Machine Learning Techniques for Building Predictive Maintenance: A Review

Adhikari, A.[1], Karunaratne, T.[2], & Sumanarathna, N.[3]

[1] School of Applied Management, University of Westminster
[2] School of Architecture, Technology and Engineering, University of Brighton
[3] School of the Built Environment, London Metropolitan University
Contact: a.adhikari2@westminster.ac.uk

ABSTRACT

Background and aim. Proper maintenance is crucial for ensuring the sustainable use of building systems and equipment throughout their life cycles. Predictive maintenance strategies aim to minimise unplanned downtime and improve equipment lifespan, but their implementation is complex. Machine learning (ML), on the other hand, offers a novel solution for making systematic predictions across various disciplines. This review analyses the interrelationships between predictive maintenance and ML techniques to identify current research trends and potential areas for further study.

Methodology. A bibliographic analysis was conducted on a sample of 102 journal articles with VOSViewer. Key topics generated by co-occurrence analysis were then discussed semi-systematically, focusing on the most popular predictive maintenance applications and ML techniques.

Results. The results show a distinct relationship between the two terms, yet co-author analysis reveals a lack of global collaboration among authors. Additionally, Support Vector Machines, Artificial Neural Networks, Deep Neural Networks, Decision Trees, Random Forests, Bayesian Networks, and K-nearest neighbours are found to be the most frequently used ML techniques.

Originality. The study recognises the current research trends and provides future research implications. This study highlights the importance of adopting ML for predictive maintenance to achieve sustainability and NetZero carbon policy goals, which have not been explicitly addressed before.

Practical or social implications. The recommendations of this research broaden the scope of predictive maintenance studies. Emphasising collaborations between authors, institutions, and countries could significantly enhance research output in Facilities Management and Building Life Cycle.

Type of paper. Research (full)

Keywords. Bibliometric analysis, Machine learning, Predictive maintenance

INTRODUCTION

Predictive maintenance has emerged as a key strategy in the sustainable management and operation of building systems and equipment, aiming to proactively identify maintenance needs before failures occur, leading to minimised unplanned downtime and extended equipment lifespan (Bouabdallaoui et al., 2021). This strategy is pivotal in the context of facilities management, where the impact of unexpected equipment failures is crucial (Valinejadshoubi et al., 2022). Recent advancements in machine learning (ML) have offered promising new tools which can be adapted to enhance predictive maintenance efforts, facilitating accurate, timely, and cost-effective solutions (Ma et al., 2020).

The application of ML in predictive maintenance represents a combination of data analytics and operational technology. This is a paradigm shift from traditional, periodic maintenance approaches to one that is data-driven and predictive in nature. ML algorithms can analyse large data sets from various sources, such as sensors and operation logs, to detect trends, predict potential failures, and propose maintenance activities proactively (Leukel et al., 2021). This shift enhances the reliability and safety of building systems while improving operational efficiency (Teoh et al., 2023).

However, the implementation of ML-based predictive maintenance in the building sector is not straightforward. The possible challenges include the complexity of integrating ML algorithms into existing maintenance frameworks, the accessibility to high-quality, relevant data, and the requirement for expertise in both domain-specific knowledge and ML technologies (Villa et al., 2022). Additionally, there are concerns about the funds for deploying such technologies, particularly regarding capital and the operational costs associated with data collection, processing, and analysis (Carvalho et al., 2019). Recent studies have focused on addressing these challenges, proposing frameworks and methodologies for integrating ML techniques into predictive maintenance strategies (Arsiwala et al., 2023; Nunes et al., 2023). These studies emphasise the need for a systematic review of current research trends, methodologies, and results related to the application of ML in building predictive maintenance.

ML plays a crucial role in improving predictive maintenance by analysing large datasets to anticipate equipment failures and schedule preventive actions, reducing downtime and costs. Despite growing recognition of ML's advantages, its systematic integration across industries remains underexplored. Few systematic reviews, such as Carvalho et al. (2019) and Scaife (2024). However, there has been a lack of studies that have considered building facility systems. Moreover, existing literature highlights gaps in understanding the synergistic effects of ML integration with predictive maintenance protocols, including challenges and benefits. Limited research explores the collective impact on operational efficiency and reliability, with few detailed case studies or empirical evidence on implementation processes, scalability, and quantifiable benefits.

This paper aims to fill this gap by conducting a Bibliometric analysis of the literature followed by a semi-systematic review of ML techniques for predictive maintenance in the building sector. For this purpose, the analysis has been conducted by selecting articles from Scopus and Web of Science. The study identifies key trends, applications, and challenges in this emerging field. Moreover, it recommends potential future research areas for authors to consider.

