World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Review Article)

Integration of AI-based predictive maintenance for energy-efficient mechanical systems

Jaymin Pareshkumar Shah *

ITM SLS Baroda University, India.

World Journal of Advanced Engineering Technology and Sciences, 2024, 11(02), 664-673

Publication history: Received on 18 March 2024; revised on 26 April 2024; accepted on 29 April 2024

Article DOI: https://doi.org/10.30574/wjaets.2024.11.2.0153

Abstract

Predictive maintenance enabled by Artificial Intelligence (AI) transforms mechanical systems by improving their reliability levels as well as energy efficiency attributes. The conventional maintenance methods that include reactive and preventive measures repeatedly produce inefficient energy usage together with elevated operation expenses. Using AI alongside machine learning predictive maintenance transforms real-time sensor data into predictions which help maintainers schedule optimal maintenance times. The proactive system helps prevent downtime and cuts down energy loss and delivers improved operational results. Current industrial applications benefit from AI methods made up of deep learning and IoT-enabled data analytics and digital twins to anticipate anomalies and detect faults in HVAC systems and production facilities as well as power generation facilities. The ongoing implementation challenges involve poor quality data as well as cybersecurity threats together with difficult integration between systems. Self-learning AI models combined with edge computing and automated intelligent systems will enable better predictive maintenance through future advancements which will generate more sustainable and energy-efficient mechanical systems.

Keywords: Predictive Maintenance; Artificial Intelligence; Energy Efficiency; Machine Learning, IoT

1. Introduction

1.1. Overview of Mechanical Systems and Their Role in Energy Efficiency

Industrial operations, energy generation and building management all rely on mechanical systems. In these systems, HVAC units, turbines, compressors and manufacturing equipment, there is substantial usage of energy. For these systems overall energy consumption, operational costs as well as environmental impact depend on system efficiency. Friction losses, heat dissipation, and degrading over time, all contributing to poor mechanical system inefficiencies lead to an increase in excess energy consumption (Hinton, 2019). Thus, it is important to ensure the mechanical systems optimal functionality in order to improve energy efficiency and sustainability.

* Corresponding author: Jaymin Pareshkumar Shah

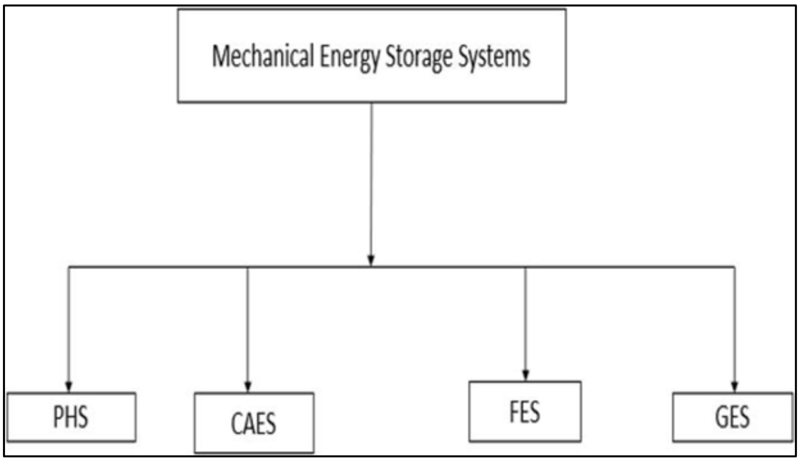

Figure 1 Mechanical energy storage system (MESS), Energy storage technologies such as pumped-hydroelectric storage (PHS), flywheel energy storage (FES), compressed air energy storage (CAES) and gravity energy storage systems (GES)

Currently, those advancements in the area of energy efficient technology have been concentrated on system design, automation and control mechanisms. Mechanical wear and unexpected failures are still major problems, however. To address these inefficiencies, predictive maintenance has an important place when it comes to system maintenance with an intelligent aspect (Farzaneh et al., 2021).

1.2. Importance of Predictive Maintenance in Reducing Energy Consumption

The emergence of the predictive maintenance has become a critical approach for increasing the energy efficiency of mechanical systems. This is opposed to reactive maintenance whereby broken machines are mended after they have run ins, or preventative maintenance where the machines are serviced as per scheduled, but not depending on the real condition of the equipment; predictive maintenance goes on a real time data analysis and predetermines which equipment failure is to be congested before it strikes. This proactive approach ensures system stays in optimum working condition hence reducing the wastegage of energy and preventing surprise breakdown (Scaife, 2023).

