018.
- (2) Table 2 reveals that the most frequent hybrid decision-making method is AHP-TOPSIS, indicating a strong preference for integrating these two techniques.

-
- (3) 25% of the articles incorporate fuzzy logic-based methods, with 65% of these studies published after 2018, reflecting a growing recognition of uncertainty-handling techniques in MSS.
 - (4) The 30% of the literature analysed deals with the MSS not using a MCDM.
 - (5) The interest of the researchers has moved towards more integrated, automated and real-time decision-making solutions.
-

5.3 RQ2: What are the main criteria used for selecting a maintenance strategy?

Following the analytical approach employed in addressing the previous research questions, this section presents the key aspects considered in categorising the analysed literature. Specifically, we outline the body of knowledge relevant to the identification of decision criteria in maintenance management decision-making (Pintelon and Gelders, 1992; Tajadod *et al.*, 2016; Avakh Darestani *et al.*, 2020; Besiktepe *et al.*, 2020). The criteria identified in the literature are grouped into five main clusters: (1) economic criteria, (2) value-added criteria, (3) safety criteria, (4) feasibility criteria and (5) technical indicators.

Starting with economic criteria, financial considerations arising from economic perspectives play a fundamental role in evaluating maintenance strategies (Avakh Darestani *et al.*, 2020). The key economic criteria identified in the literature include: (1) Single maintenance action cost (Cao *et al.*, 2013; Mariappan *et al.*, 2013) (Tuan Huynh *et al.*, 2012), defined as the direct cost incurred for each maintenance task; (2) Energy consumption cost (Xia *et al.*, 2016), referring to the cost associated with energy usage during maintenance operations, considered a direct cost; (3) Labour for maintenance (Thor *et al.*, 2013) (Majid Fouladgar *et al.*, 2012), representing the direct cost related to the workforce performing maintenance activities; (4) Software costs (Xie *et al.*, 2013; Zaim *et al.*, 2012), the indirect cost of acquiring and maintaining maintenance-supporting software, which must be allocated to each maintenance task; (5) Production losses (Majid Fouladgar *et al.*, 2012), i.e. the opportunity cost due to decreased efficiency or operational downtime during maintenance, highlighting revenue losses; (6) Training costs (Chan and Prakash, 2012; Zaim *et al.*, 2012; Hong *et al.*, 2012), the indirect cost of training employees on maintenance procedures and systems, which requires identifying appropriate allocation factors; (7) Hardware costs (Zaim *et al.*, 2012), the indirect costs of purchasing tools, machinery and other physical components needed for maintenance, which, like training costs, must be allocated to each maintenance task; (8) Spare part impact (Majid Fouladgar *et al.*, 2012) (Zaim *et al.*, 2012), encompassing the total cost of replacing components, including purchase, installation and commissioning; (9) Inventory costs (Xie *et al.*, 2013), i.e. the direct holding costs associated with storing spare parts and maintenance supplies; and (10) Inspection costs (Li *et al.*, 2017), referring to the direct cost of routine equipment inspections to assess condition and functionality.

Proceeding to the value-added criteria, it is essential to acknowledge that the impact of a maintenance strategy extends beyond immediate financial outcomes, encompassing enhancements in product quality and customer satisfaction (Avakh Darestani *et al.*, 2020). The literature identifies two principal value-added criteria: (1) product quality (Majid Fouladgar *et al.*, 2012) (Zaim *et al.*, 2012; Lesage and Dehombreux, 2012), defined as the extent to which a maintenance strategy contributes to improved product specifications and consistency and (2) profit (Zaim *et al.*, 2012), representing the net economic benefit derived from the differential between maintenance expenditures and the financial gains attributable to increased operational efficiency and product quality improvements. Despite their strategic relevance, the quantification of these criteria poses significant challenges, as it typically necessitates comprehensive control over production processes and the deployment of advanced cost accounting methodologies (Avakh Darestani *et al.*, 2020).

Safety considerations are paramount in the selection of maintenance strategies, as they directly influence both workplace conditions and overarching operational risk profiles

(Avakh Darestani *et al.*, 2020). The principal safety-related sub-criteria identified in the literature include: (1) machine safety (Ding *et al.*, 2012; Ilangkumaran and Kumanan, 2012), referring to the likelihood that component failures may lead to cascading system-wide malfunctions; (2) workplace safety (Zaim *et al.*, 2012), defined as the general safety standards and risk exposure within the operational environment; (3) employee safety (Majid Fouladgar *et al.*, 2012) (Zaim *et al.*, 2012), which pertains to the direct risks encountered by personnel during interaction with or operation of machinery; and (4) environmental impact (Majid Fouladgar *et al.*, 2012) (Zaim *et al.*, 2012), representing the ecological consequences of maintenance activities, including emissions, waste generation and resource usage. These safety-related factors constitute critical constraints within industrial production systems, and their significance becomes particularly pronounced in the context of maintenance operations, given the inherent uncertainty and variability associated with many maintenance tasks (Avakh Darestani *et al.*, 2020).

Following the discussion of the first three primary criteria, the feasibility criteria are now introduced. These address the practical considerations associated with the implementation of a maintenance strategy, particularly in relation to organisational resources and personnel capabilities (Avakh Darestani *et al.*, 2020). The key feasibility-related factors identified in the literature include: (1) managerial approval (Zaim *et al.*, 2012), defined as the degree of strategic endorsement and support from upper management; (2) employee approval (Xie *et al.*, 2013; Zaim *et al.*, 2012), referring to the level of acceptance, engagement and cooperation of the workforce with respect to proposed maintenance practices; (3) spare parts availability (Chan and Prakash, 2012), which pertains to the accessibility of necessary replacement components within the organisation's supply and logistics infrastructure; (4) personnel technical competence (Chan and Prakash, 2012; Ilangkumaran and Kumanan, 2012), i.e. the proficiency and technical skill set of the maintenance workforce required to execute the strategy effectively; and (5) technological level (Majid Fouladgar *et al.*, 2012), reflecting the adequacy of the organisation's existing technological infrastructure to support the maintenance approach. It is noteworthy that while the first, second, and fifth sub-criteria pose challenges in terms of measurability and standardisation, the third sub-criterion – spare parts availability – exhibits clearer operationalisation, with well-defined key performance indicators available for assessing its applicability to each maintenance strategy under consideration.

Finally, technical indicators offer quantifiable metrics to assess the performance and effectiveness of maintenance strategies (Bevilacqua and Braglia, 2000). The primary technical indicators identified in the literature include: (1) detectability (Ding *et al.*, 2012), defined as the capability to detect potential failures prior to the occurrence of significant damage or system disruption; (2) mean time between failures (MTBF) (Majid Fouladgar *et al.*, 2012), representing the average operational duration between successive failures, and serving as a key indicator of system reliability; (3) mean time to repair (MTTR) (Chan and Prakash, 2012) (Majid Fouladgar *et al.*, 2012), i.e. the average time required to restore equipment to functional condition following a failure; (4) severity of damage (Chan and Prakash, 2012), referring to the criticality and consequences of component failures on overall system performance; (5) machinery availability (Mariappan *et al.*, 2013), defined as the proportion of time that equipment is operational and available for use, relative to the total time, including downtime due to maintenance; and (6) reliability (Chan and Prakash, 2012), a statistical measure integrating MTBF and MTTR to characterise the long-term dependability and stability of equipment operations. Although these indicators are well-established in the literature and widely recognised in practice, their application in systematically comparing the impact of alternative maintenance strategies remains limited and underdeveloped (Ardil, 2024).

Following the presentation of the primary clusters and associated sub-criteria relevant to maintenance management decision-making, the subsequent section provides an overview of the frequency and distribution of each criterion and sub-criterion within the international scholarly literature. Table 4 synthesises the reviewed studies, outlining the specific

Table 4. List of papers about the MCDM applied in the maintenance management field