PREDICTIVE MAINTENANCE IN BUILDINGS

Predictive maintenance in buildings is a strategic approach that focuses on predicting how and when building equipment could fail, allowing maintenance to be carried out at the optimum time to prevent failure. Predictive maintenance is distinct from preventive maintenance, which relies on routine or scheduled maintenance, regardless of the actual condition of the equipment (Madureira et al., 2017). Predictive maintenance techniques typically involve monitoring and evaluating the operational data of building systems to identify trends that signal impending equipment failure (Flores-Colen & Brito, 2010).

Vibration analysis, acoustic monitoring, oil analysis, and thermal imaging are some of the well-known predictive maintenance techniques (Civerchia et al., 2017). The applications of predictive maintenance are commonly used in various building systems. The advantages of adopting such a maintenance strategy are profound, resulting in greater reliability, improved safety, and extended asset life. Moreover, this approach contributes to energy savings, as optimally maintained equipment operates more efficiently and prevents the unnecessary costs of scheduled maintenance when it is not required (Cauchi et al., 2017). Implementing predictive maintenance in buildings requires an in-depth understanding of the operational characteristics of each building equipment.

MACHINE LEARNING TECHNIQUES

ML, a subset of artificial intelligence, involves training computers to learn from data, identify patterns, and make decisions with minimal human intervention. ML has made significant advances in various fields, and its application in building management is upgrading predictive maintenance strategies (Yang et al., 2018). ML's capacity to process substantial amounts of complex data and learn from it results in high accuracy predicted outcomes (Villa et al., 2022). ML techniques consist of various algorithms designed to extract patterns and insights from data. Among them, Support Vector Machines (SVM) are effective for classification and regression tasks, separating data points using hyperplanes to maximise margins, and Artificial Neural Networks (ANN), on the other hand, consist of interconnected nodes that process information through layers to make predictions (Carvalho et al. 2019). Deep Neural Networks (DNN) extend ANN's capabilities with multiple hidden layers, enabling them to learn intricate patterns and hierarchies in data (Bouabdallaoui et al., 2021). Decision Tree (DT) ML algorithm is used for prediction-based regression or classification. Each node of the tree represents a decision, and based on a feature, different branches are created until a prediction is made at the leaf nodes (Carvalho et al., 2019). Each of these techniques has unique strengths and weaknesses, making them suitable for different applications within the realm of ML.

MACHINE LEARNING AND PREDICTIVE MAINTENANCE IN BUILDINGS

In the context of predictive maintenance in buildings, ML techniques analyse operational data from various building systems to predict equipment failures (Cheng et al., 2020). By employing advanced algorithms, ML can recognise sophisticated patterns that correlate specific conditions or anomalies with impending equipment failures. This allows for a proactive approach to maintenance, where actions are taken based on predictions of what might happen rather than reacting to what has already occurred (Hong et al., 2020). These predictions allow facility managers to schedule maintenance proactively while minimising downtime and extending equipment life. Nevertheless, the benefits outweigh the requirements and drive the adoption of ML in smart building management, leading to a new era of efficiency and intelligence in building operations (Carvalho et al., 2019).

RESEARCH METHODOLOGY

This study adopts a mixed method of bibliographic analysis and a semi-systematic analysis of existing research as the research methodology. Bibliographic analysis allows researchers to extract the essence of a considered research domain by analysing a large amount of data (Oladinrin et al., 2023). Primarily, VOSviewer is utilised to analyse the data. VOSviewer is a scientific mapping system that utilises features such as Natural Language Processing (NLP) and clustering algorithms to perform bibliometric analysis tasks (Orduña-Malea & Costas, 2021). Following the co-authorship and co-occurrence analyses, predictive maintenance studies were reviewed under different ML algorithms.

Data Collection

This study focuses only on the research on building predictive maintenance that incorporates ML for improved accuracy and efficiency. Initially, Google Books Ngram Viewer was utilised to analyse the historical trend of both terms. Ngram Viewer is a corpus of over 5 billion digitalised books that allow users to analyse historical data on keyword frequency in a diachronic context (Zięba, 2018). The term ML had exponential growth after 2010, and the term 'predictive maintenance' maintained a consistent phase throughout. Hence, the literature search was conducted from 2010 to 2024. Sources for bibliographic analysis and systematic analysis were extracted from two major databases, Scopus and Web of Science. Then, a keyword search was conducted using the advanced search method of each database using keywords such as "Predictive maintenance" AND ("Machine Learning" OR "ML" OR "Deep Learning" OR "Artificial Intelligence" OR "AI") AND ("Building" OR "Construction"). The results are further refined by adopting the keywords to filter the journal articles and reviews. The filtration process resulted in 83 articles through Scopus and 75 articles in Web of Science journals. Subsequently, a manual duplication analysis was conducted to remove duplicate articles, which resulted in 102 articles for bibliographic analysis and systematic analysis. The articles were further analysed to extract the studies conducted on FM systems of buildings, which resulted in 16 articles. These articles were reviewed under different ML techniques.

