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Artificial Intelligence-Driven Total Productive Maintenance: The Future of Maintenance in Smart Factories

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Abstract
Traditional Total Productive Maintenance (TPM) frameworks, relying on manual interventions and periodic maintenance schedules, struggle to efficiently process and act on real-time data. AI, with its powerful algorithms and machine learning capabilities, offers the potential to revolutionize TPM by enabling predictive maintenance, condition-based monitoring, and autonomous decision-making. This research explores the integration of AI into the core pillars of TPM, including Autonomous Maintenance, Planned Maintenance, Quality Maintenance, and Focused Improvement, highlighting the ways in which AI can enhance predictive accuracy, reduce downtime, and improve Overall Equipment Effectiveness (OEE). Moreover, the paper discusses the various AI applications such as predictive maintenance, digital twins, and automated Root Cause Analysis (RCA), and addresses the benefits like cost reduction, improved decision-making, and scalability. However, challenges such as data integration, high initial costs, skill gaps, and cybersecurity risks are also examined. Finally, the paper outlines future directions for AI-driven TPM, including the integration with advanced robotics, edge computing, sustainability-driven AI, and AI-enhanced workforce training. As AI continues to evolve, it holds the potential to redefine maintenance strategies, by driving greater efficiency, reliability, and sustainability in smart factories.
Keywords: *artificial intelligence, total productive maintenance, smart factories, predictive maintenance, autonomous maintenance, industry 4.0, digital twins, root cause analysis*

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I. Introduction

Over the years, manufacturers across the globe have consistently looked for better ways to improve their manufacturing processes by enhancing productivity and efficiency, and a crucial aspect is proper industrial equipment maintenance. In the past, maintenance policies have always been reactionary, disruptive, costly, and inefficient, as machines and equipment were only serviced after breakdown or when faults are detected. However, the emergence of the fourth industrial revolution and the application of Artificial intelligence (AI) and other advanced technologies have led to a better and predictive maintenance strategy known as Total Productive Maintenance (TPM).

Okpala and Egwuagu (2016) defined TPM as a philosophy of machine maintenance that involves activeparticipation of a company’s staff to ensure the enhancement of the general effectiveness of a plant,by eliminating or reducing resources and timewastage through the incorporation of the skills of theworkforce. As a maintenance strategy that entailsa modern approach for equipment and plantmaintenance, TPM accentuates all features ofproduction, as it integrates maintenance andservices of machines into a plant’s daily routine, in order to minimize unplanned and emergencystoppages and repairs to the barest minimum.According to Okpala, Anozie and Mgbemena (2020), the TPM is a crucial improvement process that emphasizeson equipment maintenance approach, and its positive impact hasmade many manufacturing companies to adopt it in order to improve organizations'responsiveness in achieving their customers’ satisfaction. TPM has traditionally played a crucial role in manufacturing, by enhancing equipment reliability, minimizing downtime, and fostering continuous improvement through employee involvement.

The tools and techniques of total productive maintenance, their purposes, and description are depicted in Table 1.

Table 1: The tools and techniques of TPM. Source: Okpala, Anozie and Ezeanyim (2018)

TPM Tools	Purpose	Description
5S Practice	Reduces time wastage and motion level	Organized approach to housekeeping that ensures tools, parts and other objects are in known, optimum locations.
Poka yoke	Prevents the occurrence of mistakes or defects.	Uses a wide variety of ingenious devices to prevent mistakes. An example is an automotive gasoline tank cap that has an attachment that prevents the cap from being lost.
One Point Lesson	To provide immediate, visual information that enables people to make correct decisions and manage their work and activities.	One point lesson uses a wide variety of signs, signals and controls, to manage people and processes.
Autonomous Maintenance	To provide personal care of equipment by the operator.	The operator of the equipment haven understood the functions of the equipment, does activities like cleaning, lubricating, dusting and inspection. This helps to prevent sudden breakdown of the machine and also give the operators the sense of ownership of the equipment.
Root Cause Analysis	Tacklesproduction problems at the base level.	When root causes are eliminated, breakdowns of equipment are reduced, which would reduce the downtime of machine and ultimately increase the Overall Equipment Effectiveness (OEE).
Kaizen(Continuous Improvement)	Institutionalizes the practice of achieving small daily improvements and improvement of overall efficiency.	Continuous Improvement refers to the idea that a large number of small improvements in processes are easier to implement than major improvements that have a large cumulative effect.