Criteria	Citations	Paper
<i>Economic criteria</i>	37	
Single maintenance action cost	15	Li <i>et al.</i> (2017), Viswanath Dhanisetty <i>et al.</i> (2018), Martinod <i>et al.</i> (2018), Cherkaoui <i>et al.</i> (2017), Ge <i>et al.</i> (2018), Ohta (2018), Alsyouf and Hamdan (2017), Xia <i>et al.</i> (2016), Lazakis and Aykut (2015), Ali and Mobin (2016), Ali and Zadeh (2015), Zhang <i>et al.</i> (2013), Cao <i>et al.</i> (2013), Mariappan <i>et al.</i> (2013), Tuan Huynh <i>et al.</i> (2012)
Energy consumption	3	Xia <i>et al.</i> (2016), Avakh Darestani <i>et al.</i> (2020)
Maintenance workforce	5	Seiti <i>et al.</i> (2018), Eseoghene Ighravwe and Oke (2020), Avakh Darestani <i>et al.</i> (2020), Thor <i>et al.</i> (2013), Majid Fouladgar <i>et al.</i> (2012)
Software	12	Kurian <i>et al.</i> (2019), Avakh Darestani <i>et al.</i> (2020), Mathew <i>et al.</i> (2020), Aghaee <i>et al.</i> (2020), Shafiee <i>et al.</i> (2019), Seiti <i>et al.</i> (2017, 2018), Kirubakaran and Ilangkumaran (2015a), Ding and Kamaruddin (2014a, b), Kirubakaran and Ilangkumaran (2015b), Xie <i>et al.</i> (2013), Zaim <i>et al.</i> (2012)
Production losses	9	Golbasi and Turan (2020), Avakh Darestani <i>et al.</i> (2020), Mathew <i>et al.</i> (2020), Li <i>et al.</i> (2017), Seiti <i>et al.</i> (2017), Kirubakaran and Ilangkumaran (2015a), Lazakis and Aykut (2015), Kirubakaran and Ilangkumaran (2015b), Majid Fouladgar <i>et al.</i> (2012)
Hardware	18	Alsyouf <i>et al.</i> (2020a, b), Avakh Darestani <i>et al.</i> (2020), Mathew <i>et al.</i> (2020), Kurian <i>et al.</i> (2019), Golbasi and Turan (2020), Mohamed and Fahmy (2020), Aghaee <i>et al.</i> (2020), Shafiee <i>et al.</i> (2019), Seiti <i>et al.</i> (2018), Seiti <i>et al.</i> (2017), Kirubakaran and Ilangkumaran (2015a), Ding and Kamaruddin (2014a, b), Kirubakaran and Ilangkumaran (2015b), Xie <i>et al.</i> (2013), Thor <i>et al.</i> (2013), Chan and Prakash (2012), Zaim <i>et al.</i> (2012), Hong <i>et al.</i> (2012)
Training	14	Arjomandi <i>et al.</i> (2021), Avakh Darestani <i>et al.</i> (2020), Mathew <i>et al.</i> (2020), Eseoghene Ighravwe and Oke (2020), Kurian <i>et al.</i> (2019), Aghaee <i>et al.</i> (2020), Shafiee <i>et al.</i> (2019), Kirubakaran and Ilangkumaran (2015a), Lazakis and Aykut (2015), Ding and Kamaruddin (2014a, b), Kirubakaran and Ilangkumaran (2015b), Xie <i>et al.</i> (2013), Thor <i>et al.</i> (2013), Zaim <i>et al.</i> (2012)
Spare part economic impact	11	Eseoghene Ighravwe and Oke (2020), Arjomandi <i>et al.</i> (2021), Avakh Darestani <i>et al.</i> (2020), Mohamed and Fahmy (2020), Aghaee <i>et al.</i> (2020), Lazakis and Aykut (2015), Ali and Zadeh (2015), Kirubakaran and Ilangkumaran (2015b), Thor <i>et al.</i> (2013), Majid Fouladgar <i>et al.</i> (2012), Zaim <i>et al.</i> (2012)
Inventory cost	11	Eseoghene Ighravwe and Oke (2020), Bahria <i>et al.</i> (2018), Seiti <i>et al.</i> (2018), Kurian <i>et al.</i> (2019), Mathew <i>et al.</i> (2020), Ohta (2018), Ge <i>et al.</i> (2017), Seiti <i>et al.</i> (2017), Kirubakaran and Ilangkumaran (2015a), Ali and Zadeh (2015) Xie <i>et al.</i> (2013)
Inspection cost	2	Li <i>et al.</i> (2017), Bahria <i>et al.</i> (2018)
Value-added Products quality	14	
	14	Kurian <i>et al.</i> (2019), Eseoghene Ighravwe and Oke (2020), Avakh Darestani <i>et al.</i> (2020), Bahria <i>et al.</i> (2018), Seiti <i>et al.</i> (2018), Seiti <i>et al.</i> (2017), Majid Fouladgar <i>et al.</i> (2012), Zaim <i>et al.</i> (2012), Lesage and Dehombreux (2012), Bahria <i>et al.</i> (2018), Aghaee <i>et al.</i> (2020), Avakh Darestani <i>et al.</i> (2020), Seiti <i>et al.</i> (2017, 2018)
Profits	7	Kurian <i>et al.</i> (2019), Hemmati <i>et al.</i> (2019), Avakh Darestani <i>et al.</i> (2020), Ohta (2018), Ge <i>et al.</i> (2017), Mariappan <i>et al.</i> (2013), Zaim <i>et al.</i> (2012)
Safety	29	
Machines safety	20	Arjomandi <i>et al.</i> (2021), Avakh Darestani <i>et al.</i> (2020), Mathew <i>et al.</i> (2020), Hemmati <i>et al.</i> (2019), Kurian <i>et al.</i> (2019), Mohamed and Fahmy (2020), Aghaee <i>et al.</i> (2020), Seiti <i>et al.</i> (2018), Ohta (2018), Ge <i>et al.</i> (2017), Seiti <i>et al.</i> (2017), Xia <i>et al.</i> (2016), Kirubakaran and Ilangkumaran (2015a), Ali and Zadeh (2015), Kirubakaran and Ilangkumaran (2015b), Xie <i>et al.</i> (2013), Thor <i>et al.</i> (2013), Farajiparvar and Mayorga (2018), Chopra <i>et al.</i> (2021), Ding <i>et al.</i> (2012)

(continued)

Table 4. Continued

Criteria	Citations	Paper
Safety and health at work	20	Kurian <i>et al.</i> (2019), Avakh Darestani <i>et al.</i> (2020), Mathew <i>et al.</i> (2020), Mohamed and Fahmy (2020), Seiti <i>et al.</i> (2018), Ohta (2018), Farajiparvar and Mayorga (2018), Ge <i>et al.</i> (2017), Seiti <i>et al.</i> (2017), Xia <i>et al.</i> (2016), Kirubakaran and Ilangkumaran (2015a), Ali and Zadeh (2015), Ding and Kamaruddin (2014a, b), Kirubakaran and Ilangkumaran (2015b), Zhang <i>et al.</i> (2013), Xie <i>et al.</i> (2013), Thor <i>et al.</i> (2013), Majid Fouladgar <i>et al.</i> (2012), Ilangkumaran and Kumanan (2012), Zaim <i>et al.</i> (2012)
Humans safety	22	Arjomandi <i>et al.</i> (2021), Avakh Darestani <i>et al.</i> (2020), Mathew <i>et al.</i> (2020), Hemmati <i>et al.</i> (2019), Eseoghene Ighravwe and Oke (2020) Kurian <i>et al.</i> (2019), Mohamed and Fahmy (2020), Aghaee <i>et al.</i> (2020), Seiti <i>et al.</i> (2018), Ohta (2018), Farajiparvar and Mayorga (2018), Ge <i>et al.</i> (2017), Seiti <i>et al.</i> (2017), Xia <i>et al.</i> (2016), Kirubakaran and Ilangkumaran (2015a), Ali and Zadeh (2015), Ding and Kamaruddin (2014a, b), Kirubakaran and Ilangkumaran (2015b), Xie <i>et al.</i> (2013), Thor <i>et al.</i> (2013), Majid Fouladgar <i>et al.</i> (2012), Zaim <i>et al.</i> (2012) Ding and Kamaruddin (2014a, b), Arjomandi <i>et al.</i> (2021), Avakh Darestani <i>et al.</i> (2020), Majid Fouladgar <i>et al.</i> (2012), Zaim <i>et al.</i> (2012), Seiti <i>et al.</i> (2018), Arjomandi <i>et al.</i> (2021), Avakh Darestani <i>et al.</i> (2020), Xia <i>et al.</i> (2016)
Environmental (External) impact	9	
Feasibility	18	
Managerial approval	6	Ohta (2018), Kurian <i>et al.</i> (2019), Avakh Darestani <i>et al.</i> (2020), Lazakis and Aykut (2015), Zaim <i>et al.</i> (2012), Ardil (2024)
Workers approval	11	Kurian <i>et al.</i> (2019), Arjomandi <i>et al.</i> (2021), Avakh Darestani <i>et al.</i> (2020), Aghaee <i>et al.</i> (2020), Seiti <i>et al.</i> (2018), Ohta (2018), Seiti <i>et al.</i> (2017), Kirubakaran and Ilangkumaran (2015a, b), Xie <i>et al.</i> (2013), Zaim <i>et al.</i> (2012) Chan and Prakash (2012), Ding <i>et al.</i> (2012), Avakh Darestani <i>et al.</i> (2020), Ali and Zadeh (2015), Chopra <i>et al.</i> (2021)
Spare parts availability	6	
Personnel technical competences	7	Mathew <i>et al.</i> (2020), Avakh Darestani <i>et al.</i> (2020), Aghaee <i>et al.</i> (2020), Xia <i>et al.</i> (2016), Ali and Zadeh (2015), Chan and Prakash (2012), Ilangkumaran and Kumanan (2012)
Company technological level	10	Seiti <i>et al.</i> (2018), Aghaee <i>et al.</i> (2020), Avakh Darestani <i>et al.</i> (2020), Ohta (2018), Seiti <i>et al.</i> (2017), Xia <i>et al.</i> (2016), Kirubakaran and Ilangkumaran (2015a), Ding and Kamaruddin (2014a, b), Xie <i>et al.</i> (2013), Majid Fouladgar <i>et al.</i> (2012)
Technical factors	39	
Detectability	14	Golbasi and Turan (2020), Kurian <i>et al.</i> (2019), Chopra <i>et al.</i> (2021), Ohta (2018), Farajiparvar and Mayorga (2018), Ge <i>et al.</i> (2017), Kirubakaran and Ilangkumaran (2015a), Ali and Zadeh (2015), Ding and Kamaruddin (2014a, b), Kirubakaran and Ilangkumaran (2015b), Ding <i>et al.</i> (2014), Xie <i>et al.</i> (2013), Thor <i>et al.</i> (2013), Ding <i>et al.</i> (2012)
MTBF	15	Golbasi and Turan (2020), Eseoghene Ighravwe and Oke (2020), Arjomandi <i>et al.</i> (2021), Mohamed and Fahmy (2020), Shahin <i>et al.</i> (2018), Farajiparvar and Mayorga (2018), Ali and Zadeh (2015), Xie <i>et al.</i> (2013), Shahin <i>et al.</i> (2013), Majid Fouladgar <i>et al.</i> (2012), Ding <i>et al.</i> (2014), Seecharan <i>et al.</i> (2018), Shahin <i>et al.</i> (2013), Thor <i>et al.</i> (2013)
MTTR	21	Golbasi and Turan (2020), Yunusa-Kaltungo and Labib (2020), Arjomandi <i>et al.</i> (2021), Chopra <i>et al.</i> (2021), Eseoghene Ighravwe and Oke (2020), Mohamed and Fahmy (2020), Aghaee <i>et al.</i> (2020), Shahin <i>et al.</i> (2018), Ali and Mobin (2016), Ali and Zadeh (2015), Ding and Kamaruddin (2014a, b), Kirubakaran and Ilangkumaran (2015b), Ding <i>et al.</i> (2014), Xie <i>et al.</i> (2013), Thor <i>et al.</i> (2013), Shahin <i>et al.</i> (2013), Thor <i>et al.</i> (2013), Chan and Prakash (2012), Majid Fouladgar <i>et al.</i> (2012), Viswanath Dhanisetty <i>et al.</i> (2018), Farajiparvar and Mayorga (2018), Seecharan <i>et al.</i> (2018)
Machine availability	4	Mariappan <i>et al.</i> (2013), Eseoghene Ighravwe and Oke (2020), Alsyouf <i>et al.</i> (2020a, b)

