Machine learning techniques for predictive maintenance of building services: a comprehensive review and research outlook

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ABSTRACT

Purpose – Predictive maintenance in buildings is crucial for minimising unplanned downtime and ~~extend~~ extending lifespan of building components~~–~~, yet its implementation remains complex. Machine learning (ML) offers a transformative approach by enabling systematic predictions and automation. This study aims to analyse the interrelationship between ML techniques and predictive maintenance ~~in~~ of building ~~servicess~~services, identifying key research trends and future directions.

Design/methodology/approach – A bibliographic analysis was conducted on 118 journal articles using VOSviewer to examine co-authorship and co-occurrence patterns. The key themes generated were then explored semi-systematically, focusing on the most frequently used ML techniques and predictive maintenance applications.

Findings – The results reveal a strong relationship between ML and predictive maintenance, with increasing research interest post-2021. Co-occurrence analysis highlights the evolution of research themes, shifting from conventional ML models to advanced techniques such as Digital Twins and Lifelong Learning with deep generative replay modeling. Among the most frequently applied ML techniques, XGBoost, Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) have demonstrated the best predictive performance in fault diagnostics and system optimisation.

Originality – This study provides a comprehensive examination of research trends, highlighting underexplored ML applications in building services predictive maintenance~~predictive maintenance~~.

Practical implications – The findings advocate for stronger interdisciplinary collaborations among researchers, institutions and industries to bridge the gap between research

advancements and real-world implementation in Facilities Management and Building Life Cycle.

Keywords Building maintenance; Building services~~Digital Twins~~; Literature review; Machine learning; Predictive maintenance

Type of paper Literature Review

1. Introduction

Predictive maintenance has become a critical strategy in the sustainable management and operation of building services systems, aiming to proactively identify maintenance needs before failures occur. This approach helps minimise unplanned downtime and extend equipment lifespan, ultimately improving efficiency and reducing costs (Bouabdallaoui *et al.*, 2021). In facilities management, where unexpected equipment failures can lead to significant operational disruptions, predictive maintenance plays a pivotal role (Valinejadshoubi *et al.*, 2022).

The emergence of machine learning (ML) has provided innovative tools to enhance predictive maintenance strategies, enabling more accurate, timely and cost-effective solutions (Ma *et al.*, 2020). ML applications in predictive maintenance mark a paradigm shift from traditional, periodic maintenance approaches to a data-driven, predictive model. By analysing large datasets collected from sensors, operational logs, and historical records, ML algorithms can detect patterns, anticipate potential failures and recommend proactive maintenance activities (Leukel *et al.*, 2021). This transition enhances building system reliability, safety and overall operational efficiency (Teoh *et al.*, 2023).

However, implementing ML-based predictive maintenance in the building services sector presents several challenges. These include the complexity of integrating ML models into existing maintenance frameworks, the availability of high-quality and relevant data and the requirement for expertise in both domain-specific knowledge and ML technologies (Villa *et al.,* 2022). Furthermore, financial constraints pose a challenge, as deploying such technologies requires significant capital and operational investment in data collection, processing and model development (Carvalho *et al.*, 2019).

Recent research has sought to address these challenges, developing frameworks and methodologies for integrating ML techniques into predictive maintenance strategies (e.g., Arsiwala *et al.*, 2023; Nunes *et al.*, 2023). These studies emphasise the need for a comprehensive review of current research trends, methodologies and empirical results related to ML applications in building predictive maintenance.

Despite growing recognition of ML's potential in predictive maintenance, its systematic integration across FM organisations, particularly in building services maintenance, remains underexplored. While previous reviews, such as Carvalho *et al.* (2019) and Scaife (2024), have examined general applications of ML in predictive maintenance, limited research has focused specifically on building facility systems. Furthermore, there is a dearth of empirical studies that have explored the integration of machine learning with predictive maintenance protocols, including the challenges, benefits and operational efficiency improvements. A few studies provide detailed case studies or empirical evidence regarding scalability, implementation processes and quantifiable benefits (e.g., Cheng *et al.*, 2020; Tomé *et al.*, 2023).

This paper aims to bridge this research gap by conducting a bibliometric analysis followed by a semi-systematic review of ML techniques for predictive maintenance in the building sector. To achieve this, the study selects and analyses research articles from Scopus and Web of Science, identifying key trends, applications, and challenges. Moreover, the paper outlines potential future research directions, providing insights for researchers and practitioners in this emerging and evolving research area.

2. Background Study - Predictive Maintenance in Buildings

Predictive maintenance in buildings is a strategic approach aimed at forecasting equipment failures to enable timely maintenance interventions. Unlike preventive maintenance, which relies on scheduled maintenance regardless of the actual condition of systems, predictive maintenance is data-driven and based on real-time monitoring (Madureira *et al.*, 2017). This technique evaluates operational data to identify patterns that indicate impending failures (Flores-Colen and Brito, 2010).

Common predictive maintenance methods include vibration analysis, acoustic monitoring, oil analysis and thermal imaging, each contributing to enhanced system reliability, safety and energy efficiency (Civerchia *et al.*, 2017). Properly maintained equipment operates optimally, reducing unnecessary costs associated with routine maintenance (Cauchi *et al.*, 2017). However, successful implementation requires a deep understanding of the operational characteristics of building systems.

2.1 Machine Learning Techniques

Machine learning, a subset of artificial intelligence, involves training algorithms to analyse data, detect patterns and make predictive decisions with minimal human intervention. ML is transforming building management by improving predictive maintenance capabilities (Yang *et al.*, 2018). Its ability to process large and complex datasets allows for more accurate failure predictions, reducing downtime and improving operational efficiency (Villa *et al.*, 2022).ML techniques consist of various algorithms designed to extract patterns and insights from data.

1. Support Vector Machines (SVM) are used for classification and regression, separating data points using hyperplanes for optimal decision-making (Carvalho *et al.*, 2019).
2. Artificial Neural Networks (ANN) consist of interconnected nodes that process information across layers to make predictions.
3. Deep Neural Networks (DNN) extend ANN by adding multiple hidden layers, enabling the detection of intricate patterns (Bouabdallaoui *et al.*, 2021).
4. Decision Trees (DT) provide a hierarchical structure for classification, segmenting data into branches that lead to predictive outcomes (Carvalho *et al.*, 2019).

Each technique has unique strengths and weaknesses, making them suitable for different applications within predictive maintenance.

2.2 Machine Learning ~~and~~ for Predictive Maintenance ~~in Buildings~~of Building Services

In the context of building services predictive maintenance, ML techniques analyse operational data to predict impending equipment failures (Cheng *et al.*, 2020). Advanced ML algorithms recognise complex correlations between operational anomalies and potential failures, shifting maintenance strategies from reactive to proactive approaches (Hong *et al.*, 2020). This transition enables ~~facility~~ facilities managers to schedule maintenance in advance, reducing downtime and extending equipment lifespan. Despite initial implementation challenges, ML-driven predictive maintenance is increasingly recognised for its ability to enhance efficiency and intelligence in smart building management (Carvalho *et al.*, 2019).

3. Methodology

This study employs a mixed-method approach, combining bibliometric analysis with a semi-systematic review of existing research. Bibliometric analysis enables researchers to systematically examine a vast amount of literature, identifying key research trends, influential studies and conceptual frameworks within a specific domain (Oladinrin *et al.*, 2023). This study primarily utilises VOSviewer, a scientific mapping tool that leverages Natural Language Processing (NLP) and clustering algorithms to conduct bibliometric analysis (Orduña-Malea and Costas, 2021). Through co-authorship and co-occurrence analyses, predictive maintenance studies were reviewed under different ML algorithms to identify prevailing research trends and gaps.

3.1 Bibliometric analysis

This study focuses exclusively on predictive maintenance research in buildings that integrates ML techniques to enhance accuracy and efficiency. Firstly, Google Books Ngram Viewer was used to analyse historical trends in the use of the terms “machine learning” (ML) and “predictive maintenance.” Ngram Viewer, which contains a corpus of over five billion digitised books, allows researchers to examine historical keyword frequency in a diachronic context (Zięba, 2018). The analysis revealed that ML experienced exponential growth after 2010, while predictive maintenance remained relatively consistent over time. Based on these trends, a literature review search was conducted considering the peer-reviewed journal articles published from 2010 to 2025 (See Figure 1 below).