RESULTS

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 Facilities Management and ML. A total of 351 authors and 102 published documents have been considered for the analysis. Based on the number of publications, Hosamo H.H., Nielsen H.K., Svennevig P.R., and Svidt K. ranked as the top four publishing authors. Based on the number of citations, Chen K., Chen W., Cheng J.C.P. and Wang Q. ranked top, scoring 235 citations for each. However, there is no common topper based on both indicators. Ashari A. from the Khalifa University of Science & Technology, Abu Dhabi, UAE, ranked among the top 10 from both indicators by publishing two documents and scoring 230 citations. The VOSviewer software facilitates the visual representation of author relationships. As Figure 1 indicates, only 11 authors out of 351 have strong collaborative relationships with each other.

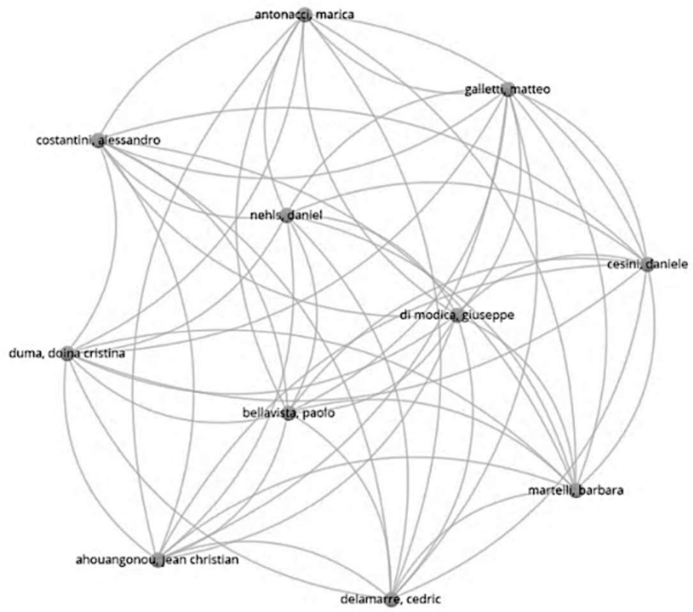

Figure 1 The network of cooperation, based on the co-authorship of the principal authors

Co-occurrence analysis

This section analyses the author's 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 35 keywords.

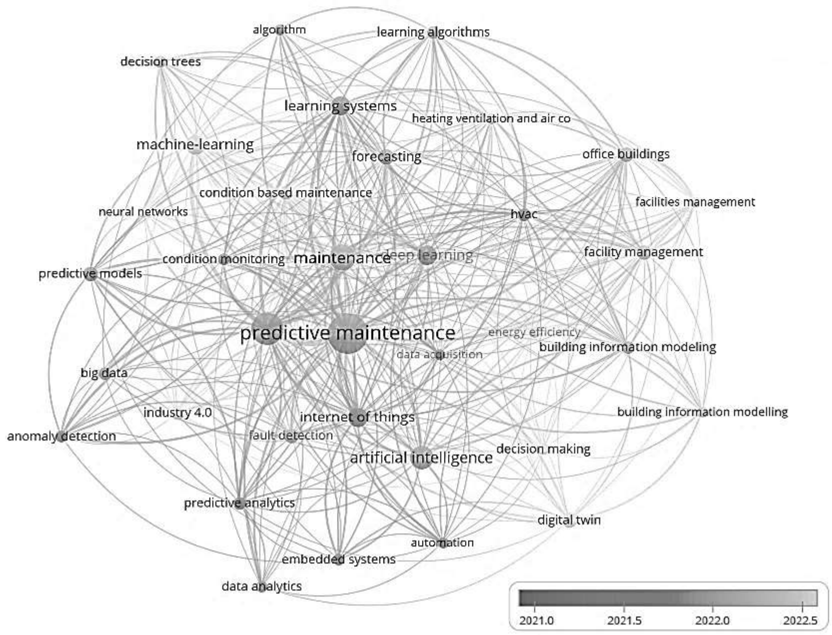

Figure 2 Cluster Visualization Map for co-occurring keywords

Among the top 10 keywords, 'Predictive Maintenance' occurred 64 times, while 'machine learning' occurred in 57 instances. Terms 'maintenance', 'internet-of-things' and 'learning systems' are also positioned among the top 10. Figure 2 visualises the keyword network and its weights. The weight of each keyword represents 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. Moreover, the keywords are clustered and visualised in different colours. VOSviewer generated four main clusters for the given dataset, with the Red cluster being the most prominent. The Red cluster includes terms such as predictive maintenance, artificial intelligence, internet of things, and condition-based maintenance. Moreover, the second cluster is Blue (Machine learning, predictive models, forecasting), the third cluster is Yellow (maintenance, deep learning, predictive analytics), and the fourth is Green (Building information modelling, facilities management, digital twin, energy efficiency).