(continued)

Table 4. Continued

Criteria	Citations	Paper
Reliability	16	Golbasi and Turan (2020), Eseoghene Ighravwe and Oke (2020), Sellitto (2022), Aghaee <i>et al.</i> (2020), Seiti <i>et al.</i> (2018), Seiti <i>et al.</i> (2017), Alsyouf and Hamdan (2017), Xia <i>et al.</i> (2016), Kirubakaran and Ilangkumaran (2015a), Lazakis and Aykut (2015), Ali and Zadeh (2015), Kirubakaran and Ilangkumaran (2015b), Faccio <i>et al.</i> (2014), Thor <i>et al.</i> (2013), Chan and Prakash (2012), Bafandegan <i>et al.</i> (2024)

contributions of individual research efforts to the identification and characterisation of critical decision factors in the context of MSS.

As illustrated in [Figure 8](#), the most frequently adopted criterion in the reviewed literature pertains to technical indicators, followed by economic criteria. Conversely, value-added considerations appear to be the least frequently utilised. Within the technical category, MTTR emerges as the most frequently employed sub-criterion, while machine availability is the least cited. This discrepancy can likely be attributed to the relative ease of data acquisition: MTTR is straightforward to calculate by measuring the time interval between the occurrence of a failure and the restoration of the equipment to operational status. In contrast, accurately quantifying machine availability is often more complex, as it requires reliable classification of downtime events – specifically distinguishing those attributable to maintenance. Such classification typically necessitates integration with advanced information systems, such as manufacturing execution systems (MES), to ensure traceability and causal identification.

An additional observation from the literature review is the prevalence of studies incorporating multiple criteria or sub-criteria. Specifically, 3 publications consider at least one sub-criterion from each of the five defined categories; 11 studies include sub-criteria from four categories; 7 studies consider sub-criteria from three categories; 12 papers include sub-criteria from two categories; and 20 papers focus exclusively on a single category. [Table 5](#) presents a coupling matrix that illustrates the co-occurrence of criteria within individual studies, thereby facilitating the identification of commonly associated decision dimensions across the analysed literature.

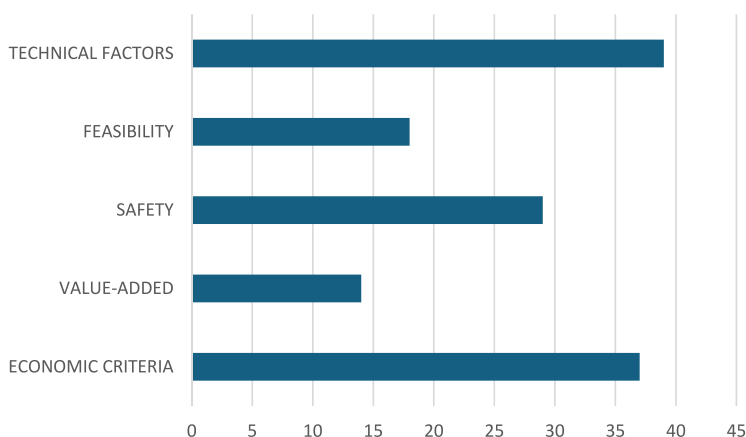


Figure 8. Occurrence of papers that for each decision criteria

Table 5. Occurrences of mixed sub-criteria belonging to different criteria clusters in the papers analysed

	Economic criteria	Value-added	Safety	Feasibility	Technical factors
Economic criteria	37	10	20	13	27
Value-added		14	11	5	9
Safety			29	14	23
Feasibility				18	14
Technical factors					39

The most frequent coupling of criteria observed in the literature involves economic and technical indicators. This is understandable, as both categories allow practitioners and researchers to compute measurable values, and in many cases, the calculation of one is dependent on knowledge of the other.

Furthermore, the temporal distribution of the previously discussed criteria can be examined. Figure 9 presents the time-based clustering of the different criteria as observed across the analysed studies.

As shown in Figure 9, during the period 2012–2015, there was a discernible focus on hardware- and cost-related criteria, including hardware, software, training and single maintenance action cost. In this early stage, much of the research concentrated on tangible and quantifiable aspects of maintenance, such as equipment condition, replacement costs and initial training investments. Notably, methodologies such as AHP and TOPSIS were frequently employed to evaluate cost-centric criteria. The inclusion of training and software as relevant factors indicates the beginning of a shift from purely mechanical concerns towards technological integration and the development of human capital. In the subsequent period (2016–2018), research matured in the domain of technical and cost-based decision-making, with continued emphasis on the single maintenance action cost, but with increased attention to training and production loss criteria. As industries adopted more structured maintenance approaches – such as preventive and predictive maintenance – economic efficiency at the task-level gained prominence. Researchers began to incorporate indirect cost elements, including production downtime and workforce-related impacts, signalling a more holistic economic evaluation. The increasing mention of software-related criteria

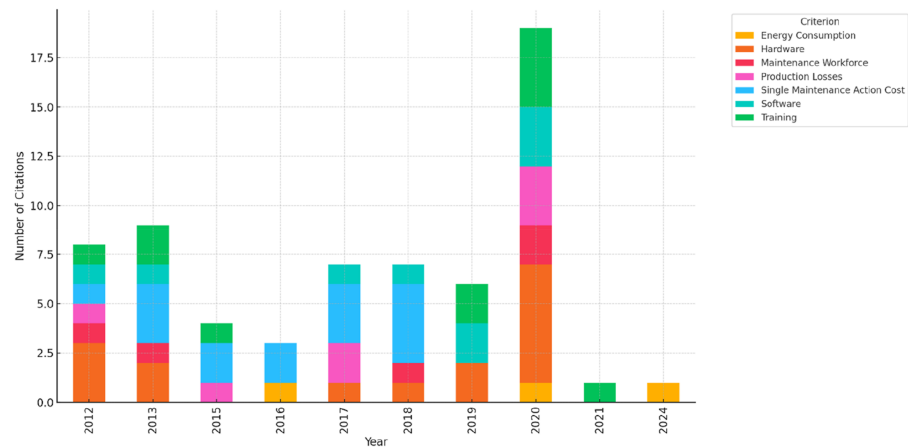


Figure 9. Time distribution of papers for each decision criteria

reflects a growing reliance on decision support systems (DSS), simulation tools and digital maintenance planning platforms. The years 2019–2020 marked a peak in the diversity of economic criteria and the integration of digital tools. Nearly all economic sub-criteria – including hardware, software, training, production losses, inventory cost, spare part impact and maintenance workforce – gained prominence. This period represents the most intensive cluster of research activity. The broadening of economic considerations illustrates a strategic shift from reactive to proactive maintenance strategies, integrating direct, indirect, human-centric and digital cost components. The influence of Industry 4.0 is evident in the widespread adoption of digital technologies, automation, real-time cost tracking and workforce upskilling. From 2021 to 2023, the literature reflects a phase of strategic realignment and stabilisation in the field of MSS and MCDM. The main trends established in the previous period persist, with consistent attention to criteria such as training, workforce and inventory costs. However, the period shows fewer notable shifts – possibly due to a post-COVID deceleration in academic output or a temporary redirection of focus towards operational resilience over optimisation. Organisations appeared to prioritise business continuity, workforce safety and digital transformation under conditions of uncertainty. While cost-efficiency remained a key concern, it was no longer the sole driver of decision-making.