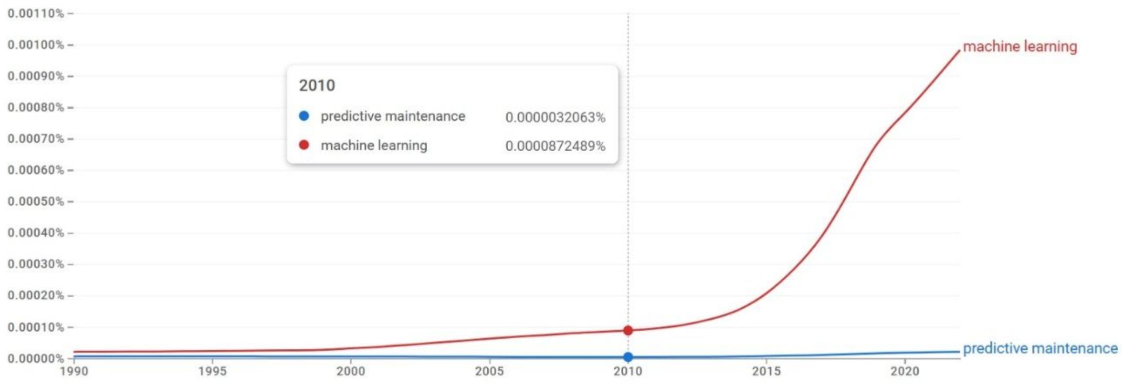

Figure 1 Frequency of the terms “Machine Learning” and “Predictive Maintenance”

Source: Authors’ own work

For bibliometric and systematic analysis, research articles were retrieved from two major academic databases: Scopus and Web of Science. A keyword-based advanced search was conducted using the following query: "Predictive maintenance" AND ("Machine Learning" OR "ML" OR "Deep Learning" OR "Artificial Intelligence" OR "AI") AND ("Building"). To refine the dataset, additional filtering criteria were applied to select only journal articles, ensuring high-quality and peer-reviewed sources. The filtration process yielded 99 articles from Scopus and 72 articles from Web of Science. To conduct the co-authorship analysis and co-occurrence analysis, the list of shortlisted articles (i.e., RIS files) obtained from Scopus and Web of Science were merged and a combined file was created using the Mendeley software. ~~To eliminate redundancy, a duplication analysis was then conducted using Mendeley~~ A duplication analysis was then conducted using Mendeley to eliminate redundancy, resulting in a final dataset of 118 journal articles.

3.1.2 Semi-systematic review

Further, abstracts were manually reviewed to filter empirical studies explicitly related to building services maintenance within Facility Management (FM)~~Facility Management (FM)~~ systems in buildings, reducing the final dataset to 20 articles. These studies, which represent real-world applications, were systematically reviewed to explore the use of different ML techniques in identifying emerging trends, practical applications, and challenges related to predictive maintenance.~~These articles were systematically reviewed and different ML~~

~~techniques were explored to identify emerging trends, applications and challenges in predictive maintenance for buildings.~~

4. Findings

4.1 Co-authorship analysis

The first step of the analysis using VOSviewer software was co-authorship analysis to identify the most influential authors who have published on FM and ML. A total of 431 authors and 118 published documents have been considered for the analysis. The analysis reveals significant fragmentation in research collaboration. Out of 431 identified authors, only 21 exhibit strong network ties, forming three primary clusters of closely linked researchers. Suhatril M. emerges as a central bridging author, facilitating connections across multiple research groups, while Yan G. also demonstrates key collaborative roles (See Figure 2 below). However, a detailed density analysis of the network highlights that many authors remain in isolated clusters, meaning that while they contribute to the field, they lack extensive co-authorship connections.

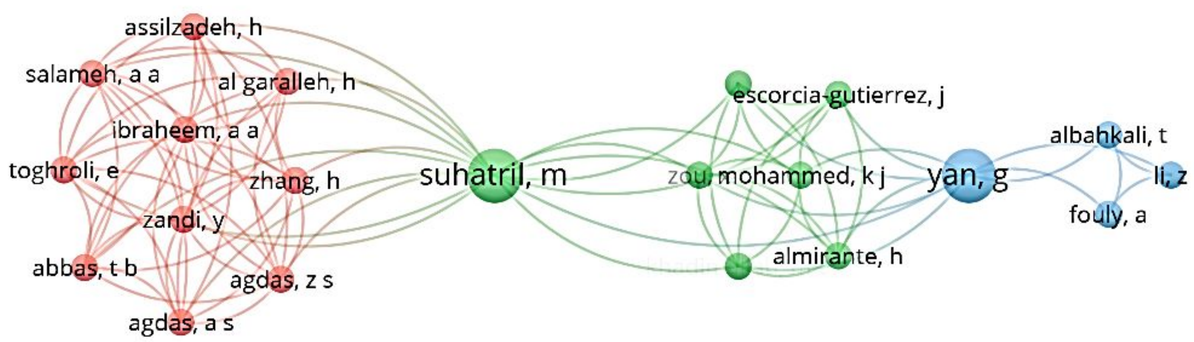

Figure 2 The network of cooperation, based on the co-authorship of the principal authors

Source: Authors' own work

4.2 Co-occurrence analysis

This section analyses the authors' keyword distribution to identify the inter-relationships. The keywords included in the titles, abstracts and keyword sections are considered for this analysis.

Keywords that occurred in more than five instances were considered, which resulted in 19 keywords. Figure 3 below visualises the keyword network and its weights. The weight of each keyword is represented by the size of the node and the distance between the two nodes represents the strength of the relationship between the two keywords. Strongly related keywords are indicated with shorter distances. The co-occurrence analysis of predictive maintenance research using machine learning highlights key research themes and their evolving focus over time. The most frequently occurring terms, represented by the largest nodes, include "predictive maintenance", "machine learning", "artificial intelligence", "model" and "framework" confirming a primary research emphasis on ML-driven predictive maintenance strategies. The colour gradient, which represents the evolution of research, shows that earlier studies (2021-2022) were centred around fault detection, strategy and diagnosis, while recent studies (2022-2023) have shifted towards optimisation, digital twins and anomaly detection. Notably, “Internet of Things (IoT)” “Building Information Modelling (BIM)” and “performance” have strong co-occurrence relationships with machine learning and predictive maintenance, emphasising the increasing role of smart building technologies in predictive systems. In particular, deep learning and optimisation appear in the latest research trends, suggesting a continued shift towards advanced computational models for improving predictive maintenance accuracy.

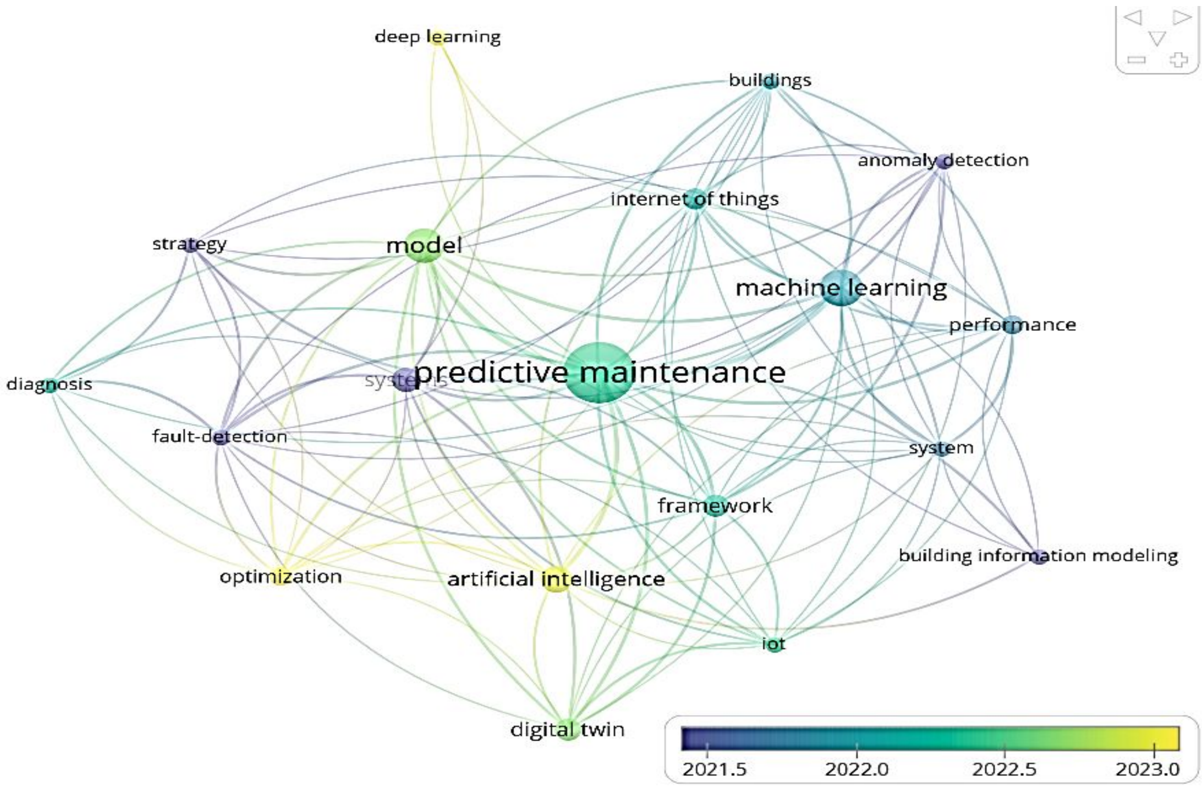

Figure 3 Cluster visualisation map for co-occurring keywords

Source: Authors' own work

4.3 Application of machine learning techniques for predictive maintenance in building services~~s~~

Table 1 below presents empirical studies and real-world applications where ML techniques were tested or evaluated for predictive maintenance in building systems, including HVAC, energy systems, and control mechanisms. Only studies with clearly defined ML application contexts were included.~~Table 1 below presents the description of empirical research in which ML applications have been adopted to perform different FM task(s)/functions(s).~~

Table 1 Empirical evidence on the application of ML for predictive maintenance in building services~~s~~

Table 1 is attached separately

The most frequently used ML techniques/algorithms for building services predictive maintenance are presented below.