Since 2021, there has been an increase in these areas. The incorporation of terms such as 'Anomaly detection', 'Predictive analytics', 'Internet of things', and 'Embedded systems' are visible in early 2021. With the rapid growth of ML techniques and the substantial consideration of sustainability, by 2022, the research interests expanded to include concepts such as 'Digital twins', 'Neural networks', 'Industry 4.0', 'Energy efficiency' and 'Facilities management'. Components of ML and predictive maintenance can be seen throughout the considered period.

Application of machine learning techniques for predictive maintenance in buildings

Table 1 presents the description of each study, FM task(s)/functions(s) focused in each study, ML applications or techniques used and author details. The most frequently used ML techniques/algorithms for building predictive maintenance are discussed next.

ARTIFICIAL NEURAL NETWORK: Among the articles considered for this review, Cheng et al. (2020) employed ANN for predictive maintenance of MEP components in buildings using data obtained from IoT sensors, BIM models, and the FM system. Moreover, Hosamo et al. (2022) conducted a similar study, adapting ANN for fault detection in Air Handling Units. The results demonstrated high prediction accuracies; however, the authors concluded that prediction accuracy depends on the type of ML technique and the quality of input data. The following year, Hosamo et al. (2023) conducted another study for predictive maintenance in HVAC systems, utilising different ML techniques. The study integrated BIM, real-time sensor data, occupant feedback, and probabilistic models to create a digital twin and employed nine multiclass classification algorithms for predicting faults. The results suggested that ANN performs better compared to other models. Finally, Pałasz and Przysowa (2019) employed ANN and two other ML techniques to predict heat meter failures. The authors improved fault detection efficiency by using hyperparameter optimisation, reaching 95%. It is evident that ANN is frequently adopted for predictive maintenance in various FM systems.

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

Description	Predictive maintenance Task(s)/ function(s)	ML techniques used	References
An ML-based framework to predict the future condition of MEP components for maintenance planning	Condition monitoring and fault alarming; condition assessment; condition prediction; maintenance planning.	ANN, SVM	Cheng et al. (2020)
A digital twin predictive maintenance framework for Fault detection and diagnosis (FDD) in air handling units	FDD of air handling units	ANN, SVM DT	Hosamo et al. (2022)
A combination of time-series modelling and ML techniques to develop an efficient fault detection for chillers	FDD of building management system	SVM	Yan et al. (2014)
A model-based fault diagnosis method for HVAC system	FDD of HVAC system	SVM	Mulumba et al. (2015);
ML-based anomaly detection methods to vertical plant wall systems to enhance predictive maintenance for the indoor climate	FDD for vertical plant wall systems / predictive maintenance for the indoor climate	NN	Liu et al. (2020)
Predictive Maintenance of the HVAC system	Prediction failures of HVAC	DNN	Bouabdallaoui et al. (2021)
Predict building occupants' complaints regarding thermal conditions	Predict building performance (Indoor cooling)	Multi-Layer Perception (MLP)	Assaf and Srour (2020)
To detect and predict HVAC issues	FDD of HVAC / predictions on comfort levels	Comfort analysis: Bayesian Networks (BN) Fault detection strategy: ANN, SVM, DT, KNN, RF, MLP, GB and XGBoost (XGB)	Hosamo et al. (2023)
To conduct fault diagnostics and predict remaining useful life estimation	Building performance	Similarity-based model	Schwartz et al. (2022)
Design of advanced heating systems for smart buildings and optimisation of stocks and maintenance processes in existing heat meter networks	Optimise heating systems; enhance the energy efficiency of buildings	SVM, ANN, and Bagging Decision Trees (BDT); Ensemble classifier	Pałasz and Przysowa (2019)
Maintenance scheduling for hospital buildings	Maintenance scheduling	Hierarchical and -means clustering algorithms	Ahmed et al. (2022)
To predict failures of smoke detectors	Prediction of potential failures of Fire alarm/smoke detectors	Autoencoder (AE) algorithm	Sousa Tomé et al. (2023)
To maintain the functionality and extend the lifetime of HVAC of hospital buildings/ operational effectiveness	Predictive maintenance of the HVAC system with a focus on the Air Handling Units	SVM, DT and KNN; Prephet forecasting and SARIMA	Al-Aomar et al. (2024)
Predictive maintenance of air conditioning systems using supervised machine learning	Fault detection (i.e., gas leakage and capacitor malfunction) of HVAC system	DT	Trivedi et al. (2019)
A new framework is introduced to optimise predictive maintenance of the HVAC system	Predictive maintenance for HVAC system	An autoencoder and a Neural Network (NN)	Tian et al. (2023)
A novel deep-learning-based method to conserve energy and mitigate emissions in building energy systems	Optimise building energy systems	DNN	Chen et al. (2024)