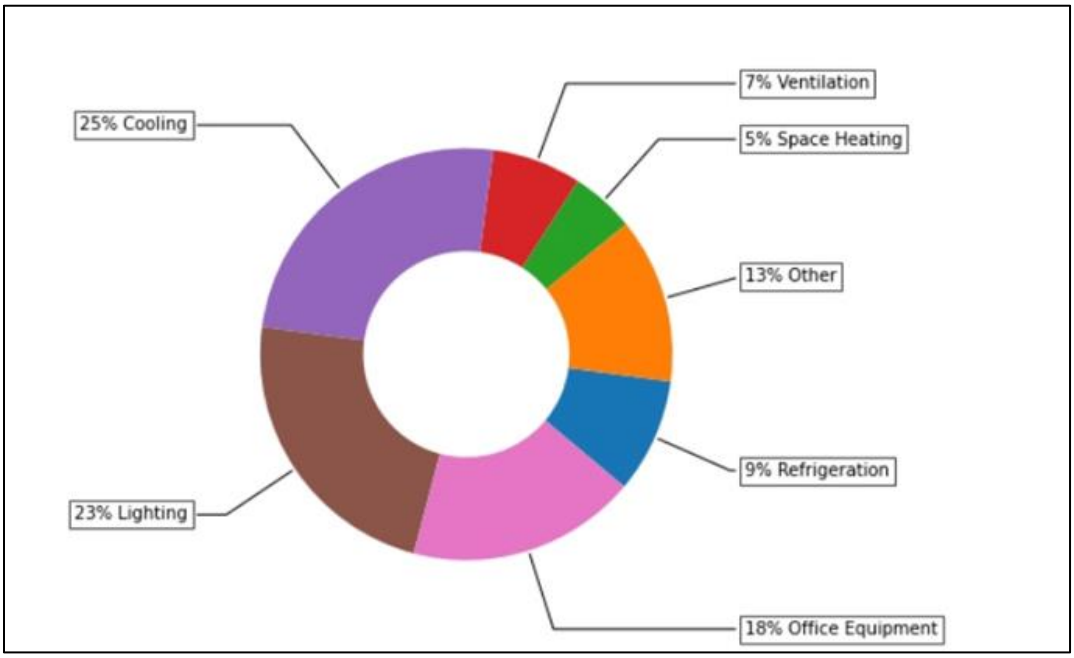

Figure 2 Energy usage data of commercial buildings in the US

Predictive maintenance involves continuous monitoring of key performance indicators, like temperature, vibration, pressure etc., to detect faults at an early stage. The operator can schedule the maintenance at the time when it is real needed and minimize the downtime and not to perform the unnecessary servicing. Predictive maintenance has also been shown to lead as much as 20% energy savings in industries (such as manufacturing and smart buildings) since it ensures that equipment is working optimally (Farzaneh et al., 2021). It also helps in reducing the frequency of repairs and replacements which in turn reduces the maintenance cost and extends the system's life at the same time.

1.3. Role of AI in Predictive Maintenance

The predictive maintenance has been transformed by Artificial Intelligence (AI) by helping us more accurately and effectively locate defects. They use machine learning algorithms which mine huge amounts of sensor data to find patterns and anomalies to indicate potential failure. The use of predictive analytics driven by AI leads to optimised maintenance schedule, reduced energy losses and increase in overall system reliability (Himeur et al., 2023). Advanced models, such as deep learning and reinforcement learning, are used with AI based on predictive maintenance systems to enhance the fault detection accuracy. They can predict failures with high precision just as maintenance teams can intervene before energy losses escalate. In addition, companies that use AI gain an edge when it comes to decision making, as AI synthesizes real-time stream of sensor data with historical performance records to develop a semi learning system that learning continuously overtime (Farzaneh et al., 2021).

Edge computing as it relates to the IoT and the use of AI has advanced the power of predictive maintenance. Real time monitoring and diagnostics through smart sensors and connected devices gives insight into equipment health in real time. Reducing energy wastage and also making sure that mechanical systems run efficiently with the minimum of human intervention (Himeur et al. 2023) is this. Overall, AI based predictive maintenance poses as a game changer when it comes to energy efficient mechanical systems. However, AI based maintenance strategies help a great deal in it by reducing energy consumption, improving system reliability and minimizing operational cost. The remainder of this article will explore deeper into the basics of predictive maintenance, what AI technologies specifically have been employed, and the challenges that are implicated with implementing these technologies.

1.4. Objectives of the Article

This research explains how artificial intelligence predictive maintenance boosts mechanical system energy efficiency. Predictive maintenance performs against traditional maintenance approaches with respect to operational efficiency and reliability and cost savings enhancement. The analysis will focus on three main AI techniques employed for predictive maintenance: machine learning models together with deep learning and IoT-driven data analytics. The study evaluates actual uses of predictive maintenance powered by AI throughout HVAC systems as well as manufacturing and power generation facilities. A study will research the basic AI approaches used in predictive maintenance while presenting strategies for handling implementation barriers toward effective deployment of AI in this field. Analysis of upcoming trends and innovations in AI-based predictive maintenance will include examinations of edge computing and self-learning systems as well as digital twins technology.