In the most recent year analysed, 2024, early indications suggest an emerging transition from an exclusive focus on digital and cost impacts to broader considerations of sustainability and resource efficiency. This shift is evidenced by increased attention to criteria such as energy consumption and machine availability, although hardware- and software-related considerations continue to feature prominently. The growing emphasis on sustainability-oriented metrics reflects alignment with global ESG agendas. The emergence of energy consumption as a criterion signals heightened awareness of both environmental and operational efficiency, moving beyond traditional cost considerations.

All of these temporal trends are summarised in [Table 6](#).

At the end the answer to the [RQ2](#) is:

- (1) The most frequently utilised criterion for selecting a maintenance policy is related to technical factors, followed by economic considerations ([Figure 8](#)).
- (2) A significant number of studies incorporate multiple criteria to support the decision-making process for optimising maintenance strategies ([Table 5](#)).
- (3) The most commonly observed coupling of criteria involves the combination of technical factors and economic indicators. This is likely due to the interdependence in their evaluation, as the computation of one often requires knowledge of the other ([Table 5](#)).
- (4) In recent years, the temporal evolution of criteria employed in MCDM for MSS demonstrates a progressive shift towards ESG-aligned and sustainability-oriented frameworks ([Table 6](#)).

Table 6. Time trajectory of the criteria used in MSDM for MSS

Period	Dominant criteria	Notable shifts
2012–2015	Hardware, Training, Cost	Physical asset-focused decisions
2016–2018	Cost, Training, Software	Rise of cost awareness, intro to digital tools
2019–2020	All (esp. Hardware, Software)	Peak diversity and integration of tech and cost
2021–2023	Training, Inventory, Workforce	Stabilisation; people and process focused
2024-today	Energy Consumption, Availability	ESG-driven, efficiency and sustainability

6. Conclusions

This study provided a comprehensive and structured review of maintenance strategies and decision-making methodologies in the industrial sector through a SLR covering the period from 2012 to 2024. The investigation began by reaffirming the critical importance of MSS in shaping cost efficiency, operational performance and workplace safety within manufacturing contexts. The literature analysis addressed three key research questions, examining the most commonly adopted maintenance strategies, the methodologies applied in their selection and the criteria that guide these decisions. The review revealed a clear evolution in maintenance practices, transitioning from traditional approaches such as CM and TBM towards more proactive and technologically driven strategies like CBM and PdM. Although PdM is emerging as the most promising approach, its implementation remains limited due to high costs, data infrastructure requirements and the need for skilled personnel. In terms of decision-support methodologies, MCDM techniques were found to be central to maintenance policy selection. Among these, AHP, TOPSIS and fuzzy variants such as F-AHP and Fuzzy-TOPSIS were most prevalent, often used in hybrid combinations to improve decision robustness. However, the use of MCDM methods has declined slightly in recent years, with a notable shift towards AI-driven predictive models and integrated decision systems. This transition reflects a broader industry movement towards dynamic, real-time and data-intensive maintenance environments. The criteria for selecting maintenance strategies were found to be multifaceted and often interdependent. Technical factors – such as MTBF, MTTR and reliability – emerged as the most frequently applied, followed closely by economic considerations, including maintenance costs, production losses and inventory impacts. Safety and feasibility factors also played a prominent role, with increasing attention to environmental impact and workforce readiness. Notably, recent literature shows a shift towards ESG and sustainability-driven criteria, especially in the most recent publications of 2024, suggesting a paradigm change in how maintenance decisions are aligned with broader corporate responsibility goals.

Despite these valuable insights, several limitations remain. First, there is a fragmented adoption of newer strategies like PdM across industries, indicating a gap between research advancements and practical implementation. Second, the dominance of traditional MCDM techniques suggests limited experimentation with novel or AI-based frameworks, particularly in real-time decision environments. Furthermore, many studies lack consideration of uncertainty modelling, human factors and cross-functional integration between maintenance and production planning, which are crucial in real-world applications.

Future research should therefore focus on the development and validation of integrated decision-support systems that combine MCDM logic with AI and machine learning to handle the complexity and uncertainty inherent in MSS. Emphasis should also be placed on contextualising strategies for specific industries, scaling PdM frameworks for small and medium enterprises and embedding sustainability and resilience as core evaluation criteria.

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References

- Abdulgader, F.S., Eid, R. and Daneshvar Rouyendegh, B. (2018), "Development of decision support model for selecting a maintenance plan using a fuzzy MCDM approach: a theoretical framework", *Applied Computational Intelligence and Soft Computing*, Vol. 2018 No. 1, pp. 9346945-14, doi: [10.1155/2018/9346945](https://doi.org/10.1155/2018/9346945).
- Afsharnia, F. and Rohani, A. (2023), "Repair and maintenance management system of food processing equipment", in *Advances in Reliability, Failure and Risk Analysis*, Springer Nature Singapore, Singapore, pp. 357-375.
- Afsharnia, F., Asoodar, M.A., Abdeslahi, A. and Marzban, A. (2015), "Repair and maintenance capability and facilities availability for MF 285 tractor operators in North of Khouzestan province", *International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering*, Vol. 9 No. 6, pp. 1153-1156.

- Afsharnia, F., Marzban, A., Asoodar, M. and Abdeslahi, A. (2021), "Preventive maintenance optimization of sugarcane harvester machine based on FT-Bayesian network reliability", *International Journal of Quality and Reliability Management*, Vol. 38 No. 3, pp. 722-750, doi: [10.1108/ijqrm-01-2020-0015](https://doi.org/10.1108/ijqrm-01-2020-0015).
- Aghaee, A., Aghaee, M., Fathi, M.R., Shoa'bin, S. and Sobhani, S.M. (2020), "A novel fuzzy hybrid multi-criteria decision-making approach for evaluating maintenance strategies in petrochemical industry", *Journal of Quality in Maintenance Engineering*, Vol. 27 No. 2, pp. 351-365, doi: [10.1108/jqme-04-2019-0036](https://doi.org/10.1108/jqme-04-2019-0036).
- Ahmadian, S., Alabdullah, T.T.Y. and Motaghian, I. (2023), "Maintenance and repairs system of automotive industry for sustainable internationalization", *International Journal on Advanced Technology, Engineering, And Information System*, Vol. 2, pp. 106-123, doi: [10.55047/ijateis.v2i2.804](https://doi.org/10.55047/ijateis.v2i2.804).
- Alinezhad, A., Khalili, J., Alinezhad, A. and Khalili, J. (2019), *WASPAS Method. New Methods and Applications in Multiple Attribute Decision Making (MADM)*, pp. 93-98.
- Ali, R. and Mobin, M. (2016), "Maintenance decision making, supported by computerized maintenance management system", *2016 Annual Reliability and Maintainability Symposium (RAMS)*, Vol. 1, doi: [10.1109/rams.2016.7448086](https://doi.org/10.1109/rams.2016.7448086).
- Ali, A. and Zadeh, S.A. (2015), "An integrated fuzzy analytic hierarchy process and fuzzy multiple-criteria decision-making simulation approach for maintenance policy selection", *Simulation*, Vol. 92 No. 1, pp. 3-18, doi: [10.1177/0037549715616686](https://doi.org/10.1177/0037549715616686).
- Alsyouf, I. and Hamdan, S. (2017), "A multi-objective optimization of maintenance policies using weighted comprehensive criterion method (WCCM)", *2017 7th International Conference on Modeling, Simulation, and Applied Optimization (ICMSAO)*, doi: [10.1109/icmsao.2017.7934852](https://doi.org/10.1109/icmsao.2017.7934852).
- Alsyouf, I., Alawaysheh, I., Tahboub, Z.E.A. and Almahasneh, H.S. (2020a), "Selecting maintenance practices based on environmental criteria: a comparative analysis of theory and practice in the public transport sector in UAE", *International Journal of System Assurance Engineering and Management*, Vol. 11 No. 6, pp. 1133-1155, doi: [10.1007/s13198-020-00964-1](https://doi.org/10.1007/s13198-020-00964-1).
- Alsyouf, I., Hamdan, S., Shamsuzzaman, M., Haridy, S. and Alawaysheh, I. (2020b), "On preventive maintenance policies: a selection framework", *Journal of Quality in Maintenance Engineering*, Vol. 27 No. 1, pp. 225-252, doi: [10.1108/jqme-10-2018-0085](https://doi.org/10.1108/jqme-10-2018-0085).
- Ardil, C. (2024), "A neutral set approach for applying TOPSIS in maintenance strategy selection", *International Journal of Computer and Systems Engineering*, Vol. 18 No. 4, pp. 225-234.
- Arjomandi, M.A., Dinmohammadi, F., Mosallanezhad, B. and Shafiee, M. (2021), "A fuzzy DEMATEL-ANP-VIKOR analytical model for maintenance strategy selection of safety critical assets", *Advances in Mechanical Engineering*, Vol. 13 No. 4, doi: [10.1177/1687814021994965](https://doi.org/10.1177/1687814021994965).
- Avakh Darestani, S., Palizban, T. and Rana, I. (2020), "Maintenance strategy selection: a combined goal programming approach and BWM-TOPSIS for paper production industry", *Journal of Quality in Maintenance Engineering*, Vol. 28 No. 1, pp. 14-36, doi: [10.1108/jqme-03-2019-0022](https://doi.org/10.1108/jqme-03-2019-0022).
- Bafandegan Emrooz, V., Kazemi, M., Doostparast, M. and Pooya, A. (2024), "Improving industrial maintenance efficiency: a holistic approach to integrated production and maintenance planning with human error optimization", *Process Integration and Optimization for Sustainability*, Vol. 8 No. 2, pp. 539-564, doi: [10.1007/s41660-023-00374-3](https://doi.org/10.1007/s41660-023-00374-3).
- Bahria, N., Chelbi, A., Bouchriha, H. and Dridi, I.H. (2018), "Integrated production, statistical process control, and maintenance policy for unreliable manufacturing systems", *International Journal of Production Research*, Vol. 57 No. 8, pp. 2548-2570, doi: [10.1080/00207543.2018.1530472](https://doi.org/10.1080/00207543.2018.1530472).
- Besiktepe, D., Ozbek, M.E. and Atadero, R.A. (2020), "Identification of the criteria for building maintenance decisions in facility management: first step to developing a multi-criteria decision-making approach", *Buildings*, Vol. 10 No. 9, p. 166, doi: [10.3390/buildings10090166](https://doi.org/10.3390/buildings10090166).