SUPPORT VECTOR MACHINE: Similar to ANN, SVM is a common ML algorithm used in predictive maintenance functions. Researchers such as Cheng et al. (2020), Hosamo et al. (2022), Hosamo et al. (2023), and Pałasz & Przysowa (2019) have employed SVM alongside ANN in their studies. Yan et al. (2014) also conducted a fault detection and diagnosis (FDD) study on chillers using SVM. They investigated five faults: 1. Reduced condenser water flow (F1), 2. Reduced evaporator water flow (F2), 3. Condenser fouling (F3), 4. Non-condensables in refrigerant (F4), and 5. Refrigerant leak (F5) by utilising existing FDD techniques and the proposed SVM approaches. The results indicate a significant improvement in accuracy and a reduction in false alarms. Another FDD study conducted by Mulumba et al. (2015) concluded that the SVM-based approach outperformed traditional methods in terms of performance evaluation metrics such as precision, recall, and F-measure.

DEEP NEURAL NETWORK: DNN is one of the most advanced ML algorithms used in predictive maintenance research in the recent past. Bouabdallaoui et al. (2021) proposed a five-step predictive maintenance framework, including data collection, processing, model development, fault notification and model improvement. The authors developed an LSTM (Long-short Term Memory) network to train the collected data and detect faults in HVAC systems. The authors have identified several challenges from the study, such as the scarcity of public datasets, long-term investments in building profiTable solutions and developing a tailor-made solution for different building types. Additionally, a recent study conducted by Chen et al. (2024) proposed a novel lifelong learning method with deep generative replay to conserve building energy and mitigate emissions. The results indicated a 53.4% increase in accuracy compared to the standard methods, which reached 0.89. A comparison study with other ML techniques, such as SVR, KNN, RF and XGBoost, suggested a 10% to 20% performance enhancement of the proposed method.

BAYESIAN NETWORK: Hosamo et al. (2023), in their study, developed a digital twin framework to predict comfort performance evaluation of building occupants and automated fault detection. The Bayesian Network model served the former purpose, predicting comfort performance based on a probabilistic approach. The model has been developed using Python box in Dynamo. Information such as building features, HVAC readings, occupancy density, etc., were considered data.

K-NEAREST NEIGHBOURS: Followed by an in-depth analysis based on the Bayesian Network model regarding building occupants' comfort level in indoor environments, Hosamo et al. (2023) trained several ML models (as the digital twin framework) for automatic fault detection of the HVAC system; KNN is one of them. KNN is a supervised ML technique that classifies the types of faults in the HVAC system. However, the authors found that another ML technique, the Extreme Gradient Boosting (XGB) algorithm, provided the most accurate predictions. Furthermore, Random Forest delivered the fastest outcome in their study. Similarly, in their recent study, Al-Aomar et al. (2024) developed a KNN ML model, in addition to different ML models, to predict the maintenance of the HVAC system in a hospital building focusing on AHU units.

DECISION TREE AND RANDOM FOREST: As explained by Trivedi et al. (2019), in their study on predicting faults of the HVAC system, a simple DT model does not have a good predicting power. Hence, enhanced methods such as Random Forest should be adopted to improve the prediction accuracy. Pałasz and Przysowa's (2019) study on the optimisation of heater meters shows the empirical evidence on different ML models predicting failures of heater meters. A Bagging Decision Tree (BDT) is one of the ML techniques used to develop the ensemble classifier. BDT is derived by training multiple DTs on different subsets independently. The final prediction (classification) is obtained by considering the majority of predictions of all trees.

DISCUSSION

With the advancement of ML techniques over the years, predictive maintenance research has also shown rapid growth. By the year 2021, the study focused on utilising concepts such as 'Internet of Things' (Gordon, 2021), 'Transfer learning' (Gribbestad et al., 2021), and 'Deep Learning' (Berghout et al., 2021; Bouabdallaoui et al., 2021) for various predictive maintenance applications. More recent research focused on the latest applications such as 'AI-assisted Digital Twins' (De Donato et al., 2023; Hodavand et al., 2023), 'Industry 4.0' (Mohapatra et al., 2023) and 'Lifelong Learning' (Chen et al., 2024). A recent study by Scaife (2024) revealed that AI and ML generate opportunities to conduct remote monitoring, fully automated control of facility systems, immediate awareness of emergent conditions and accurate predictive maintenance operations with minimal labour.