2. Fundamentals of Predictive Maintenance

2.1. Definition and Comparison with Reactive and Preventive Maintenance

In predictive maintenance, data is used to drive operating equipment in real time based on monitoring and advanced analytics before equipment failure happens. Predictive maintenance differs from the usual maintenance practices as it uses artificial intelligence (AI), artificial intelligence, and sensor data to give early indications of faults so that appropriate measures can be taken (Scaife, 2023).

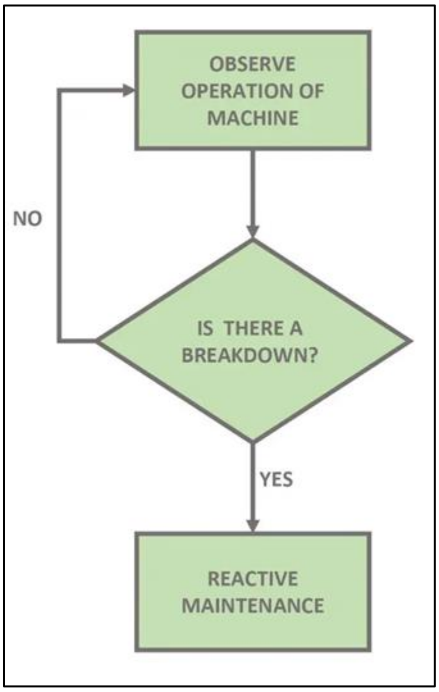

Figure 3 Reactive Maintenance

There is three broad classification of maintenance strategies such as reactive maintenance, preventive maintenance and predictive maintenance. Reactive maintenance (run to failure) is when equipment is repaired only after having failed. Despite reducing down time costs in advance, it results in unexpected downtimes, high repair costs and too much energy consumption (Himeur et al., 2023). On the other hand, preventive maintenance is the scheduled servicing at pre-defined intervals or based on a set standard of usage. It reduces the risk of unexpected failure but this comes with the drawback of causing unnecessary maintenance activities and resource wastage since it does not take into consideration of actual equipment condition (Farzaneh et al. 2021) On the contrary, predictive maintenance changes equipment health dynamically and intervenes only when needed.

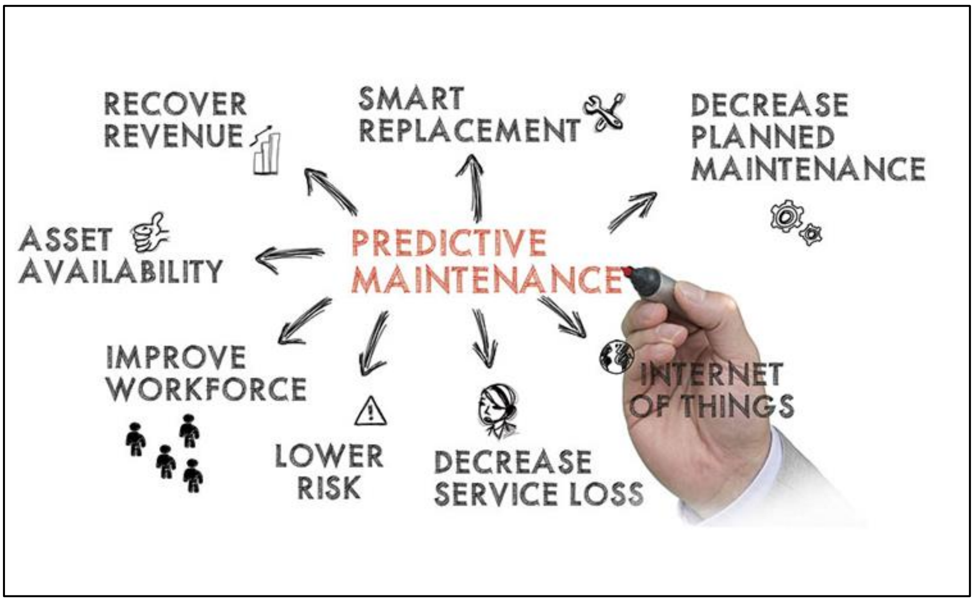

Figure 4 5 Steps of Predictive Maintenance

Using AI based diagnostics, predictive maintenance improves maintenance schedules and makes system reliable and cuts operational cost. It was shown by (Edwards & Bunker, 2023) that unplanned downtime can be reduced by up to 50%, at the same time that overall maintenance costs may decrease by 10–40%.

2.2. Key Components of Predictive Maintenance: Sensors, Data Analytics, and Machine Learning

Predictive maintenance relies on three core components: sensors, data analytics, and machine learning algorithms.