4.3.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) have become a widely used ML approach for predictive maintenance due to their ability to model non-linear time series trends (Cheng *et al.*, 2020). Among early research, Pałasz and Przysowa (2019) applied ANN alongside two other ML techniques to predict heat meter failures. By employing hyperparameter optimisation, the authors improved fault detection efficiency, achieving 95% accuracy. Moreover, Cheng *et al.* (2020) applied ANN for predictive maintenance of MEP components in buildings, utilising data from IoT sensors, BIM models, and FM systems. While this study reported over 96% prediction accuracy, the authors identified a direct correlation between dataset quality and error rates. They further noted that ~~facility~~ facilities managers need to train new datasets for different MEP components, indicating challenges in model generalisation. In a related study, Hosamo *et al.* (2022) adapted ANN for fault detection in Air Handling Units (AHUs). Their results showed high prediction accuracy; however, the authors concluded that ML technique choice and input data quality significantly affect model performance. The following year, Hosamo *et al.* (2023) expanded on this by developing a predictive maintenance model for HVAC systems. This study integrated BIM, real-time sensor data, occupant feedback and probabilistic models to construct a digital twin. The authors tested nine multiclass classification algorithms for fault prediction, finding that Extreme Gradient Boosting (XGBoost) outperformed ANN with 2.5% higher accuracy. However, ANN remained among the high-performing models, achieving 0.89 precision and 0.88 accuracy.

4.3.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a widely used ML algorithm for predictive maintenance, often integrated with ANN. Researchers such as Cheng *et al.* (2020), Hosamo *et al.* (2022, 2023), and Pałasz and Przysowa (2019) have combined SVM with ANN in their predictive maintenance studies. Yan *et al.* (2014) applied SVM for fault detection and diagnosis (FDD) in chillers, integrating it with an Auto-Regressive Model with Exogenous Variables (ARX). Their results demonstrated that SVM+ARX outperformed a Multilayer Perceptron (MLP) model, achieving 90% accuracy. Expanding on this work, Mulumba *et al.* (2015) refined the system, improving precision to 93.5% and an F1-score of 92.3%, surpassing eight other ML models. Recent studies, including those by Al-Aomar *et al.* (2024), Es-sakali *et al.* (2024) and Amin *et al.* (2024), have further explored SVM in predictive maintenance. However, their results indicate that SVM underperforms compared to advanced ML models such as XGBoost, *K-Nearest Neighbours* (KNN) and Random Forest (RF), which exhibit higher accuracy and computational efficiency.

4.3.3 Deep Neural Network (DNN)

DNNs have emerged as an advanced ML approach in predictive maintenance research. Bouabdallaoui *et al.* (2021) developed a five-step predictive maintenance framework, incorporating data collection, processing, model development, fault notification and model improvement. They employed Long Short-Term Memory (LSTM) networks to detect faults in HVAC systems. However, their study highlighted several challenges, including the scarcity of public datasets, the long-term investment required for profitable solutions, and the need for tailor-made models for different building types. In a more recent study, Chen *et al.* (2024) introduced a lifelong learning approach with deep generative replay, aimed at conserving building energy and reducing emissions. Their results showed a 53.4% increase in accuracy compared to conventional methods, achieving 0.89 accuracy. Additionally, comparisons with SVR, KNN, RF and XGBoost indicated that the proposed approach delivered a 10% to 20% improvement in performance. Furthermore, Iuculano and Babar (2024) examined the potential of LSTM networks in forecasting elevator failures, demonstrating that LSTM models could predict failures up to 60 days in advance. However, no conclusive evidence exists to confirm that DNN consistently outperforms other ML models in predictive maintenance.

4.3.4 Decision Tree (DT) and Random Forest (RF)

Decision Tree (DT) is a widely used ML algorithm for predictive maintenance; however, Trivedi *et al.* (2019) noted that a simple DT model lacks strong predictive power for HVAC fault detection. To enhance prediction accuracy, more advanced models like RF are often preferred. Pałasz and Przysowa (2019) explored different ML models for heater meter failure prediction and implemented Bagging Decision Trees (BDT) as part of an ensemble classifier. Their results demonstrated that BDT outperformed ANN and SVM across multiple performance metrics, including recall, precision and accuracy. Similarly, Al-Aomar *et al.* (2024) examined predictive maintenance for hospital HVAC systems and found that RF models delivered better performance than traditional DT models. However, Hosamo *et al.* (2023) reported that ANN, SVM and RF models performed better than DT in their predictive maintenance study. In another study, Es-sakali *et al.* (2024) developed a predictive maintenance system for refrigerant leaks in Variable Refrigerant Floor (VRF) systems. Their analysis confirmed that RF significantly outperformed DT in fault detection accuracy. Despite these variations in performance, these studies collectively highlight the potential of DT and RF for predictive maintenance applications, while emphasising the superior accuracy of ensemble models like RF over standalone DT models.

4.3.5 K-Nearest Neighbours (KNN)

KNN is a supervised ML algorithm commonly used for fault classification in HVAC systems (Hosamo *et al.*, 2023). Several studies, including Hosamo *et al.* (2023), Es-sakali *et al.* (2024), and Al-Aomar *et al.* (2024), have integrated KNN into predictive maintenance models. While KNN has demonstrated high accuracy, there is no conclusive evidence that it consistently outperforms other ML models in predictive maintenance applications. Bam *et al.* (2024) tested a multi-class classification framework using benchmark HVAC datasets and compared KNN and RF models. Their findings revealed that RF outperformed KNN in both accuracy and computational efficiency, reinforcing the notion that ensemble methods provide superior predictive power.

4.3.6 XGBoost

XGBoost, adopted by Chen and Guestrin (2016), is a high-performance, scalable tree-boosting system widely applied in predictive modeling. Researchers frequently use XGBoost due to its robustness and computational efficiency. For instance, Hosamo *et al.* (2023) concluded that XGBoost outperformed eight other ML models in predictive maintenance for HVAC systems. Similarly, Amin *et al.* (2024) demonstrated that XGBoost effectively predicted maintenance schedules and energy consumption in Active Chilled Beam (ACB) systems, reducing operational downtimes. Moreover, a comparative study by Alijoyo *et al.* (2024) found that

XGBoost outperformed Naïve Bayes, RNN, SVM, and LSTM in fault detection for IoT-based smart home networks, further reinforcing its applicability in predictive maintenance.

5. Discussion

With the continuous evolution of ML techniques, research in predictive maintenance of building services has shown exponential growth over the past decade. By 2021, research efforts were concentrated on leveraging IoT connectivity (Gordon, 2021; Dahanayake and Sumanarathna, 2022), transfer learning (Gribbestad *et al.*, 2021) and deep learning models (Berghout *et al.*, 2021; Bouabdallaoui *et al.*, 2021) to develop predictive maintenance frameworks. More recent studies, have shifted towards AI-assisted digital twins (De Donato *et al.*, 2023; Hodavand *et al.*, 2023), Industry 4.0 applications (Mohapatra *et al.*, 2023) and lifelong learning models (Chen *et al.*, 2024), indicating a transition from static predictive maintenance approaches to self-learning, adaptive and real-time predictive maintenance solutions. A recent study by Scaife (2024) highlighted that AI and ML have unlocked new opportunities for remote monitoring, autonomous system control, real-time failure detection and optimised facility operations, reducing dependency on manual inspections and labour-intensive maintenance tasks.

5.1 The role of machine learning in enhancing predictive maintenance

The co-occurrence analysis confirms the strong interdependency between predictive maintenance and ML, with research trends shifting towards optimisation-based models, anomaly detection techniques and deep learning applications. The clustering of keywords suggests that ML is being increasingly integrated with facility management technologies, including BIM, IoT and digital twins, reinforcing the role of smart technologies in predictive maintenance. Optimisation, performance monitoring and AI-driven fault diagnostics have gained prominence in recent studies, indicating a movement toward more efficient and automated predictive maintenance solutions.