Moreover, the analysis reveals a strong correlation between predictive maintenance and ML. Yet, there is a lack of collaboration among authors around the globe. The reason might be that influential authors fluent in predictive maintenance and ML areas have yet to emerge. Researchers have recognised that this research area is new and significantly impacts achieving sustainability goals (Cardoso et al., 2023).
From the semi-systematic review conducted on the empirical studies focused on predictive maintenance in buildings, ML techniques such as SVM, ANN, DNN, DT RF, BN, and KNN are found to be the most frequently used in the context of different FM services. Each ML technique has strengths and weaknesses in predictive maintenance tasks such as fault diagnostics, detection, and optimisation. DNN is commonly employed and demonstrates high prediction accuracies. DNN offers advanced capabilities but faces challenges such as data scarcity. BN provide probabilistic predictions, while DT-based methods like Random Forest and BDT enhance classification-based prediction accuracy. The choice of technique depends on factors such as the nature of the data, specific application requirements, and available resources. Based on the findings of this study, it is recommended that researchers need to focus on integrating Digital Twins and Generative ML algorithms to enhance the energy efficiency and automation of the predictive maintenance processes (van Dinte et al., 2022).

CONCLUSIONS

This study examines the research trends in predictive maintenance and ML through bibliographic analysis and semi-systematic literature review. Results from analysing 102 journal articles are categorised under Co-authorship and Co-occurrence analysis in the Results section. The findings highlight significant advancements and increasing research interest post-2021, emphasising ML's crucial role in enhancing predictive maintenance strategies. Beyond academic relevance, there is a need to evaluate the practical application of these technologies in the Facility Management (FM) industry. ML's predictive capabilities can optimise resource allocation, minimise downtime, and extend the lifespan of building systems. Future research should focus on practical implementation strategies to advance FM practices, including clear guidelines for integrating ML into FM workflows, case studies in diverse building environments, and cost-effective solutions for small to medium-sized enterprises. Additionally, integrating Digital Twins and Generative ML algorithms can enhance energy efficiency and automation, while research should align with sustainability goals and Net-zero carbon policies.

REFERENCES

Ahmed, R., Nasiri, F., & Zayed, T. (2022). Two-stage predictive maintenance planning for hospital buildings: a multiple-objective optimization-based clustering approach. *Journal of Performance of Constructed Facilities*, *36*(1), 04021105. https://doi.org/10.1061/(ASCE)CF.1943-5509.0001691.

Al-Aomar, R., AlTal, M., & Abel, J. (2024). A data-driven predictive maintenance model for hospital HVAC system with machine learning. *Building Research & Information*, *52*(1-2), 207-224. https://doi.org/10.1080/09613218.2023.2206989.

Arsiwala, A., Elghaish, F., & Zoher, M. (2023). Digital twin with Machine learning for predictive monitoring of CO2 equivalent from existing buildings. *Energy and Buildings*, *284*. https://doi.org/10.1016/j.enbuild.2023.112851

Assaf, S., & Srour, I. (2021). Using a data driven neural network approach to forecast building occupant complaints. *Building and Environment*, *200*, 107972. https://doi.org/10.1016/j.buildenv.2021.107972.

Berghout, T., Mouss, L.-H., Bentrcia, T., Elbouchikhi, E., & Benbouzid, M. (2021). A deep supervised learning approach for condition-based maintenance of naval propulsion systems. *Ocean Engineering*, *221*. https://doi.org/10.1016/j.oceaneng.2020.108525

Bouabdallaoui, Y., Lafhaj, Z., Yim, P., Ducoulombier, L., & Bennadji, B. (2021). Predictive maintenance in building facilities: A machine learning-based approach. *Sensors (Switzerland)*, *21*(4), 1–15. https://doi.org/10.3390/s21041044

Cardoso, A., Oliveira, J., Neto, D., Fernandes, M., Petrella, L., Henriques, J., Gil, P., Silva, C., Ribeiro, B., Hilliger, B., Hilliger, B., & Rebahi, Y. (2023). Technical Components Integration Using APIs for Predictive Maintenance in the Context of Industry 4.0 Digital Transformation. In *Lecture Notes in Networks and Systems: Vol. 763 LNNS*. https://doi.org/10.1007/978-3-031-42467-0_89

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers and Industrial Engineering*, *137*. https://doi.org/10.1016/j.cie.2019.106024