- Sensors: IoT based sensors are installed in modern mechanical systems, which are continuously monitoring such parameters as vibration, temperature, pressure and energy consumption. Real time data thus provided by these sensors form the base for the predictive analytics (Hu & You, 2023). To provide an example, smart sensors are used to track airflow and identify anomalies that may signal future failures (Devaraj, 2023).
- Data Analytics: Sensor data is collected and analyzed in an advanced manner to detect performance trends as well as fault patterns. Raw sensor readings are processed by the vast amount of the information that goes into AI driven analytics platforms and transformed into actionable insights (Hati, 2021). An important predictive approach is to employ techniques like anomaly detection and time series forecasting in order to predict potential equipment failures before escalating (Chen et al., 2023).
- Machine Learning Algorithms: Predictive maintenance systems that base on AI leverage the machine learning models to identify defect pattern and predict RUL of equipment. The historical failure data are used to train supervised learning models, and unsupervised learning algorithms locate deviations from normal operating conditions (Ahmed et al., 2022). The accuracy of fault detection is further enhanced with the use of deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in engaging in complex, non-linear relationships in sensor data (Long, 2023).

2.3. Benefits: Reduced Downtime, Cost Savings, and Improved System Performance

The implementation of AI predictive maintenance holds several advantages, which make it critically important to the enhancement of energy efficiency and operational performance:

- Reduced Downtime: Predictive maintenance senses early signs of failure and thus reduces unexpected breakdowns and continuos operation of the system. This is especially important where equipment failure can cause large productivity losses as in energy intensive industries (Confalonieri et al., 2015).
- Cost Savings: Predictive maintenance takes away unnecessary maintenance tasks as well as emergency repair bills. It is known that AI based on maintenance strategies can reduce maintenance expenses up to 30% compared to the traditional approach (Raihan, 2023).
- Improved System Performance: Mechanical systems perform at the optimal level without periods when they are not used and reduce energy wastage and extend equipment lifespan. For instance, AI driven HVAC systems have now reduced up to 25 % energy usage by changing configurations depending on predictive insights (Edwards & Bunker 2023).

Predictive maintenance has helped the integration of AI, IoT and big data analytics in the prediction process, changing the paradigm of the traditional maintenance practices to smarter and much more energy efficient mechanical systems. In the next section, we will examine certain AI techniques employed in predictive maintenance with the outcomes on system reliability and energy efficiency.

3. AI Techniques for Predictive Maintenance

3.1. Machine Learning Models: Supervised, Unsupervised, and Reinforcement Learning

Supervised learning as well as unsupervised learning are used through predictive maintenance to discover possible failures and optimal maintenance schedules using past and live data. It is supervised learning where each data point is labeled with known outcome. For instance, algorithms, including Support Vector Machines and Artificial Neural Networks, have been used to identify the operational state of machinery such as on normal or faulty state (Ahmed et al., 2022; Scaife, 2023). This methodology is particularly useful in environments where lots of historical data are available, for instance, in the energy intensive manufacturing plants (Confalonieri et al., 2015). On the other hand, there is no labeled data utilized with unsupervised learning. Rather, it clusters or spots the outliers based on data. It has been used in smart building management systems to continuously monitor the system behavior (Farzaneh et al., 2021; Raihan, 2023) and this method is beneficial with where faults are infrequent or new failure modes arises. Another promising approach is Reinforcement learning, that learns agent to make sequential decisions with its environment by both interacting with it. Reinforcement learning can also learn the optimal maintenance policy by trial and error so as to minimize downtime and operational costs and thereby provide the basis for dynamic maintenance scheduling in complex mechanical systems (Hinton, 2019; Rathore, 2016).

3.2. Deep Learning for Fault Detection and Anomaly Detection

With the recent advances of deep learning techniques, fault detection and anomaly detection have improved drastically through automatically extracting high level, and complex features from a large number of sensor measurements. The convolutional neural networks (CNNs), recurrent neural networks (RNNs), incl.LSTMS (Long Short Term Memory networks) are heavily used in these tasks since they allow to process and to analyze the time series data coming out of the industrial equipment. For example, deep learning models are used in detecting subtle anomalies that occur on the energy efficient building envelope to prompt corrective action before catastrophic failures (Long, 2023).

Moreover, autoencoder architectures such as Variational Autoencoders (VAEs) have successfully been implemented to learn the normal system operation patterns. However, if the system's operation deviates from learned patterns, large reconstruction errors indicate the possible existence of faults, and prompt measures can be taken to correct them. In particular, this approach is useful for the on-device predictive maintenance systems in recent studies (Chen et al, 2023; Scaife, 2023) for which low power consumption and real time operation are required. Considering its capacity to continuously improve its predictive accuracy, deep learning is now a critical part of modern predictive maintenance frameworks to expose its beholder to the complex and dynamic settings.