The semi-systematic review highlights that a diverse range of ML techniques, including SVM, ANN, DNN, DT, RF, Bayesian Networks (BN), KNN and XGBoost, are widely applied across various FM services. However, not all models yield consistently high performance. DNN models, despite their capability to handle complex patterns, often require large datasets, making them computationally expensive and less adaptable to small-scale FM systems. Similarly, Bayesian Networks provide probabilistic predictions but struggle with high-dimensional data. Decision Tree-based models (DT, RF and BDT) offer robust classification capabilities, yet their interpretability and scalability remain challenging in high-frequency predictive maintenance tasks.

A particularly notable finding from the review is the consistent outperformance of XGBoost over other ML models. Hosamo *et al*. (2023) found that XGBoost outperformed eight other ML models in HVAC system predictive maintenance, demonstrating superior precision and accuracy. Similarly, Amin *et al.* (2024) showed that XGBoost effectively predicted maintenance schedules and energy consumption in Active Chilled Beam (ACB) systems, minimising downtime and optimising energy efficiency. Alijoyo *et al.* (2024) conducted a comparative study and concluded that XGBoost performed better than other well-established ML techniques, such as Naïve Bayes, SVM, RNN and LSTM, particularly in fault detection for IoT-based smart home networks. These findings suggest that XGBoost is emerging as a leading model for fault classification, anomaly detection and predictive maintenance optimisation in smart building applications.

5.2 Challenges in research collaboration

Despite the growing significance of ML in predictive maintenance, the co-authorship analysis reveals a lack of global collaboration among researchers. The findings indicate that only 21 out of 431 authors have strong co-authorship ties, suggesting that research in this domain remains highly fragmented. Instead of forming a globally connected research network, authors appear to be working in isolated clusters, often focusing on region-specific applications of ML in predictive maintenance. This lack of cross-disciplinary collaboration may be hindering the development of standardised ML-driven maintenance frameworks, limiting the scalability and practical implementation of predictive maintenance models across different FM organisations and systems. A key reason for this disconnected research landscape is that highly influential researchers specialising in both predictive maintenance and ML have yet to emerge. Establishing interdisciplinary research collaborations is crucial for advancing predictive maintenance technologies and ensuring their widespread adoption across industries.

The fragmented nature of current research collaboration has important implications for both the quality and future direction of work in this area. When researchers operate in isolated clusters, it can lead to duplicated efforts, inconsistent methods, and missed opportunities to explore emerging or underdeveloped topics (Ucar *et al.,* 2024). It also makes it more difficult to establish common standards around ethical considerations or to influence policy decisions through collective evidence (Pinheiro *et al.*, 2021; Rane *et al.*, 2024). As a result, the potential for these research efforts to be translated into commercially viable systems or tools becomes limited, particularly where practical deployment and industry adoption are concerned. To help address these issues, future research should prioritise cross-disciplinary and cross-institutional collaboration, encourage the development and sharing of open datasets, and adopt consistent evaluation approaches (Rane *et al.*, 2024). Hence, these steps would support more robust and transferable findings and contribute to a more coherent research agenda for predictive maintenance in building services.

6. Conclusion

This study explores research trends in building services predictive maintenance and machine learning through bibliographic analysis and a semi-systematic literature review, examining 118 journal articles. The findings, categorised under co-authorship and co-occurrence analyses, reveal significant advancements post-2021, demonstrating the increasing role of ML in predictive maintenance strategies. While research has predominantly focused on developing novel ML-based predictive maintenance frameworks, there is still a gap in practical implementation within the FM industry.

Beyond academic contributions, future research should prioritise real-world applications by establishing structured implementation strategies for integrating ML models into FM workflows. This includes developing standardised guidelines, conducting case studies across diverse building environments and creating cost-effective solutions tailored for small to medium-sized enterprises (SMEs). Furthermore, XGBoost and other high-performing ML algorithms should be further explored due to their proven effectiveness in predictive maintenance tasks.

In particular, the integration of Digital Twins and Generative AI models presents a transformative opportunity to enhance automation, adaptability and energy efficiency in predictive maintenance. Future research should also align with sustainability goals and Net-zero carbon policies, ensuring that ML-driven predictive maintenance solutions contribute to resource optimisation and long-term environmental impact reduction. Strengthening global research collaborations and interdisciplinary knowledge sharing will be essential in overcoming current research fragmentation and standardising ML-based predictive maintenance frameworks for scalable, real-world adoption.

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Machine learning techniques for predictive maintenance of building services: a comprehensive review and research outlook

ABSTRACT

Purpose – Predictive maintenance in buildings is crucial for minimising unplanned downtime and extending lifespan of building components, yet its implementation remains complex. Machine learning (ML) offers a transformative approach by enabling systematic predictions and automation. This study aims to analyse the interrelationship between ML techniques and predictive maintenance of building services, identifying key research trends and future directions.

Design/methodology/approach – A bibliographic analysis was conducted on 118 journal articles using VOSviewer to examine co-authorship and co-occurrence patterns. The key themes generated were then explored semi-systematically, focusing on the most frequently used ML techniques and predictive maintenance applications.

Findings – The results reveal a strong relationship between ML and predictive maintenance, with increasing research interest post-2021. Co-occurrence analysis highlights the evolution of research themes, shifting from conventional ML models to advanced techniques such as Digital Twins and Lifelong Learning with deep generative replay modeling. Among the most frequently applied ML techniques, XGBoost, Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) have demonstrated the best predictive performance in fault diagnostics and system optimisation.

Originality – This study provides a comprehensive examination of research trends, highlighting underexplored ML applications in building services predictive maintenance.

Practical implications – The findings advocate for stronger interdisciplinary collaborations among researchers, institutions and industries to bridge the gap between research advancements and real-world implementation in Facilities Management and Building Life Cycle.

Keywords Building maintenance; Building services; Literature review; Machine learning; Predictive maintenance

Type of paper Literature Review

1. Introduction

Predictive maintenance has become a critical strategy in the sustainable management and operation of building services systems, aiming to proactively identify maintenance needs before failures occur. This approach helps minimise unplanned downtime and extend equipment lifespan, ultimately improving efficiency and reducing costs (Bouabdallaoui *et al.*, 2021). In facilities management, where unexpected equipment failures can lead to significant operational disruptions, predictive maintenance plays a pivotal role (Valinejadshoubi *et al.*, 2022).

The emergence of machine learning (ML) has provided innovative tools to enhance predictive maintenance strategies, enabling more accurate, timely and cost-effective solutions (Ma *et al.*, 2020). ML applications in predictive maintenance mark a paradigm shift from traditional, periodic maintenance approaches to a data-driven, predictive model. By analysing large datasets collected from sensors, operational logs, and historical records, ML algorithms can detect patterns, anticipate potential failures and recommend proactive maintenance activities (Leukel *et al.*, 2021). This transition enhances building system reliability, safety and overall operational efficiency (Teoh *et al.*, 2023).

However, implementing ML-based predictive maintenance in the building services sector presents several challenges. These include the complexity of integrating ML models into existing maintenance frameworks, the availability of high-quality and relevant data and the requirement for expertise in both domain-specific knowledge and ML technologies (Villa *et al.,* 2022). Furthermore, financial constraints pose a challenge, as deploying such technologies requires significant capital and operational investment in data collection, processing and model development (Carvalho *et al.*, 2019).

Recent research has sought to address these challenges, developing frameworks and methodologies for integrating ML techniques into predictive maintenance strategies (e.g., Arsiwala *et al.*, 2023; Nunes *et al.*, 2023). These studies emphasise the need for a comprehensive review of current research trends, methodologies and empirical results related to ML applications in building predictive maintenance.

Despite growing recognition of ML's potential in predictive maintenance, its systematic integration across FM organisations, particularly in building services maintenance, remains underexplored. While previous reviews, such as Carvalho *et al.* (2019) and Scaife (2024), have examined general applications of ML in predictive maintenance, limited research has focused specifically on building facility systems. Furthermore, there is a dearth of empirical studies that have explored the integration of machine learning with predictive maintenance protocols, including the challenges, benefits and operational efficiency improvements. A few studies provide detailed case studies or empirical evidence regarding scalability, implementation processes and quantifiable benefits (e.g., Cheng *et al.*, 2020; Tomé *et al.*, 2023).

This paper aims to bridge this research gap by conducting a bibliometric analysis followed by a semi-systematic review of ML techniques for predictive maintenance in the building sector. To achieve this, the study selects and analyses research articles from Scopus and Web of Science, identifying key trends, applications, and challenges. Moreover, the paper outlines potential future research directions, providing insights for researchers and practitioners in this emerging and evolving research area.