- Bevilacqua, M. and Braglia, M. (2000), "The analytic hierarchy process applied to maintenance strategy selection", *Reliability Engineering and System Safety*, Vol. 70 No. 1, pp. 71-83, doi: [10.1016/S0951-8320\(00\)00047-8](https://doi.org/10.1016/S0951-8320(00)00047-8).
- Bousdekis, A., Lepenioti, K., Apostolou, D. and Mentzas, G. (2021), "A review of data-driven decision-making methods for Industry 4.0 maintenance applications", *Electronics*, Vol. 10 No. 7, p. 828, doi: [10.3390/electronics10070828](https://doi.org/10.3390/electronics10070828).
- Cao, D., Sun, Y. and Guo, H. (2013), "Optimizing maintenance policies based on discrete event simulation and the OCBA mechanism", *2013 Proceedings Annual Reliability and Maintainability Symposium (RAMS)*, doi: [10.1109/rams.2013.6517635](https://doi.org/10.1109/rams.2013.6517635).
- Celen, M. and Djurdjanovic, D. (2020), "Integrated maintenance and operations decision making with imperfect degradation state observations", *Journal of Manufacturing Systems*, Vol. 55, pp. 302-316, doi: [10.1016/j.jmsy.2020.03.010](https://doi.org/10.1016/j.jmsy.2020.03.010).
- Chan, F.T.S. and Prakash, A. (2012), "Maintenance policy selection in manufacturing firms using the fuzzy MCDM approach", *International Journal of Production Research*, Vol. 50 No. 23, pp. 7044-7056, doi: [10.1080/00207543.2011.653451](https://doi.org/10.1080/00207543.2011.653451).
- Chang, F., Zhou, G., Huang, Q., Ding, K., Cheng, W., Hui, J., Zhi, Y. and Zhang, C. (2023), "A dynamic multi-layer maintenance service network evolution and decision-making method for service-oriented complex equipment", *Computers and Industrial Engineering*, Vol. 181, 109319, doi: [10.1016/j.cie.2023.109319](https://doi.org/10.1016/j.cie.2023.109319).
- Cherkaoui, H., Tuan Huynh, K. and Grall, A. (2016), "Towards an efficient and robust maintenance decision-making", *2016 Second International Symposium on Stochastic Models in Reliability Engineering, Life Science and Operations Management (SMRLO)*, pp. 225-232, doi: [10.1109/smrlo.2016.46](https://doi.org/10.1109/smrlo.2016.46).
- Cherkaoui, H., Huynh, K.T. and Grall, A. (2017), "Quantitative assessments of performance and robustness of maintenance policies for stochastically deteriorating production systems", *International Journal of Production Research*, Vol. 56 No. 3, pp. 1089-1108, doi: [10.1080/00207543.2017.1370563](https://doi.org/10.1080/00207543.2017.1370563).
- Chopra, A., Sachdeva, A. and Bhardwaj, A. (2021), "Selection of appropriate maintenance strategy using fuzzy VIKOR technique: application in paper industry", *International Journal of Quality and Reliability Management*, Vol. 39 No. 5, pp. 1226-1248, doi: [10.1108/ijqrm-03-2020-0070](https://doi.org/10.1108/ijqrm-03-2020-0070).
- Clemente, T., Almeida-Filho, A., Alencar, M. and Cavalcante, C. (2013), "A decision support system based on RCM approach to define maintenance strategies", *Lecture Notes in Business Information Processing*, pp. 122-133, doi: [10.1007/978-3-642-36611-6_9](https://doi.org/10.1007/978-3-642-36611-6_9).
- Dayo-Olupona, O., Genc, B., Celik, T. and Bada, S. (2023), "Adoptable approaches to predictive maintenance in mining industry: an overview", *Resources Policy*, Vol. 86, 104291, doi: [10.1016/j.resourpol.2023.104291](https://doi.org/10.1016/j.resourpol.2023.104291).
- Ding, S.-H. and Kamaruddin, S. (2014a), "Assessment of distance-based multi-attribute group decision-making methods from a maintenance strategy perspective", *Journal of Industrial Engineering International*, Vol. 11 No. 1, pp. 73-85, doi: [10.1007/s40092-014-0078-2](https://doi.org/10.1007/s40092-014-0078-2).
- Ding, S.-H. and Kamaruddin, S. (2014b), "Maintenance policy optimization—literature review and directions", *The International Journal of Advanced Manufacturing Technology*, Vol. 76 Nos 5-8, pp. 1263-1283, doi: [10.1007/s00170-014-6341-2](https://doi.org/10.1007/s00170-014-6341-2).
- Ding, S.H., Goh, T.T., Tan, P.S., Ching Wee, S. and Kamaruddin, S. (2012), "Implementation of decision tree for maintenance policy decision making - a case study in semiconductor industry", *Advanced Materials Research*, Vols 591-593, pp. 704-707, doi: [10.4028/www.scientific.net/amr.591-593.704](https://doi.org/10.4028/www.scientific.net/amr.591-593.704).
- Ding, S.-H., Kamaruddin, S. and Abdul Azid, I. (2014), "Maintenance policy selection model – a case study in the palm oil industry", *Journal of Manufacturing Technology Management*, Vol. 25 No. 3, pp. 415-435, doi: [10.1108/jmtm-03-2012-0032](https://doi.org/10.1108/jmtm-03-2012-0032).
- Dinh, D.H., Do, P., Hoang, V.T., Vo, N.T. and Bang, T.Q. (2024), "A predictive maintenance policy for manufacturing systems considering degradation of health monitoring device", *Reliability Engineering and System Safety*, Vol. 248, 110177, doi: [10.1016/j.res.2024.110177](https://doi.org/10.1016/j.res.2024.110177).