3.3. AI-Driven Data Analytics and Pattern Recognition

The fundamental ingredients to make the predictive maintenance work are the integration of AI driven data analytics and advanced pattern recognition techniques. AI systems can process big amounts of data from different sensors and find the hidden pattern and correlations that aren't easy to find by simple technique. In addition to improving fault diagnosis, this addition strengthens the entire decision making process by offering actionable insights for maintenance planning (Hu & You, 2023; Ohalete et al, 2023). In practice, the real use of AI driven data analytics consists in working with statistical methods combined with machine learning algorithms for continuous monitoring and analysis of equipment behavior. For instance, vibration and thermal data from HVAC systems has been ran through pattern recognition algorithms to anticipate possible failings to increase energy efficiency and enhance system reliability (Edwards & Bunker, 2023, Bilal et al., 2023). Additionally, physics informed neural networks improve upon predictive control strategies, which are timely and effective (Saadane et al., 2022). The data driven approaches are these, which underlie a proactive maintenance culture that not only decreases downtime but also yield huge cost and energy conservation (Kamisetty, 2022; Franki et al., 2023)..

4. Energy Efficiency through AI-Based Maintenance

4.1. AI's Impact on Energy Consumption Optimization

AI based maintenance is a breakthrough force that has found itself applied to different sectors in order to optimize energy consumption. Advanced predictive algorithms enable operators to always keep an eye on the state of equipment performance and detect signs of early inefficiency, which can be dealt with in time. Such a proactive approach eliminates such wasted energy that sprouts up in the course of overcompensation in case of the system failures or in less than optimal operating conditions. For example, in smart buildings, AI has been used to real time control operational parameters in such a manner that can reduce energy consumption significantly while maintaining comfort level (Farzaneh et al., 2021). In a similar fashion in energy intensive manufacturing environment, AI based maintenance strategies help maintain the machines based upon the actual equipments conditions rather than the time schedules and machines are operated accordingly, which results in systems operating within their most energy efficacious operation (Confalonieri et al., 2015). However, this continuous optimization not only saves energy bills but also plays its part toward reducing carbon emissions in line with broader sustainability goals.