Cauchi, N., Macek, K., & Abate, A. (2017). Model-based predictive maintenance in building automation systems with user discomfort. *Energy*, 138, 306–315. https://doi.org/https://doi.org/10.1016/j.energy.2017.07.104

Chen, S., Ge, W., Liang, X., Jin, X., & Du, Z. (2024). Lifelong learning with deep conditional generative replay for dynamic and adaptive modeling towards net zero emissions target in building energy system. *Applied Energy*, *353*. https://doi.org/10.1016/j.apenergy.2023.122189

Cheng, J. C. P., Chen, W., Chen, K., & Wang, Q. (2020). Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms. Automation in Construction, 112, 103087. https://doi.org/https://doi.org/10.1016/j.autcon.2020.103087

Civerchia, F., Bocchino, S., Salvadori, C., Rossi, E., Maggiani, L., & Petracca, M. (2017). Industrial Internet of Things monitoring solution for advanced predictive maintenance applications. Journal of Industrial Information Integration, 7, 4–12. https://doi.org/https://doi.org/10.1016/j.jii.2017.02.003

De Donato, L., Dirnfeld, R., Somma, A., De Benedictis, A., Flammini, F., Marrone, S., Saman Azari, M., & Vittorini, V. (2023). Towards AI-assisted digital twins for smart railways: preliminary guideline and reference architecture. *Journal of Reliable Intelligent Environments*, *9*(3), 303–317. https://doi.org/10.1007/s40860-023-00208-6

Flores-Colen, I., & de Brito, J. (2010). A systematic approach for maintenance budgeting of buildings façades based on predictive and preventive strategies. Construction and Building Materials, 24(9), 1718–1729. https://doi.org/https://doi.org/10.1016/j.conbuildmat.2010.02.017

Gordon, A. (2021). Internet of things-based real-time production logistics, big data-driven decision-making processes, and industrial artificial intelligence in sustainable cyber-physical manufacturing systems. *Journal of Self-Governance and Management Economics*, *9*(3), 61–73. https://doi.org/10.22381/jsme9320215

Gribbestad, M., Hassan, M. U., & Hameed, I. A. (2021). Transfer learning for prognostics and health management (Phm) of marine air compressors†. *Journal of Marine Science and Engineering*, *9*(1), 1–20. https://doi.org/10.3390/jmse9010047

Hodavand, F., Ramaji, I. J., & Sadeghi, N. (2023). Digital Twin for Fault Detection and Diagnosis of Building Operations: A Systematic Review. *Buildings*, *13*(6). https://doi.org/10.3390/buildings13061426

Hong, T., Wang, Z., Luo, X., & Zhang, W. (2020). State-of-the-art on research and applications of machine learning in the building life cycle. Energy and Buildings, 212, 109831. https://doi.org/https://doi.org/10.1016/j.enbuild.2020.109831

Hosamo, H. H., Nielsen, H. K., Kraniotis, D., Svennevig, P. R., & Svidt, K. (2023). Improving building occupant comfort through a digital twin approach: A Bayesian network model and predictive maintenance method. *Energy and Buildings*, *288*, 112992. https://doi.org/10.1016/j.enbuild.2023.112992.

Hosamo, H. H., Svennevig, P. R., Svidt, K., Han, D., & Nielsen, H. K. (2022). A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics. *Energy and Buildings*, *261*, 111988. https://doi.org/10.1016/j.enbuild.2022.111988

Leukel, J., González, J., & Riekert, M. (2021). Adoption of machine learning technology for failure prediction in industrial maintenance: A systematic review. *Journal of Manufacturing Systems*, *61*, 87–96. https://doi.org/10.1016/j.jmsy.2021.08.012

Liu, Y., Pang, Z., Karlsson, M., & Gong, S. (2020). Anomaly detection based on machine learning in IoT-based vertical plant wall for indoor climate control. *Building and Environment*, *183*, 107212. https://doi.org/10.1016/j.buildenv.2020.107212.

Ma, Z., Ren, Y., Xiang, X., & Turk, Z. (2020). Data-driven decision-making for equipment maintenance. *Automation in Construction*, *112*. https://doi.org/10.1016/j.autcon.2020.103103

Madureira, S., Flores-Colen, I., de Brito, J., & Pereira, C. (2017). Maintenance planning of facades in current buildings. Construction and Building Materials, 147, 790–802. https://doi.org/https://doi.org/10.1016/j.conbuildmat.2017.04.195

Mohapatra, A. G., Mohanty, A., Pradhan, N. R., Mohanty, S. N., Gupta, D., Alharbi, M., Alkhayyat, A., & Khanna, A. (2023). An Industry 4.0 implementation of a condition monitoring system and IoT-enabled predictive maintenance scheme for diesel generators. *Alexandria Engineering Journal*, *76*, 525–541. https://doi.org/10.1016/j.aej.2023.06.026

Mulumba, T., Afshari, A., Yan, K., Shen, W., & Norford, L. K. (2015). Robust model-based fault diagnosis for air handling units. *Energy and Buildings*, *86*, 698-707. https://doi.org/10.1016/j.enbuild.2014.10.069.