- Djebala, A., Ouelaa, N. and Khemissi Babouri, M. (2015), "Optimization of a maintenance policy in industrial field: case study", *Design and Modeling of Mechanical Systems - II*, pp. 169-178, doi: [10.1007/978-3-319-17527-017](https://doi.org/10.1007/978-3-319-17527-017).
- Emie Schutz, J. (2014), "Optimal 'sporadic' and systematic preventive maintenance policy for leased equipment under various operating conditions", *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications*, pp. 451-458, doi: [10.1007/978-3-662-44739-055](https://doi.org/10.1007/978-3-662-44739-055).
- Ersöz, O.Ö., İnal, A.F., Aktepe, A., Türker, A.K. and Ersöz, S. (2022), "A systematic literature review of the predictive maintenance from transportation systems aspect", *Sustainability*, Vol. 14 No. 21, 14536, doi: [10.3390/su142114536](https://doi.org/10.3390/su142114536).
- Eseoghene Ighravwe, D. and Oke, S.A. (2020), "A two-stage fuzzy multi-criteria approach for proactive maintenance strategy selection for manufacturing systems", *SN Applied Sciences*, Vol. 2 No. 10, 1683, doi: [10.1007/s42452-020-03484-6](https://doi.org/10.1007/s42452-020-03484-6).
- Faccio, M., Persona, A., Sgarbossa, F. and Zanin, G. (2014), "Industrial maintenance policy development: a quantitative framework", *International Journal of Production Economics*, Vol. 147, pp. 85-93, doi: [10.1016/j.ijpe.2012.08.018](https://doi.org/10.1016/j.ijpe.2012.08.018).
- Farajiparvar, N. and Mayorga, R.V. (2018), "Maintenance policy selection using fuzzy failure modes and effective analysis and key performance indicators", *International Journal of Productivity and Quality Management*, Vol. 25 No. 2, p. 170, doi: [10.1504/ijpqm.2018.094760](https://doi.org/10.1504/ijpqm.2018.094760).
- Feng, M. and Li, Y. (2022), "Predictive maintenance decision making based on reinforcement learning in multistage production systems", *IEEE Access*, Vol. 10, doi: [10.1109/access.2022.3151170](https://doi.org/10.1109/access.2022.3151170).
- Ge, Y., Xiao, M., Yang, Z., Zhang, L., Hu, Z. and Feng, D. (2017), "An integrated logarithmic fuzzy preference programming based methodology for optimum maintenance strategies selection", *Applied Soft Computing*, Vol. 60, pp. 591-601, doi: [10.1016/j.asoc.2017.07.021](https://doi.org/10.1016/j.asoc.2017.07.021).
- Ge, Y., Xiao, M., Yang, Z. and Hou, X. (2018), "Research on complex weapon system maintenance decision-making under uncertainty", *Procedia Computer Science*, Vol. 131, pp. 887-894, doi: [10.1016/j.procs.2018.04.296](https://doi.org/10.1016/j.procs.2018.04.296).
- Golbasi, O. and Turan, M.O. (2020), "A discrete-event simulation algorithm for the optimization of multi-scenario maintenance policies", *Computers and Industrial Engineering*, Vol. 145, 106514, doi: [10.1016/j.cie.2020.106514](https://doi.org/10.1016/j.cie.2020.106514).
- Gonçalves, C.D.F., Dias, J.A.M. and Cruz-Machado, V.A. (2014), "Decision methodology for maintenance KPI selection: based on ELECTRE I", *Proceedings of the Eighth International Conference on Management Science and Engineering Management: Focused on Computing and Engineering Management*, Springer Berlin Heidelberg, pp. 1001-1012.
- He, Y., Gu, C., Chen, Z. and Han, X. (2017), "Integrated predictive maintenance strategy for manufacturing systems by combining quality control and mission reliability analysis", *International Journal of Production Research*, Vol. 55 No. 19, pp. 5841-5862, doi: [10.1080/00207543.2017.1346843](https://doi.org/10.1080/00207543.2017.1346843).
- Hemmati, N., Rahiminezhad Galankashi, M., Imani, D.M. and Farughi, H. (2018), "Maintenance policy selection: a fuzzy-ANP approach", *Journal of Manufacturing Technology Management*, Vol. 29 No. 7, pp. 1253-1268, doi: [10.1108/jmtm-06-2017-0109](https://doi.org/10.1108/jmtm-06-2017-0109).
- Hemmati, N., Rahiminezhad Galankashi, M., Imani, D.M. and Rafiei, F.M. (2019), "An integrated fuzzy-AHP and TOPSIS approach for maintenance policy selection", *International Journal of Quality and Reliability Management*, Vol. 37 Nos 9/10, pp. 1275-1299, doi: [10.1108/ijqrm-10-2018-0283](https://doi.org/10.1108/ijqrm-10-2018-0283).
- Holgado, M., Macchi, M. and Evans, S. (2020), "Exploring the impacts and contributions of maintenance function for sustainable manufacturing", *International Journal of Production Research*, Vol. 58 No. 23, pp. 7292-7310, doi: [10.1080/00207543.2020.1808257](https://doi.org/10.1080/00207543.2020.1808257).
- Hong, D.S., Kamaruddin, S. and Abdul Azid, I. (2012), "Maintenance policy selection: a review towards building proper selection model", *International Journal of Industrial and Systems Engineering*, Vol. 10 No. 3, p. 355, doi: [10.1504/ijise.2012.045680](https://doi.org/10.1504/ijise.2012.045680).

- Ilangkumaran, M. and Kumanan, S. (2012), "Application of hybrid VIKOR model in selection of maintenance strategy", *International Journal of Information Systems and Supply Chain Management*, Vol. 5, pp. 59-81, doi: [10.4018/jisscm.2012040104](https://doi.org/10.4018/jisscm.2012040104).
- Jardine, A.K. and Tsang, A.H. (2005), *Maintenance, Replacement, and Reliability: Theory and Applications*, CRC Press.
- Jiang, W., Cui, L. and Liang, X. (2024), "Optimal maintenance policies for three-unit parallel production systems considering yields", *Reliability Engineering and System Safety*, Vol. 248, 110163, doi: [10.1016/j.res.2024.110163](https://doi.org/10.1016/j.res.2024.110163).
- Kirubakaran, B. and Ilangkumaran, M. (2015a), "Selection of optimum maintenance strategy based on F-AHP integrated with GRA-TOPSIS", *Annals of Operations Research*, Vol. 245 Nos 1-2, pp. 285-313, doi: [10.1007/s10479-014-1775-3](https://doi.org/10.1007/s10479-014-1775-3).
- Kirubakaran, B. and Ilangkumaran, M. (2015b), "The selection of optimum maintenance strategy based on ANP integrated with GRA-TOPSIS", *Journal for Global Business Advancement*, Vol. 8 No. 2, p. 190, doi: [10.1504/jgba.2015.069530](https://doi.org/10.1504/jgba.2015.069530).
- Kuo, T. (2017), "A review of some modified grey relational analysis models", *Journal of Grey System*, Vol. 29 No. 3, pp. 70-78.
- Kurian, M.C., Shalij, P.R. and Pramod, V.R. (2019), "Maintenance strategy selection in a cement industry using analytic network process", *Journal of Quality in Maintenance Engineering*, Vol. 26 No. 4, pp. 509-525, doi: [10.1108/jqme-07-2017-0048](https://doi.org/10.1108/jqme-07-2017-0048).
- Lazakis, I. and Aykut, O.E. (2015), "Selection of the best maintenance approach in the maritime industry under fuzzy multiple attributive group decision-making environment", *Proceedings of the Institution of Mechanical Engineers - Part M: Journal of Engineering for the Maritime Environment*, Vol. 230 No. 2, pp. 297-309, doi: [10.1177/1475090215569819](https://doi.org/10.1177/1475090215569819).
- Lesage, A. and Dehombreux, P. (2012), "Maintenance quality control: a first methodological approach for maintenance policy optimization", *IFAC Proceedings*, Vol. 45 No. 6, pp. 1041-1046, doi: [10.3182/20120523-3-ro-2023.00382](https://doi.org/10.3182/20120523-3-ro-2023.00382).
- Li, Y., Chen, L., Pan, E. and Chen, Z. (2017), "Jointly optimal design of perfect maintenance policy and CUSUM control chart", *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, pp. 1920-1924, doi: [10.1109/ieem.2017.8290226](https://doi.org/10.1109/ieem.2017.8290226).
- Li, J., Schaefer, D. and Milisavljevic-Syed, J. (2022), "A decision-based framework for predictive maintenance technique selection in Industry 4.0", *Procedia CIRP*, Vol. 107, pp. 77-82, doi: [10.1016/j.procir.2022.04.013](https://doi.org/10.1016/j.procir.2022.04.013), available at: <https://www.sciencedirect.com/science/article/pii/S2212827122002293>
- Lu, B., Zhou, X. and Li, Y. (2016), "Joint modeling of preventive maintenance and quality improvement for deteriorating single-machine manufacturing systems", *Computers and Industrial Engineering*, Vol. 91, pp. 188-196, doi: [10.1016/j.cie.2015.11.019](https://doi.org/10.1016/j.cie.2015.11.019).
- Luo, Z., Xiong, T., Chen, M., Kong, M. and Zhang, C. (2024), "Assisted decision making for conditional maintenance of distribution network equipment based on multi-task deep learning", *International Journal of Computer Applications in Technology*, Vol. 74 Nos 1-2, pp. 63-72, doi: [10.1504/ijcat.2024.141362](https://doi.org/10.1504/ijcat.2024.141362).
- Majid Fouladgar, M., Yazdani-Chamzini, A., Lashgari, A., Zavadskas, E.K. and Turskis, Z. (2012), "Maintenance strategy selection using ahp and copras under fuzzy environment/prieZi Uros strategijos parinki- mas taikant ahp ir copras metodus neapibreztose situacijose.", *International Journal of Strategic Property Management*, Vol. 16 No. 1, pp. 85-104, doi: [10.3846/1648715x.2012.666657](https://doi.org/10.3846/1648715x.2012.666657).
- Maletić, M., Maletić, D., Dahlgaard, J.J., Dahlgaard-Park, S.M. and Gomišček, B. (2015), "Effect of sustainability-oriented innovation practices on the overall organisational performance: an empirical examination", *Total Quality Management and Business Excellence*, Vol. 26 Nos 9-10, pp. 988-1001.
- Mariappan, V., Subash Babu, A., Amonkar, U.J., Dhawalikar, M.N. and Sakhardande, M.J. (2013), "Integrated graphical model to evaluate multi-criteria maintenance policies for degradable systems", *International Journal of System Assurance Engineering and Management*, Vol. 4 No. 1, pp. 67-77, doi: [10.1007/s13198-012-0138-1](https://doi.org/10.1007/s13198-012-0138-1).