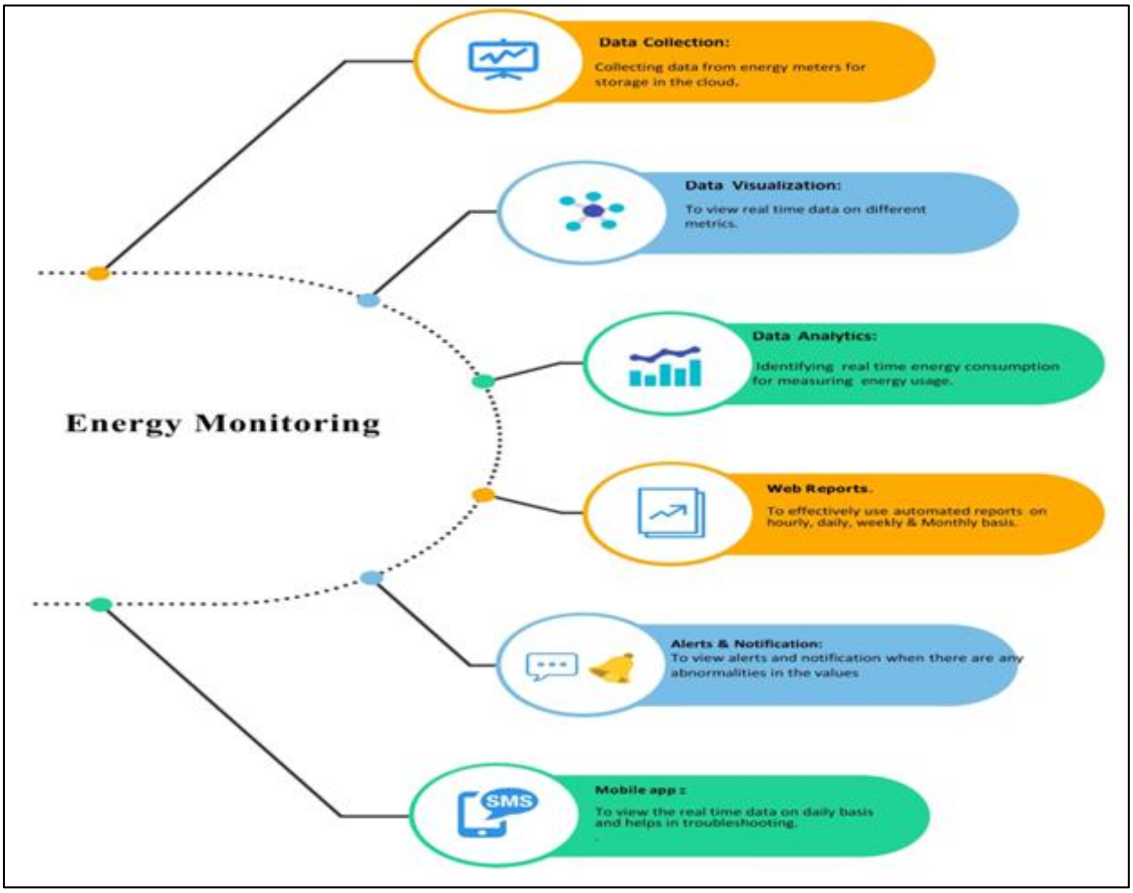

Figure 5 AI-based Real Time Energy Monitoring

4.2. Case Studies: AI-Driven Predictive Maintenance in HVAC, Industrial Machinery, and Power Plants

Case studies of using AI-driven to predict maintenance in numerous industries show that they are effective. Some AI solutions are already used in the monitoring of parameters such as airflow, temperature and humidity in HVAC that are necessary in both the increase in energy efficiency as well as the occupant comfort. Research has shown that AI powered HVAC systems are able to save a considerable amount of energy by changing its operational settings based on the real-time data (Edwards & Bunker, 2023). AI based systems have provided capabilities to monitor critical machinery and production lines in industrial settings. One example is the utilization of AI driven decision systems to integrate to reduce unplanned downtimes and to improve energy utilization in manufacturing plants as was done with AI driven decision systems that predicted failures before they failed (Confalonieri et al., 2015). In addition, AI is being used to improve performance of renewable energy assets in the power sector such as solar and wind farms. Described are these systems which are directly applied to predict maintenance needs using real time analytics and thereby ensuring that power generation is efficient and reliable in any condition of operation (Ohalete et al., 2023). In each of these examples, the applicability of AI to not only be better but can be used to save significant amounts of energy across dissimilar activities.

4.3. Metrics for Evaluating Energy Efficiency Improvements

The evaluation of performance of AI based maintenance initiatives is made with a set of performance metrics that measure both operational and energy efficiency benefits. Key metrics include:

- Energy Consumption Reduction: Determining the amount of energy that is directly affected of optimized maintenance and operational adjustments. It is often stated as a percentage reduction of the baseline measurements that had been recorded before the use of AI solutions (Farzaneh et al., 2021; Edwards & Bunker, 2023).
- Downtime Reduction: Estimating the reduction in the unexpected downtime caused by preemptive maintenance interventions. Improved energy efficiency is directly linked to reduced down time (Confalonieri et al., 2015), as equipment is kept top level in terms of peak performance.

- Maintenance Cost Savings: Determining the cost benefits of a small reduction in the number of emergency repairs and fewer maintenance activities. Indirectly, lower maintenance costs indicate that the energy consumption rate of systems has been kept within their optimal range (Raihan, 2023).
- Operational Performance Metrics: Measuring incremental progress in key performance indicators like the system reliability, production output and overall equipment effectiveness (OEE). Usage of these metrics allow the contribution of energy efficiency enhancements to larger operational excellence (Himeur et al., 2023) to be quantified.

Through the use of these metrics, by doing so, organizations can validate the importance of using AI in maintenance, but also refine their strategies to maximize the benefits of energy consumption and operational performance.

5. Challenges and Implementation Strategies

5.1. Data Quality and Availability Issues

Realizing the benefits of AI driven predictive maintenance comes down to ensuring the data that the software is trained on is available and valuable. Sensor data must be reliable in order for the machine learning model to predict the early signs of an equipment failure. However, in many industrial environments data is noisy, incomplete or inconsistent because of sensor malfunctions or integration issues. Such errors can distort predictions used in predictive models and can produce unhealthy maintenance decisions. Such an address addresses these issues requires deployment of robust data acquisition systems and use of data cleansing and validation techniques. In particular, energy efficient operation relies on having data of high quality (Chen et al., 2023; Hati, 2021), which can be supported through advanced filtering methods and sensor network redundancy.

5.2. Integration with Existing Maintenance Systems

Another big challenge is to integrate the AI solutions with legacy maintenance systems. However, existing systems were not conceived under circumstances in which it was easy to digitally connect and hence encounter issues of compatibility when tried to integrate present day AI technologies. Retrofitting much older equipment with IoT sensors and data communication protocols to this integration will require a lot of effort. Additionally, new AI based processes must develop in step with well defined workflows. Successful integration not only fills the technological gap, but it also makes sure the new insights from the AI systems will be applied in daily maintenance operations with the aim to increase energy efficiency and operational reliability (Confalonieri et al., 2015; Devaraj, 2023).

5.3. Cybersecurity and Data Privacy Concerns

Considering the scale of data collection that AI-predictive maintenance demands along with a need for connectivity across a network, cybersecurity and data privacy are essential concerns. As industrial systems are now more and more interconnected, they become more easily accessible for a cyberattack, which may have negative consequences like data breaches or manipulation of the maintenance processes. To make sure that they are data transmission and storage is secure, you have to deploy strong cybersecurity measures like encryption, multi factor authentication and network traffic monitoring. In addition, organizations also need to comply with data privacy regulations and industry standards in order to protect data for the very sensitive operational data from the unauthorized access. A solution to these issues is crucial not only for property protection and operational data but also for the trust of stakeholders in energy-efficient projects (Himeur et al., 2023; Raihan, 2023).