2. Background Study - Predictive Maintenance in Buildings

Predictive maintenance in buildings is a strategic approach aimed at forecasting equipment failures to enable timely maintenance interventions. Unlike preventive maintenance, which relies on scheduled maintenance regardless of the actual condition of systems, predictive maintenance is data-driven and based on real-time monitoring (Madureira *et al.*, 2017). This technique evaluates operational data to identify patterns that indicate impending failures (Flores-Colen and Brito, 2010).

Common predictive maintenance methods include vibration analysis, acoustic monitoring, oil analysis and thermal imaging, each contributing to enhanced system reliability, safety and energy efficiency (Civerchia *et al.*, 2017). Properly maintained equipment operates optimally, reducing unnecessary costs associated with routine maintenance (Cauchi *et al.*, 2017). However, successful implementation requires a deep understanding of the operational characteristics of building systems.

2.1 Machine Learning Techniques

Machine learning, a subset of artificial intelligence, involves training algorithms to analyse data, detect patterns and make predictive decisions with minimal human intervention. ML is transforming building management by improving predictive maintenance capabilities (Yang *et al.*, 2018). Its ability to process large and complex datasets allows for more accurate failure predictions, reducing downtime and improving operational efficiency (Villa *et al.*, 2022).ML techniques consist of various algorithms designed to extract patterns and insights from data.

1. Support Vector Machines (SVM) are used for classification and regression, separating data points using hyperplanes for optimal decision-making (Carvalho *et al.*, 2019).
2. Artificial Neural Networks (ANN) consist of interconnected nodes that process information across layers to make predictions.
3. Deep Neural Networks (DNN) extend ANN by adding multiple hidden layers, enabling the detection of intricate patterns (Bouabdallaoui *et al.*, 2021).
4. Decision Trees (DT) provide a hierarchical structure for classification, segmenting data into branches that lead to predictive outcomes (Carvalho *et al.*, 2019).

Each technique has unique strengths and weaknesses, making them suitable for different applications within predictive maintenance.

2.2 Machine Learning for Predictive Maintenance of Building Services

In the context of building services predictive maintenance, ML techniques analyse operational data to predict impending equipment failures (Cheng *et al.*, 2020). Advanced ML algorithms recognise complex correlations between operational anomalies and potential failures, shifting maintenance strategies from reactive to proactive approaches (Hong *et al.*, 2020). This transition enables facilities managers to schedule maintenance in advance, reducing downtime and extending equipment lifespan. Despite initial implementation challenges, ML-driven predictive maintenance is increasingly recognised for its ability to enhance efficiency and intelligence in smart building management (Carvalho *et al.*, 2019).

3. Methodology

This study employs a mixed-method approach, combining bibliometric analysis with a semi-systematic review of existing research. Bibliometric analysis enables researchers to systematically examine a vast amount of literature, identifying key research trends, influential studies and conceptual frameworks within a specific domain (Oladinrin *et al.*, 2023). This study primarily utilises VOSviewer, a scientific mapping tool that leverages Natural Language Processing (NLP) and clustering algorithms to conduct bibliometric analysis (Orduña-Malea and Costas, 2021). Through co-authorship and co-occurrence analyses, predictive maintenance studies were reviewed under different ML algorithms to identify prevailing research trends and gaps.

3.1 Bibliometric analysis

This study focuses exclusively on predictive maintenance research in buildings that integrates ML techniques to enhance accuracy and efficiency. Firstly, Google Books Ngram Viewer was used to analyse historical trends in the use of the terms “machine learning” (ML) and “predictive maintenance.” Ngram Viewer, which contains a corpus of over five billion digitised books, allows researchers to examine historical keyword frequency in a diachronic context (Zięba, 2018). The analysis revealed that ML experienced exponential growth after 2010, while predictive maintenance remained relatively consistent over time. Based on these trends, a literature review search was conducted considering the peer-reviewed journal articles published from 2010 to 2025 (See Figure 1 below).

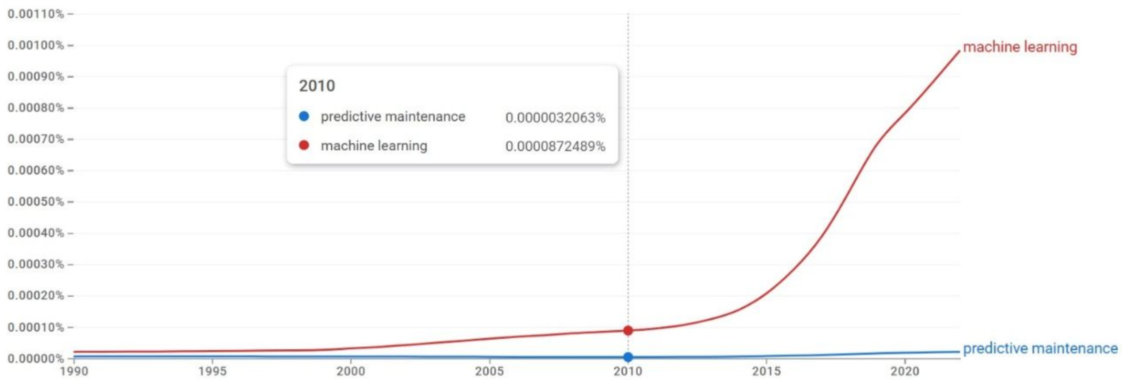

Figure 1 Frequency of the terms “Machine Learning” and “Predictive Maintenance”
Source: Authors’ own work

For bibliometric and systematic analysis, research articles were retrieved from two major academic databases: Scopus and Web of Science. A keyword-based advanced search was conducted using the following query: "Predictive maintenance" AND ("Machine Learning" OR

"ML" OR "Deep Learning" OR "Artificial Intelligence" OR "AI") AND ("Building"). To refine the dataset, additional filtering criteria were applied to select only journal articles, ensuring high-quality and peer-reviewed sources. The filtration process yielded 99 articles from Scopus and 72 articles from Web of Science. To conduct the co-authorship analysis and co-occurrence analysis, the list of shortlisted articles (i.e., RIS files) obtained from Scopus and Web of Science were merged and a combined file was created using the Mendeley software. A duplication analysis was then conducted using Mendeley to eliminate redundancy, resulting in a final dataset of 118 journal articles.

3.1.2 Semi-systematic review

Further, abstracts were manually reviewed to filter empirical studies explicitly related to building services maintenance within Facility Management (FM) systems in buildings, reducing the final dataset to 20 articles. These studies, which represent real-world applications, were systematically reviewed to explore the use of different ML techniques in identifying emerging trends, practical applications, and challenges related to predictive maintenance.

4. Findings

4.1 Co-authorship analysis

The first step of the analysis using VOSviewer software was co-authorship analysis to identify the most influential authors who have published on FM and ML. A total of 431 authors and 118 published documents have been considered for the analysis. The analysis reveals significant fragmentation in research collaboration. Out of 431 identified authors, only 21 exhibit strong network ties, forming three primary clusters of closely linked researchers. Suhatril M. emerges as a central bridging author, facilitating connections across multiple research groups, while Yan G. also demonstrates key collaborative roles (See Figure 2 below). However, a detailed density analysis of the network highlights that many authors remain in isolated clusters, meaning that while they contribute to the field, they lack extensive co-authorship connections.

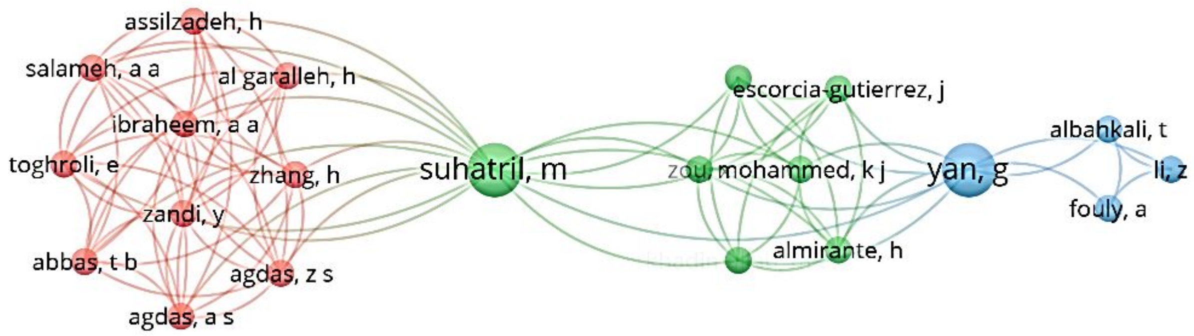

Figure 2 The network of cooperation, based on the co-authorship of the principal authors

Source: Authors' own work

4.2 Co-occurrence analysis

This section analyses the authors' keyword distribution to identify the inter-relationships. The keywords included in the titles, abstracts and keyword sections are considered for this analysis. Keywords that occurred in more than five instances were considered, which resulted in 19 keywords. Figure 3 below visualises the keyword network and its weights. The weight of each keyword is represented by the size of the node and the distance between the two nodes represents the strength of the relationship between the two keywords. Strongly related keywords are indicated with shorter distances. The co-occurrence analysis of predictive maintenance research using machine learning highlights key research themes and their evolving focus over time. The most frequently occurring terms, represented by the largest nodes, include "predictive maintenance", "machine learning", "artificial intelligence", "model" and "framework" confirming a primary research emphasis on ML-driven predictive maintenance strategies. The colour gradient, which represents the evolution of research, shows that earlier studies (2021-2022) were centred around fault detection, strategy and diagnosis, while recent studies (2022-2023) have shifted towards optimisation, digital twins and anomaly detection. Notably, "Internet of Things (IoT)" "Building Information Modelling (BIM)" and "performance" have strong co-occurrence relationships with machine learning and predictive maintenance, emphasising the increasing role of smart building technologies in predictive systems. In particular, deep learning and optimisation appear in the latest research trends, suggesting a continued shift towards advanced computational models for improving predictive maintenance accuracy.