- Martin, H., Mohammed, F., Lal, K. and Shannon, R. (2019), "Maintenance strategy selection for optimum efficiency – application of AHP constant sum", *Facilities*, Vol. 38 Nos 5/6, pp. 421-444, doi: [10.1108/f-05-2018-0060](https://doi.org/10.1108/f-05-2018-0060).
- Martinod, R.M., Bistorin, O., Castaneda, L.F. and Rezg, N. (2018), "Maintenance policy optimisation for multi-component systems considering degradation of components and imperfect maintenance actions", *Computers and Industrial Engineering*, Vol. 124, pp. 100-112, doi: [10.1016/j.cie.2018.07.019](https://doi.org/10.1016/j.cie.2018.07.019).
- Mathew, M., Chakraborty, R.K. and Ryan, M.J. (2020), "Selection of an optimal maintenance strategy under uncertain conditions: an interval type-2 fuzzy AHP-TOPSIS method", *IEEE Transactions on Engineering Management*, Vol. 69 No. 4, pp. 1-14, doi: [10.1109/tem.2020.2977141](https://doi.org/10.1109/tem.2020.2977141).
- Meddaoui, A. and Bouami, D. (2014), "Decision making in maintenance using analytical hierarchy process and time-driven activity based costing", *International Journal of Productivity and Quality Management*, Vol. 13 No. 4, p. 450, doi: [10.1504/ijpqm.2014.062222](https://doi.org/10.1504/ijpqm.2014.062222).
- Mohamed, F.M. and Fahmy, S.A. (2020), "Maintenance strategy selection using AHP: a case study in the oil and gas industry", available at: <https://ieeexplore.ieee.org/abstract/document/9101952>
- Ohta, R. (2018), "Selection of industrial maintenance strategy: classical AHP and fuzzy AHP applications", *International Journal of the Analytic Hierarchy Process*, Vol. 10 No. 2, doi: [10.13033/ijahp.v10i2.551](https://doi.org/10.13033/ijahp.v10i2.551).
- Oudjedi Damerdj, R. and Noureddine, M. (2017), "Maintenance decision-making under the cost criterion and the competing risks approach", *International Journal of Decision Support System Technology*, Vol. 9 No. 1, pp. 32-48, doi: [10.4018/ijdsst.2017010103](https://doi.org/10.4018/ijdsst.2017010103).
- Park, G.J. (2007), "Axiomatic design", *Analytic Methods for Design Practice*, pp. 17-105.
- Patil, A., Soni, G., Prakash, A. and Karwasra, K. (2021), "Maintenance strategy selection: a comprehensive review of current paradigms and solution approaches", *International Journal of Quality and Reliability Management*, Vol. 39 No. 3, pp. 675-703, doi: [10.1108/ijqrm-04-2021-0105](https://doi.org/10.1108/ijqrm-04-2021-0105).
- Patil, A., Soni, G., Prakash, A. and Karwasra, K. (2022), "Maintenance strategy selection: a comprehensive review of current paradigms and solution approaches", *International Journal of Quality and Reliability Management*, Vol. 39 No. 3, pp. 675-703, doi: [10.1108/ijqrm-04-2021-0105](https://doi.org/10.1108/ijqrm-04-2021-0105).
- Pinciroli, L., Baraldi, P. and Zio, E. (2023), "Maintenance optimization in Industry 4.0", *Reliability Engineering and System Safety*, Vol. 234, 109204, doi: [10.1016/j.res.2023.109204](https://doi.org/10.1016/j.res.2023.109204).
- Pintelon, L.M. and Gelders, L.F. (1992), "Maintenance management decision making", *European Journal of Operational Research*, Vol. 58 No. 3, pp. 301-317, doi: [10.1016/0377-2217\(92\)90062-e](https://doi.org/10.1016/0377-2217(92)90062-e).
- Rakyt, M., Bubenik, P., Binasova, V., Gabajova, G. and Staffenova, K. (2024), "The change in maintenance strategy on the efficiency and quality of the production system", *Electronics*, Vol. 13 No. 17, p. 3449, doi: [10.3390/electronics13173449](https://doi.org/10.3390/electronics13173449).
- Ruschel, E., Portela Santos, E.A. and Loures, E.D.F.R. (2017), "Industrial maintenance decision-making: a systematic literature review", *Journal of Manufacturing Systems*, Vol. 45, pp. 180-194, doi: [10.1016/j.jmsy.2017.09.003](https://doi.org/10.1016/j.jmsy.2017.09.003).
- Saihi, A., Ben-Daya, M. and As'ad, R. (2023), "Underpinning success factors of maintenance digital transformation: a hybrid reactive Delphi approach", *International Journal of Production Economics*, Vol. 255, 108701, doi: [10.1016/j.ijpe.2022.108701](https://doi.org/10.1016/j.ijpe.2022.108701).
- Savsar, M. (2013), "Simulation analysis of the effects of maintenance policies on manufacturing line productivity", *Applied Mechanics and Materials*, Vol. 390, pp. 646-652, doi: [10.4028/www.scientific.net/amm.390.646](https://doi.org/10.4028/www.scientific.net/amm.390.646).
- Seecharan, T., Labib, A. and Jardine, A. (2018), "Maintenance strategies: decision making grid vs jack-knife diagram", *Journal of Quality in Maintenance Engineering*, Vol. 24 No. 1, pp. 61-78, doi: [10.1108/jqme-06-2016-0023](https://doi.org/10.1108/jqme-06-2016-0023).
- Seiti, H., Tagipour, R., Hafezalkotob, A. and Asgari, F. (2017), "Maintenance strategy selection with risky evaluations using RAHP", *Journal of Multi-Criteria Decision Analysis*, Vol. 24 Nos 5-6, pp. 257-274, doi: [10.1002/mcda.1618](https://doi.org/10.1002/mcda.1618).