5.4. Strategies for Overcoming Implementation Barriers

In order to overcome these challenges in the implementation, organizations should take a multi-faceted strategy. Third, in order to improve data reliability and accuracy, first it is necessary to invest in highly capable sensor networks and advanced data management systems. We can run towards a phased integration approach to shift from old systems to modern AI powered platforms with the step by step upgrades, without disturbing existing operations. Technology providers as well as industry experts may also assist with the integration process through sharing their knowledge and experience about specific operational context. Moreover, appropriate steps have to be taken to ensure that the implementation of cybersecurity protocols and adherence to data privacy regulations shall maintain the integrity of the maintenance systems. Finally, continuous training and development of staff to 'what can be' new technology handling is essential to keeping the human element abreast of technological advancement. Such strategies not only mitigate the risks, but also open the door for the gains of all the benefits from the implementation of predective maintenance with AI, in the improvement of the efficiency of energy and the operational performance (Ahmed et al., 2022; Rathore, 2016; Saadane et al., 2022).

6. Future Trends and Innovations

6.1. Role of IoT and Edge Computing in AI-Driven Predictive Maintenance

This is where the Internet of Things (IoT) and edge computing have converged with AI enabled predictive maintenance as it has ushered in faster and localized data processing, as well as real time decision making. More recently, high amount of granular operational data is being collected from machinery deployed in industrial environments using IoT devices with advanced sensors. This means that the data is processed close to the source and the latency can be reduced, thus enhancing the responsiveness of predictive maintenance systems. As a sector, it is particularly transformational in such specialized sectors as HVAC, renewable energy, and manufacturing, where quick analysis of sensor data is essential to avoid equipment breakdown and seeking ways to absorb higher energy use. For example, placing edge computing solutions can reduce energy consumption and downtime of important systems, opening up new possibilities for autonomous and more efficient operations of maintenance (Devaraj, 2023; Kamisetty, 2022).

6.2. Development of Self-Learning Systems for Enhanced Efficiency

Self learning system is the next evolution of the predictive maintenance, in which the accuracy and the efficiency of the AI models get better and better with time. They rely on ultra powerful advanced machine learning and deep learning and reinforce themselves to survive on new patterns and operational conditions without the need of human intervention. With growing amount of data, the algorithms become more and more proficient at predicting faults, to help in detecting fault and schedule for proactive maintenance. This self adaptive behavior not only improves reliability of mechanical systems but also minimize energy use by keeping equipment operating at is peak performance. Self learning systems have an iterative nature and that will help to reduce maintenance costs as well as improved efficiency of all operations in smart buildings as well as in industrial plants (Scaife, 2023; Raihan, 2023).

6.3. Integration of AI with Digital Twins for Real-Time Monitoring

Recognizing the recent development of integrating AI with digital twins for the use of real time monitoring and predictive maintenance, has emerged as powerful innovation in the realm. Digital twins are virtual replicas of a real world physical system, which can be used to simulate in real time, what would be the behavior in real world. Through these digital models, organizations can build a dynamic and real-time feedback loop whereby the digital twin is continually updated by the sensor data in real time using AI algorithms. It allows to identify potential problems in an early stage and take proactive actions to preserve energy efficiency and system reliability. Due to the existing practice of applying digital twins to optimize the performance of complex systems like energy efficient building envelope and industrial machinery by simulating multiple scenarios and predicting the impacts on performance before they can be applied (Hu & You, 2023; Long, 2023), this idea also holds value in a manufacturing context.

7. Conclusion

The incorporation of AI based predictive maintenance constitutes a new paradigm for improvement in the energy efficiency and reliability of mechanical systems. Using real time data analytics, machine learning, IoT based monitoring, the costs of downtime are greatly reduced, and maintenance costs are optimized with a reduction of energy consumption. Artificial intelligence (AI) technologies like deep learning and digital twins can facilitate fault detected with high precision and proactive maintenance scheduling at the whole life cycle of the system to keep the system remains in the performance. While the quality of the data, security of the data and the integration with legacy systems are all challenging to implement, AI predictive maintenance is going to be an industry standard. In the next couple of decades, future advancements in edge computing and self-learning AI models will make these systems much more sustainable, cheaper, and more intelligent when it comes to maintenance in a host of sectors.

References

[1] Confalonieri, M., Barni, A., Valente, A., Cinus, M., & Pedrazzoli, P. (2015, June). An AI based decision support system for preventive maintenance and production optimization in energy intensive manufacturing plants. In 2015 IEEE international conference on engineering, technology and innovation/international technology management conference (ICE/ITMC) (pp. 1-8). IEEE.