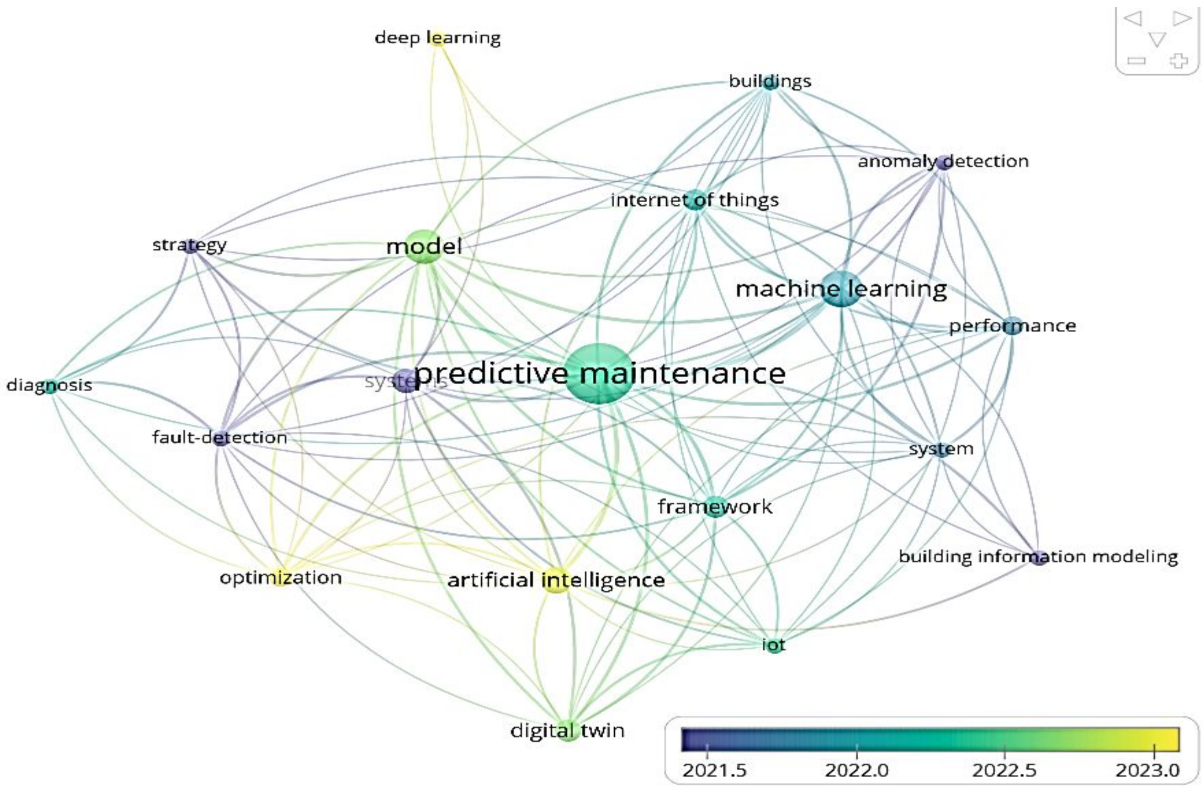

Figure 3 Cluster visualisation map for co-occurring keywords

Source: Authors' own work

4.3 Application of machine learning techniques for predictive maintenance in building services

Table 1 below presents empirical studies and real-world applications where ML techniques were tested or evaluated for predictive maintenance in building systems, including HVAC, energy systems, and control mechanisms. Only studies with clearly defined ML application contexts were included.

Table 1 Empirical evidence on the application of ML for predictive maintenance in building services

Table 1 is attached separately

The most frequently used ML techniques/algorithms for building services predictive maintenance are presented below.

4.3.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) have become a widely used ML approach for predictive maintenance due to their ability to model non-linear time series trends (Cheng *et al.*, 2020). Among early research, Pałasz and Przysowa (2019) applied ANN alongside two other ML techniques to predict heat meter failures. By employing hyperparameter optimisation, the authors improved fault detection efficiency, achieving 95% accuracy. Moreover, Cheng *et al.* (2020) applied ANN for predictive maintenance of MEP components in buildings, utilising data from IoT sensors, BIM models, and FM systems. While this study reported over 96% prediction accuracy, the authors identified a direct correlation between dataset quality and error rates. They further noted that facilities managers need to train new datasets for different MEP components, indicating challenges in model generalisation. In a related study, Hosamo *et al.* (2022) adapted ANN for fault detection in Air Handling Units (AHUs). Their results showed high prediction accuracy; however, the authors concluded that ML technique choice and input data quality significantly affect model performance. The following year, Hosamo *et al.* (2023) expanded on this by developing a predictive maintenance model for HVAC systems. This study integrated BIM, real-time sensor data, occupant feedback and probabilistic models to construct a digital twin. The authors tested nine multiclass classification algorithms for fault prediction, finding that Extreme Gradient Boosting (XGBoost) outperformed ANN with 2.5% higher accuracy. However, ANN remained among the high-performing models, achieving 0.89 precision and 0.88 accuracy.

4.3.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a widely used ML algorithm for predictive maintenance, often integrated with ANN. Researchers such as Cheng *et al.* (2020), Hosamo *et al.* (2022, 2023), and Pałasz and Przysowa (2019) have combined SVM with ANN in their predictive maintenance studies. Yan *et al.* (2014) applied SVM for fault detection and diagnosis (FDD) in chillers, integrating it with an Auto-Regressive Model with Exogenous Variables (ARX). Their results demonstrated that SVM+ARX outperformed a Multilayer Perceptron (MLP) model, achieving 90% accuracy. Expanding on this work, Mulumba *et al.* (2015) refined the system, improving precision to 93.5% and an F1-score of 92.3%, surpassing eight other ML models. Recent studies, including those by Al-Aomar *et al.* (2024), Es-sakali *et al.* (2024) and Amin *et al.* (2024), have further explored SVM in predictive maintenance. However, their results indicate that SVM underperforms compared to advanced ML models such as XGBoost, *K-Nearest Neighbours* (KNN) and Random Forest (RF), which exhibit higher accuracy and computational efficiency.

4.3.3 Deep Neural Network (DNN)

DNNs have emerged as an advanced ML approach in predictive maintenance research. Bouabdallaoui *et al.* (2021) developed a five-step predictive maintenance framework, incorporating data collection, processing, model development, fault notification and model improvement. They employed Long Short-Term Memory (LSTM) networks to detect faults in HVAC systems. However, their study highlighted several challenges, including the scarcity of public datasets, the long-term investment required for profitable solutions, and the need for tailor-made models for different building types. In a more recent study, Chen *et al.* (2024) introduced a lifelong learning approach with deep generative replay, aimed at conserving building energy and reducing emissions. Their results showed a 53.4% increase in accuracy compared to conventional methods, achieving 0.89 accuracy. Additionally, comparisons with SVR, KNN, RF and XGBoost indicated that the proposed approach delivered a 10% to 20% improvement in performance. Furthermore, Iuculano and Babar (2024) examined the potential of LSTM networks in forecasting elevator failures, demonstrating that LSTM models could predict failures up to 60 days in advance. However, no conclusive evidence exists to confirm that DNN consistently outperforms other ML models in predictive maintenance.