- Seiti, H., Hafezalkotob, A. and Fattahi, R. (2018), "Extending a pessimistic–optimistic fuzzy information axiom based approach considering acceptable risk: application in the selection of maintenance strategy", *Applied Soft Computing*, Vol. 67, pp. 895-909, doi: [10.1016/j.asoc.2017.11.017](https://doi.org/10.1016/j.asoc.2017.11.017).
- Sellitto, M.A. (2022), "Expected utility of maintenance policies under different manufacturing competitive priorities: a case study in the process industry", *CIRP Journal of Manufacturing Science and Technology*, Vol. 38, pp. 717-723, doi: [10.1016/j.cirpj.2022.06.012](https://doi.org/10.1016/j.cirpj.2022.06.012).
- Shafiee, M. (2015), "Maintenance strategy selection problem: an MCDM overview", *Journal of Quality in Maintenance Engineering*, Vol. 21 No. 4, pp. 378-402, doi: [10.1108/jqme-09-2013-0063](https://doi.org/10.1108/jqme-09-2013-0063).
- Shafiee, M., Labib, A., Maiti, J. and Starr, A. (2019), "Maintenance strategy selection for multi-component systems using a combined analytic network process and cost-risk criticality model", *Proceedings of the Institution of Mechanical Engineers - Part O: Journal of Risk and Reliability*, Vol. 233 No. 2, pp. 89-104, doi: [10.1177/1748006x17712071](https://doi.org/10.1177/1748006x17712071).
- Shahin, A., Ghofrani Isfahani, N. and Tabatabaei, S.A.N. (2013), "Determining appropriate maintenance strategy based on decision making grid, sigma level, and process capability index - with a case study in a steel company", *International Journal of Applied Management Science*, Vol. 5 No. 3, p. 265, doi: [10.1504/ijams.2013.055442](https://doi.org/10.1504/ijams.2013.055442).
- Shahin, A., Aminsabouri, N. and Kianfar, K. (2018), "Developing a decision making grid for determining proactive maintenance tactics", *Journal of Manufacturing Technology Management*, Vol. 29 No. 8, pp. 1296-1315, doi: [10.1108/jmtm-12-2017-0273](https://doi.org/10.1108/jmtm-12-2017-0273).
- Soltanali, H., Khojastehpour, M. and Kheybari, S. (2023), "Evaluating the critical success factors for maintenance management in agro-industries using multi-criteria decision-making techniques", *Operations Management Research*, Vol. 16 No. 2, pp. 949-968, doi: [10.1007/s12063-023-00348-1](https://doi.org/10.1007/s12063-023-00348-1).
- Swanson, L. (2001), "Linking maintenance strategies to performance", *International Journal of Production Economics*, Vol. 70 No. 3, pp. 237-244, doi: [10.1016/s0925-5273\(00\)00067-0](https://doi.org/10.1016/s0925-5273(00)00067-0).
- Tajadod, M., Abedini, M., Rategari, A. and Mobin, M. (2016), "A comparison of multi-criteria decision making approaches for maintenance strategy selection (a case study)", *International Journal of Strategic Decision Sciences*, Vol. 7 No. 3, pp. 51-69.
- Thakkar, J.J. (2021), "Decision-making trial and evaluation laboratory (DEMATEL)", *Multi-criteria decision making*, pp. 139-159.
- Thor, J., Ding, S.H. and Kamaruddin, S. (2013), "Development of maintenance policy evaluation model: a case study of the semiconductor industry for achieving production demand", *International Journal of Logistics Systems and Management*, Vol. 15 No. 4, pp. 405-423, doi: [10.1504/ijlsm.2013.054899](https://doi.org/10.1504/ijlsm.2013.054899).
- Tuan Huynh, K., Barros, A. and Berenguer, C. (2012), "Maintenance decisionmaking for systems operating under indirect condition monitoring: value of online information and impact of measurement uncertainty", *IEEE Transactions on Reliability*, Vol. 61 No. 2, pp. 410-425, doi: [10.1109/tr.2012.2194174](https://doi.org/10.1109/tr.2012.2194174).
- UNI EN 13306 (2018), *Manutenzione - Terminologia Di Manutenzione*, Standard, International Organization for Standardization, Geneva, CH.
- Urbani, M., Brunelli, M. and Collan, M. (2020), "A comparison of maintenance policies for multi-component systems through discrete event simulation of faults", *IEEE Access*, Vol. 8, pp. 143654-143664, doi: [10.1109/access.2020.3014147](https://doi.org/10.1109/access.2020.3014147).
- Viswanath Dhanisetty, V.S., Verhagen, W.J.C. and Curran, R. (2018), "Multi-criteria weighted decision making for operational maintenance processes", *Journal of Air Transport Management*, Vol. 68, pp. 152-164, doi: [10.1016/j.jairtraman.2017.09.005](https://doi.org/10.1016/j.jairtraman.2017.09.005).
- Vrignat, P., Kratz, F. and Avila, M. (2022), "Sustainable manufacturing, maintenance policies, prognostics and health management: a literature review", *Reliability Engineering and System Safety*, Vol. 218, 108140, doi: [10.1016/j.res.2021.108140](https://doi.org/10.1016/j.res.2021.108140).

- Werbińska-Wojciechowska, S., Giel, R. and Winiarska, K. (2024), "Digital twin approach for operation and maintenance of transportation system—Systematic review", *Sensors*, Vol. 24 No. 18, p. 6069, doi: [10.3390/s24186069](https://doi.org/10.3390/s24186069).
- Wu, S. and Asadi, M. (2024), "A preventive maintenance policy and a method to approximate the failure process for multi-component systems", *European Journal of Operational Research*, Vol. 318 No. 3, pp. 825-835, doi: [10.1016/j.ejor.2024.05.039](https://doi.org/10.1016/j.ejor.2024.05.039).
- Xia, W., Shi, Q., Wang, F., Ge, H. and Chen, C. (2016), "Research on network maintenance strategy selection based on analytic hierarchy process and technique for order preference by similarity to ideal solution algorithm", *Journal of Shanghai Jiaotong University*, Vol. 21 No. 5, pp. 588-593, doi: [10.1007/s12204-016-1767-3](https://doi.org/10.1007/s12204-016-1767-3).
- Xie, H., Shi, L. and Xu, H. (2013), "Transformer maintenance policies selection based on an improved fuzzy analytic hierarchy process", *Journal of Computers*, Vol. 8 No. 5, doi: [10.4304/jcp.8.5.1343-1350](https://doi.org/10.4304/jcp.8.5.1343-1350).
- Yazdi, M. (2024), "Maintenance strategies and optimization techniques", in *Advances in Computational Mathematics for Industrial System Reliability and Maintainability*, Springer Nature Switzerland, Cham, pp. 43-58.
- Youssef Mahamoud, N., Dehombreux, P., Pirlot, M. and Roble, H.E. (2016), "Decision-support approach for selecting the suitable maintenance policy", *2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, doi: [10.1109/ieem.2016.7798099](https://doi.org/10.1109/ieem.2016.7798099).
- Yunusa-Kaltungo, A. and Labib, A. (2020), "A hybrid of industrial maintenance decision making grids", *Production Planning Control*, Vol. 32 No. 5, pp. 1-18, doi: [10.1080/09537287.2020.1741046](https://doi.org/10.1080/09537287.2020.1741046).
- Zaim, S., Ali, T., Acar, M.F., Al-Turki, U. and Demirel, O.F. (2012), "Maintenance strategy selection using AHP and ANP algorithms: a case study", *Journal of Quality in Maintenance Engineering*, Vol. 18 No. 1, pp. 16-29, doi: [10.1108/13552511211226166](https://doi.org/10.1108/13552511211226166).
- Zavadskas, E.K., Kaklauskas, A., Peldschus, F. and Turskis, Z. (2007), "Multi-attribute assessment of road design solutions by using the COPRAS method", *The Baltic Journal of Road and Bridge Engineering*, Vol. 2 No. 4, pp. 195-203.
- Zhang, Z., Wu, S., Li, B. and Lee, S. (2013), "Optimal maintenance policy for multi-component systems under Markovian environment changes", *Expert Systems with Applications*, Vol. 40 No. 18, pp. 7391-7399, doi: [10.1016/j.eswa.2013.07.003](https://doi.org/10.1016/j.eswa.2013.07.003).

Further reading

- Bokrantz, J., Skoogh, A., Berlin, C. and Stahre, J. (2021), "Smart maintenance: a research agenda for industrial maintenance management", *International Journal of Production Economics*, Vol. 224, 107547, doi: [10.1016/j.ijpe.2019.107547](https://doi.org/10.1016/j.ijpe.2019.107547).
- Bottani, E., Ferretti, G., Montanari, R. and Vignali, G. (2014), "An empirical study on the relationships between maintenance policies and approaches among Italian companies", *Journal of Quality in Maintenance Engineering*, Vol. 20 No. 2, pp. 135-162, doi: [10.1108/jqme-11-2012-0039](https://doi.org/10.1108/jqme-11-2012-0039).
- Cesar, D.F.G.A., Dias, J.A.M.A. and Machado, V.A.C. (2014), "Decision methodology for maintenance KPI selection: based on ELECTRE I", *Proceedings of the Eighth International Conference on Management Science and Engineering Management*, pp. 1001-1012, doi: [10.1007/978-3-642-55122-287](https://doi.org/10.1007/978-3-642-55122-287).
- Garcia Marquez, F.P., Pliego, A., Lorente, J.E. and Trapero, J.R. (2013), "A new ranking method approach for decision making in maintenance management", *Lecture Notes in Electrical Engineering*, pp. 27-38, doi: [10.1007/978-3-642-40078-02](https://doi.org/10.1007/978-3-642-40078-02).
- Jitesh, J. (2021), *Thakkar. Decision-Making Trial and Evaluation Laboratory (DEMATEL)*, Springer, Singapore, pp. 139-159, ISBN. 978-981-33-47458, doi: [10.1007/978-981-33-4745-89](https://doi.org/10.1007/978-981-33-4745-89).
- Juan Jose Montero, J.E., Vingerhoeds, R., Grabot, B. and Ebastien Schwartz, S. (2021), "An ontology model for maintenance strategy selection and assessment", *Journal of Intelligent Manufacturing*, Vol. 34 No. 3, pp. 1369-1387, doi: [10.1007/s10845-021-01855-3](https://doi.org/10.1007/s10845-021-01855-3).

- Marttonen-Arola, S., Baglee, D., Kinnunen, S.-K. and Holgado, M. (2020), "Introducing lean into maintenance data management: a decision making approach", *Engineering Assets and Public Infrastructures in the Age of Digitalization*, pp. 249-257, doi: [10.1007/978-3-030-48021-928](https://doi.org/10.1007/978-3-030-48021-928).
- Sabaei, D., Erkoyuncu, J. and Roy, R. (2015), "A review of multi-criteria decision making methods for enhanced maintenance delivery", *Procedia CIRP*, Vol. 37, pp. 30-35, doi: [10.1016/j.procir.2015.08.086](https://doi.org/10.1016/j.procir.2015.08.086).
- Velmurugan, R.S., Dhingra, T. and Velmurugan (2021), *Asset Maintenance Management in Industry*, Springer International Publishing.

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