[2] Farzaneh, H., Malehmirchegini, L., Bejan, A., Afolabi, T., Mulumba, A., & Daka, P. P. (2021). Artificial intelligence evolution in smart buildings for energy efficiency. Applied Sciences, 11(2), 763.

[3] Long, L. D. (2023). An AI-driven model for predicting and optimizing energy-efficient building envelopes. Alexandria Engineering Journal, 79, 480-501.

[4] Kamisetty, A. (2022). AI-Driven Robotics in Solar and Wind Energy Maintenance: A Path toward Sustainability.

[5] Hati, A. S. (2021). A comprehensive review of energy-efficiency of ventilation system using Artificial Intelligence. Renewable and sustainable energy reviews, 146, 111153.

[6] Hinton, G. (2019). AI-Assisted Development of Sustainable Mechanical Systems. International Journal of Unique and New Updates, ISSN: 3079-4722, 1(1), 7-15.

[7] Franki, V., Majnarić, D., & Višković, A. (2023). A comprehensive review of artificial intelligence (AI) companies in the power sector. Energies, 16(3), 1077.

[8] Chen, Z., Gao, Y., & Liang, J. (2023). Lopdm: A low-power on-device predictive maintenance system based on self-powered sensing and tinyml. IEEE Transactions on Instrumentation and Measurement, 72, 1-13.

[9] Scaife, A. (2023). Improve predictive maintenance through the application of artificial intelligence: A systematic review. Authorea Preprints.

[10] Raihan, A. (2023). A comprehensive review of artificial intelligence and machine learning applications in energy sector. Journal of Technology Innovations and Energy, 2(4), 1-26.

[11] Hu, G., & You, F. (2023). An AI framework integrating physics-informed neural network with predictive control for energy-efficient food production in the built environment. Applied Energy, 348, 121450.

[12] Devaraj, S. M. (2023). The future of hvac systems: ai, cloud, and the internet of things (iot). Technology (ijcet), 14(2), 269-278.

[13] Edwards, J., & Bunker, K. (2023). Artificial Intelligence-Powered HVAC Systems for Enhancing Comfort and Energy Efficiency in Smart Buildings. Journal ID, 4195, 6829.

[14] Ohalete, N. C., Aderibigbe, A. O., Ani, E. C., Ohenhen, P. E., Daraojimba, D. O., & Odulaja, B. A. (2023). AI-driven solutions in renewable energy: A review of data science applications in solar and wind energy optimization. World Journal of Advanced Research and Reviews, 20(3), 401-417.

[15] Himeur, Y., Elnour, M., Fadli, F., Meskin, N., Petri, I., Rezgui, Y., ... & Amira, A. (2023). AI-big data analytics for building automation and management systems: a survey, actual challenges and future perspectives. Artificial Intelligence Review, 56(6), 4929-5021.

[16] Rathore, B. (2016). The Next Frontier: How the Integration of AI Transforms Manufacturing for a Sustainable Future. International Journal of New Media Studies (IJNMS), 3(2), 1-7.

[17] Saadane, R., Chehri, A., & Jeon, S. (2022). AI-based modeling and data-driven evaluation for smart farming-oriented big data architecture using IoT with energy harvesting capabilities. Sustainable Energy Technologies and Assessments, 52, 102093.

[18] Ahmed, I., Jeon, G., & Piccialli, F. (2022). From artificial intelligence to explainable artificial intelligence in industry 4.0: a survey on what, how, and where. IEEE Transactions on Industrial Informatics, 18(8), 5031-5042.

[19] Bilal, M., Afzal, M., Irfan, M., & Musarat, M. A. (2023). Energy Efficient Buildings in the Industry 4.0 Era: A Review. Preprints, 2023100301.

[20] Editorial Team (10 February 2023) What is Reactive Maintenance?. https://biblus.accasoftware.com/en/what-is-reactive-maintenance-3-practical-examples/

[21] Roland Plett (2023) Energy - Oil & Gas, Mining and Utilities. How Predictive Maintenance Works – 5 Steps. https://blogs.cisco.com/energy/how-predictive-maintenance-works-5-steps

[22] Jayakumar PV (Jun , 2022). IOT, AI-based Real Time Energy Monitoring

[23] Chukwuemeka Emmanuel Okafor and Komla Agbenyo Folly (2023) Mechanical Energy Storage Systems and Their Applications in Power Systems. https://www.intechopen.com/chapters/86953

[24] Hossain, J.; Kadir, A.F.A.; Hanafi, A.N.; Shareef, H.; Khatib, T.; Baharin, K.A.; Sulaima, M.F. A Review on Optimal Energy Management in Commercial Buildings. Energies 2023, 16, 1609. https://doi.org/10.3390/en16041609