4.3.4 Decision Tree (DT) and Random Forest (RF)

Decision Tree (DT) is a widely used ML algorithm for predictive maintenance; however, Trivedi *et al.* (2019) noted that a simple DT model lacks strong predictive power for HVAC fault detection. To enhance prediction accuracy, more advanced models like RF are often preferred. Pałasz and Przysowa (2019) explored different ML models for heater meter failure prediction and implemented Bagging Decision Trees (BDT) as part of an ensemble classifier. Their results demonstrated that BDT outperformed ANN and SVM across multiple performance metrics, including recall, precision and accuracy. Similarly, Al-Aomar *et al.* (2024) examined predictive maintenance for hospital HVAC systems and found that RF models delivered better performance than traditional DT models. However, Hosamo *et al.* (2023) reported that ANN, SVM and RF models performed better than DT in their predictive maintenance study. In another study, Es-sakali *et al.* (2024) developed a predictive maintenance system for refrigerant leaks in Variable Refrigerant Floor (VRF) systems. Their analysis confirmed that RF significantly outperformed DT in fault detection accuracy. Despite these variations in performance, these studies collectively highlight the potential of DT and RF for predictive maintenance applications, while emphasising the superior accuracy of ensemble models like RF over standalone DT models.

4.3.5 K-Nearest Neighbours (KNN)

KNN is a supervised ML algorithm commonly used for fault classification in HVAC systems (Hosamo *et al.*, 2023). Several studies, including Hosamo *et al.* (2023), Es-sakali *et al.* (2024), and Al-Aomar *et al.* (2024), have integrated KNN into predictive maintenance models. While KNN has demonstrated high accuracy, there is no conclusive evidence that it consistently outperforms other ML models in predictive maintenance applications. Bam *et al.* (2024) tested a multi-class classification framework using benchmark HVAC datasets and compared KNN and RF models. Their findings revealed that RF outperformed KNN in both accuracy and computational efficiency, reinforcing the notion that ensemble methods provide superior predictive power.

4.3.6 XGBoost

XGBoost, adopted by Chen and Guestrin (2016), is a high-performance, scalable tree-boosting system widely applied in predictive modeling. Researchers frequently use XGBoost due to its robustness and computational efficiency. For instance, Hosamo *et al.* (2023) concluded that XGBoost outperformed eight other ML models in predictive maintenance for HVAC systems. Similarly, Amin *et al.* (2024) demonstrated that XGBoost effectively predicted maintenance schedules and energy consumption in Active Chilled Beam (ACB) systems, reducing operational downtimes. Moreover, a comparative study by Alijoyo *et al.* (2024) found that XGBoost outperformed Naïve Bayes, RNN, SVM, and LSTM in fault detection for IoT-based smart home networks, further reinforcing its applicability in predictive maintenance.

5. Discussion

With the continuous evolution of ML techniques, research in predictive maintenance of building services has shown exponential growth over the past decade. By 2021, research efforts were concentrated on leveraging IoT connectivity (Gordon, 2021; Dahanayake and Sumanarathna, 2022), transfer learning (Gribbestad *et al.*, 2021) and deep learning models (Berghout *et al.*, 2021; Bouabdallaoui *et al.*, 2021) to develop predictive maintenance frameworks. More recent studies, have shifted towards AI-assisted digital twins (De Donato *et al.*, 2023; Hodavand *et al.*, 2023), Industry 4.0 applications (Mohapatra *et al.*, 2023) and lifelong learning models (Chen *et al.*, 2024), indicating a transition from static predictive maintenance approaches to self-learning, adaptive and real-time predictive maintenance solutions. A recent study by Scaife (2024) highlighted that AI and ML have unlocked new opportunities for remote monitoring, autonomous system control, real-time failure detection and optimised facility operations, reducing dependency on manual inspections and labour-intensive maintenance tasks.

5.1 The role of machine learning in enhancing predictive maintenance

The co-occurrence analysis confirms the strong interdependency between predictive maintenance and ML, with research trends shifting towards optimisation-based models, anomaly detection techniques and deep learning applications. The clustering of keywords suggests that ML is being increasingly integrated with facility management technologies, including BIM, IoT and digital twins, reinforcing the role of smart technologies in predictive maintenance. Optimisation, performance monitoring and AI-driven fault diagnostics have gained prominence in recent studies, indicating a movement toward more efficient and automated predictive maintenance solutions.

The semi-systematic review highlights that a diverse range of ML techniques, including SVM, ANN, DNN, DT, RF, Bayesian Networks (BN), KNN and XGBoost, are widely applied across various FM services. However, not all models yield consistently high performance. DNN models, despite their capability to handle complex patterns, often require large datasets, making them computationally expensive and less adaptable to small-scale FM systems. Similarly, Bayesian Networks provide probabilistic predictions but struggle with high-dimensional data. Decision Tree-based models (DT, RF and BDT) offer robust classification capabilities, yet their interpretability and scalability remain challenging in high-frequency predictive maintenance tasks.

A particularly notable finding from the review is the consistent outperformance of XGBoost over other ML models. Hosamo *et al*. (2023) found that XGBoost outperformed eight other ML models in HVAC system predictive maintenance, demonstrating superior precision and accuracy. Similarly, Amin *et al*. (2024) showed that XGBoost effectively predicted maintenance schedules and energy consumption in Active Chilled Beam (ACB) systems, minimising downtime and optimising energy efficiency. Alijoyo *et al.* (2024) conducted a comparative study and concluded that XGBoost performed better than other well-established ML techniques, such as Naïve Bayes, SVM, RNN and LSTM, particularly in fault detection for IoT-based smart home networks. These findings suggest that XGBoost is emerging as a leading model for fault classification, anomaly detection and predictive maintenance optimisation in smart building applications.

5.2 Challenges in research collaboration

Despite the growing significance of ML in predictive maintenance, the co-authorship analysis reveals a lack of global collaboration among researchers. The findings indicate that only 21 out of 431 authors have strong co-authorship ties, suggesting that research in this domain remains highly fragmented. Instead of forming a globally connected research network, authors appear to be working in isolated clusters, often focusing on region-specific applications of ML in predictive maintenance. This lack of cross-disciplinary collaboration may be hindering the development of standardised ML-driven maintenance frameworks, limiting the scalability and practical implementation of predictive maintenance models across different FM organisations and systems. A key reason for this disconnected research landscape is that highly influential researchers specialising in both predictive maintenance and ML have yet to emerge.

Establishing interdisciplinary research collaborations is crucial for advancing predictive maintenance technologies and ensuring their widespread adoption across industries.

The fragmented nature of current research collaboration has important implications for both the quality and future direction of work in this area. When researchers operate in isolated clusters, it can lead to duplicated efforts, inconsistent methods, and missed opportunities to explore emerging or underdeveloped topics (Ucar *et al.,* 2024). It also makes it more difficult to establish common standards around ethical considerations or to influence policy decisions through collective evidence (Pinheiro *et al.*, 2021; Rane *et al.*, 2024). As a result, the potential for these research efforts to be translated into commercially viable systems or tools becomes limited, particularly where practical deployment and industry adoption are concerned. To help address these issues, future research should prioritise cross-disciplinary and cross-institutional collaboration, encourage the development and sharing of open datasets, and adopt consistent evaluation approaches (Rane *et al.*, 2024). Hence, these steps would support more robust and transferable findings and contribute to a more coherent research agenda for predictive maintenance in building services.

6. Conclusion

This study explores research trends in building services predictive maintenance and machine learning through bibliographic analysis and a semi-systematic literature review, examining 118 journal articles. The findings, categorised under co-authorship and co-occurrence analyses, reveal significant advancements post-2021, demonstrating the increasing role of ML in predictive maintenance strategies. While research has predominantly focused on developing novel ML-based predictive maintenance frameworks, there is still a gap in practical implementation within the FM industry.

Beyond academic contributions, future research should prioritise real-world applications by establishing structured implementation strategies for integrating ML models into FM workflows. This includes developing standardised guidelines, conducting case studies across diverse building environments and creating cost-effective solutions tailored for small to medium-sized enterprises (SMEs). Furthermore, XGBoost and other high-performing ML algorithms should be further explored due to their proven effectiveness in predictive maintenance tasks.

In particular, the integration of Digital Twins and Generative AI models presents a transformative opportunity to enhance automation, adaptability and energy efficiency in predictive maintenance. Future research should also align with sustainability goals and Net-zero carbon policies, ensuring that ML-driven predictive maintenance solutions contribute to resource optimisation and long-term environmental impact reduction. Strengthening global research collaborations and interdisciplinary knowledge sharing will be essential in overcoming current research fragmentation and standardising ML-based predictive maintenance frameworks for scalable, real-world adoption.