Nunes, P., Santos, J., & Rocha, E. (2023). Challenges in predictive maintenance – A review. *CIRP Journal of Manufacturing Science and Technology*, *40*, 53–67. https://doi.org/10.1016/j.cirpj.2022.11.004

Oladinrin, O. T., Arif, M., Rana, M. Q., & Gyoh, L. (2023). Interrelations between construction ethics and innovation: a bibliometric analysis using VOSviewer. *Construction Innovation*, *23*(3), 505–523. https://doi.org/10.1108/CI-07-2021-0130

Orduña-Malea, E., & Costas, R. (2021). Link-based approach to study scientific software usage: the case of VOSviewer. *Scientometrics*, *126*(9), 8153–8186. https://doi.org/10.1007/s11192-021-04082-y

Pałasz, P., & Przysowa, R. (2019). Using Different ML Algorithms and Hyperparameter Optimization to Predict Heat Meters' Failures. *Applied Sciences*, *9*(18), 3719. https://doi.org/10.3390/app9183719.

Scaife, A. D. (2024). Improve predictive maintenance through the application of artificial intelligence: A systematic review. *Results in Engineering*, *21*. https://doi.org/10.1016/j.rineng.2023.101645

Schwartz, S., Jiménez, J. J. M., Vingerhoeds, R., & Salaün, M. (2022). An unsupervised approach for health index building and for similarity-based remaining useful life estimation. *Computers in Industry*, *141*, 103716. https://doi.org/10.1016/j.compind.2022.103716.

Sousa Tomé, E., Ribeiro, R. P., Dutra, I., & Rodrigues, A. (2023). An online anomaly detection approach for fault detection on fire alarm systems. *Sensors*, *23*(10), 4902. https://doi.org/10.3390/s23104902.

Teoh, Y. K., Gill, S. S., & Parlikad, A. K. (2023). IoT and Fog-Computing-Based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 Using Machine Learning. *IEEE Internet of Things Journal*, *10*(3), 2087–2094. https://doi.org/10.1109/JIOT.2021.3050441

Tian, R., Gomez-Rosero, S., & Capretz, M. A. (2023). Health Prognostics Classification with Autoencoders for Predictive Maintenance of HVAC Systems. *Energies*, *16*(20), 7094. https://doi.org/10.3390/en16207094.

Trivedi, S., Bhola, S., Talegaonkar, A., Gaur, P., & Sharma, S. (2019, December). Predictive maintenance of air conditioning systems using supervised machine learning. In *2019 20th International Conference on Intelligent System Application to Power Systems (ISAP)* (pp. 1-6). IEEE. https://doi.org/10.1109/ISAP48318.2019.9065995.

Valinejadshoubi, M., Moselhi, O., & Bagchi, A. (2022). Integrating BIM into sensor-based facilities management operations. *Journal of Facilities Management*, *20*(3), 385–400. https://doi.org/10.1108/JFM-08-2020-0055

van Dinter, R., Tekinerdogan, B., & Catal, C. (2022). Predictive maintenance using digital twins: A systematic literature review. *Information and Software Technology*, *151*, 107008. https://doi.org/10.1016/j.infsof.2022.107008.

Villa, V., Bruno, G., Aliev, K., Piantanida, P., Corneli, A., & Antonelli, D. (2022). Machine Learning Framework for the Sustainable Maintenance of Building Facilities. *Sustainability (Switzerland)*, *14*(2). https://doi.org/10.3390/su14020681

Yan, K., Shen, W., Mulumba, T., & Afshari, A. (2014). ARX model based fault detection and diagnosis for chillers using support vector machines. *Energy and Buildings*, *81*, 287–295. https://doi.org/10.1016/j.enbuild.2014.05.049

Yang, C., Shen, W., Chen, Q., & Gunay, B. (2018). A practical solution for HVAC prognostics: Failure mode and effects analysis in building maintenance. *Journal of Building Engineering*, 15, 26–32. https://doi.org/https://doi.org/10.1016/j.jobe.2017.10.013

Zięba, A. (2018). Google books ngram viewer in socio-cultural research. *Research in Language*, *16*(3), 357–376. https://doi.org/10.2478/rela-2018-0015