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Table 1 Empirical evidence on the application of ML for predictive maintenance in buildings

ML Techniques Used	Predictive Maintenance Function	Summary of Contributions	References
SVM, DT, KNN, SARIMA	Predictive maintenance for HVAC system in hospitals	A data-driven predictive maintenance model for hospital HVAC systems, using real-time sensor data for fault detection and long-term condition forecasting.	Al-Aomar *et al*. (2024)
DT, RF, KNN, SVM	Predictive maintenance and fault detection for VRF HVAC systems	An AI-driven predictive maintenance system to anticipate refrigerant leaks in VRF systems, leveraging advanced fault detection and diagnosis strategies.	Es-sakali *et al*. (2024)
Semi-Supervised Learning, Anomaly Detection	Fault detection on fire alarm systems	An online anomaly detection approach for fire alarm systems, utilising machine learning techniques to predict sensor failures and improve maintenance schedules.	Tomé *et al*. (2023)
ARX, SVM	Fault detection and diagnosis for chillers	Combines ARX models and SVM for enhanced fault detection in chiller systems, reducing false alarm rates and improving maintenance scheduling.	Yan *et al*. (2014)
XGBoost, SVM, ANN	Predictive maintenance for Active Chilled Beam (ACB) systems	Uses XGBoost and ML models to predict maintenance schedules and energy consumption in Active Chilled Beam (ACB) systems.	Amin *et al*. (2024)
ANN, SVM	Predictive maintenance of MEP components in buildings	A data-driven predictive maintenance framework using BIM and IoT, with ML models for condition forecasting.	Cheng *et al*. (2020)
Autoencoders	Fault diagnosis and predictive maintenance for HVAC	Utilizes deep learning autoencoders for predictive maintenance in HVAC systems, focusing on health prognostics for system efficiency.	Tian *et al*. (2023)
Gaussian Mixture Model, Isolation Forest, Local Outlier Factor	Novelty detection for predictive maintenance	A methodology for extrapolation detection in building energy models to validate ML models' performance.	Rätz *et al*. (2024)
DL, IoT	Energy efficiency and predictive maintenance in older buildings	A deep learning-enhanced IoT-based energy monitoring system for retrofitting older buildings, optimising energy consumption and predicting faults.	Arun *et al*. (2024)
Lifelong Learning, Deep Generative Replay	Dynamic and adaptive predictive maintenance for net-zero energy buildings	A lifelong learning model with deep generative replay to enhance predictive maintenance strategies for energy-efficient buildings.	Chen *et al*. (2024)
ML, Anomaly Detection, Autoencoders	Predictive maintenance for building HVAC systems	An ML-based approach for predictive maintenance, utilising autoencoders for fault detection in HVAC components.	Bouabdallaoui *et al*. (2021)
ANN, SVM DT	FDD of air handling units	A digital twin predictive maintenance framework for Fault detection and diagnosis (FDD) in air handling units	Hosamo *et al*. (2022)

BN, ANN, SVM, DT, KNN, RF, MLP, GB and XGBoost (XGB)	FDD of HVAC / predictions on comfort levels	Integrates Bayesian networks and digital twins to enhance predictive maintenance strategies, improving occupant comfort in HVAC systems.	Hosamo *et al.* (2023)
SVM, ARX	Fault detection and diagnosis in air handling units	Combines ARX models and SVM for enhanced fault detection in air handling units, ensuring optimal maintenance strategies.	Mulumba *et al.* (2015)
Artificial Intelligence, IoT, Cloud Computing	Smart grid energy management and predictive maintenance	An AI-driven IoT-based framework for smart grid energy management, integrating predictive maintenance strategies.	Ferrández-Pastor *et al.* (2019)
ANN, Bagging Decision Tree (BDT), (SVM)	Predictive maintenance for smart heating systems	Utilizes ML models with hyperparameter optimisation and ensemble learning to predict failures in heat meters for smart buildings.	Pałasz and Przysowa (2019)
RF, KNN	Fault detection and severity estimation for chillers and air handling units	A multi-class classification ML framework for predictive maintenance in HVAC systems, using benchmark datasets.	Bam *et al.* (2024)
IoT, AI, ML	Dynamic predictive maintenance for heritage and smart buildings	An AI-driven predictive maintenance system for optimising monitoring and planning strategies in historic and smart city infrastructures.	Pacifico *et al.* (2024)
LSTM	Predicting elevator breakdowns	Uses LSTM to analyse monitoring data for elevator failure prediction, reducing downtime and improving safety.	Iuculano and Barbar (2024)
XGBoost, FO	Predictive maintenance in Zigbee-enabled smart home networks	An AI-powered fault detection model using XGBoost and Firefly Optimisation for IoT-based smart home networks.	Alijoyo *et al.* (2024)

Source: Authors' own work

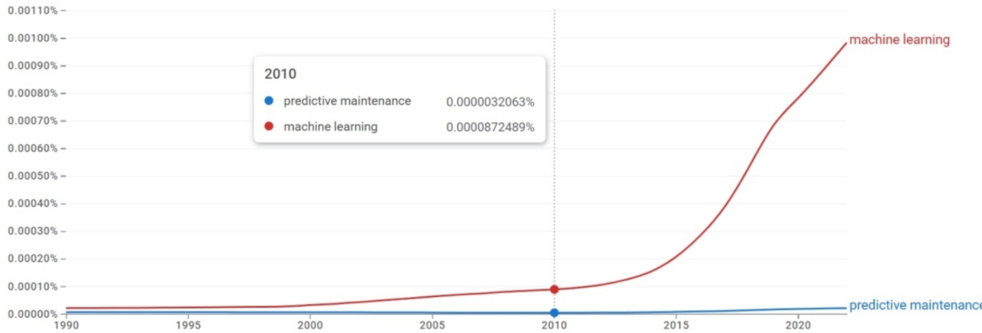

Figure 1 Frequency of the terms “Machine Learning” and “Predictive Maintenance”

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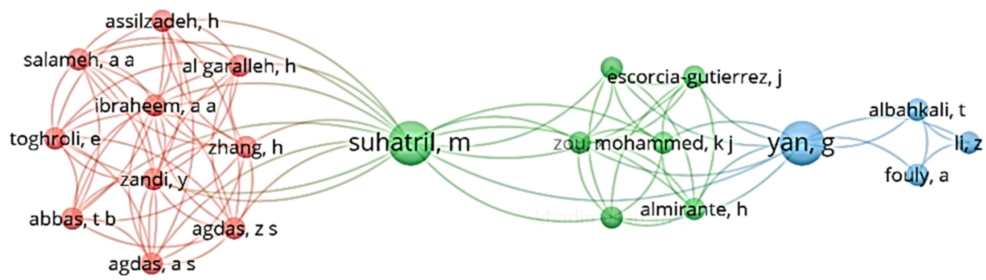

Figure 2 The network of cooperation, based on the co-authorship of the principal authors

404x136mm (87 x 87 DPI)

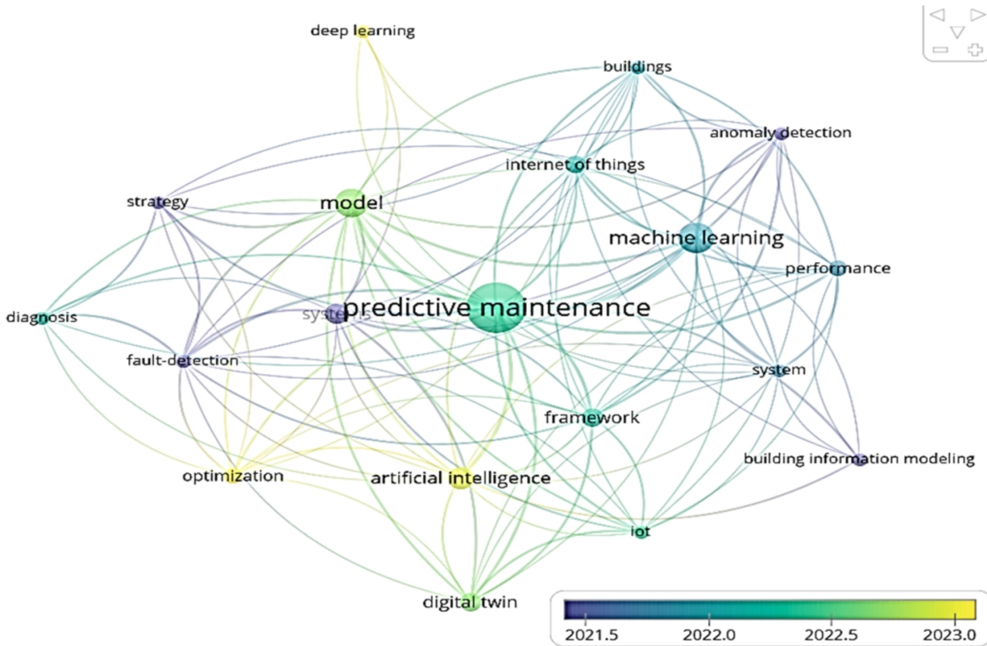

Figure 3 Cluster visualisation map for co-occurring keywords

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