Despite its benefits, traditional TPM frameworks, reliant on human intervention and scheduled maintenance routines, struggle to keep up with the fast-paced, data-driven demands of smart factories. However, as manufacturing enters the Industry 4.0 era, traditional TPM faces challenges in handling the vast volumes and complexity of data generated in smart factory environments. The integration of TPM with smart technologies such as IoT devices and sensors improves predictive maintenance and operational effectiveness, boosting equipment performance (Anagnostara et al., 2024; Nadaf, 2024).

The real-time data generated by IoT systems and sensors in these factories presents opportunities to optimize maintenance, but is too complex for traditional methods (Amangeldy and Bissembayev, 2024). Artificial Intelligence (AI) has emerged as a key solution that enhances TPM by processing large datasets in real-time. Through machine learning and predictive analytics, AI forecasts equipment failures, automates maintenance tasks, and optimizes schedules, representing a transformative shift in maintenance strategies.

TPM itself, originating in Japan, emphasizes proactive maintenance practices, such as autonomous, planned, and preventive maintenance, involving the entire workforce to maximize equipment effectiveness. Advanced techniques like machine learning and Bayesian inference further enhance predictive maintenance accuracy (Qi et al., 2024). The rise of Industry 4.0 has led to the creation of smart factories that are automated, interconnected, and powered by IoT, cloud computing, and AI technologies. These factories rely on continuous data collection and predictive maintenance, significantly reducing downtime by enabling proactive interventions (Mosleuzzaman et al., 2024).

While traditional TPM frameworks depend on periodic inspections and human decision-making, these approaches face limitations in the face of the fast, real-time data processing required by smart factory environments. This hampers their ability to fully exploit the benefits of Industry 4.0 technologies (Nwabueze et al., 2024; Azevedo and Almeida, 2024). AI, by contrast, empowers maintenance strategies through real-time data analysis, improving predictive maintenance, automating tasks, and optimizing resource allocation, thereby increasing equipment reliability and lifespan (Lee et al., 2024). Nonetheless, challenges such as cybersecurity risks and the need for workforce adaptation remain critical in fully utilizing the potential of AI in manufacturing (Shrouf et al., 2024).

1. AI-Driven Total Productive Maintenance: A Paradigm Shift

Artificial Intelligence (AI) is an array of technologies that equip computers to accomplish diverse advanced functions, which include the capacity to see, comprehend, appraise and translate both spoken and written languages, analyze and predict data, make proposals and suggestions, and more (Okpala and Okpala, 2024).The integration of Artificial Intelligence (AI) with TPM represents a transformative shift in maintenance strategies, especially in smart factories. Okpala, Igbokwe and Nwankwo (2023), explained that AI's proactive approach enables manufacturers to pre-emptively address issues, decrease downtime, and also optimize resource allocation,thereby leading to enhanced overall efficiency. They pointed out that one of the key areas where AI is making remarkable in-roads is in the optimization of production processes, where machine learning algorithms are applied in the analysis of historical production data, patterns identification, as well as in the prediction of potential bottlenecks or inefficiencies.

AI enhances traditional TPM pillars by enabling proactive, efficient, and data-driven maintenance processes. In the context of Industry 4.0, where interconnected systems generate vast amounts of real-time data, AI's ability to analyze and optimize maintenance tasks is revolutionizing equipment reliability and production quality.AI-powered monitoring tools enable real-time anomaly detection and predictive maintenance, and enhances equipment reliability and operational efficiency. By analyzing sensor data, AI detects irregularities such as temperature, vibration, and pressure, providing timely maintenance recommendations to reduce equipment failures (Gowekar, 2024; Simion et al., 2024). Machine learning optimizes maintenance schedules, balancing preventive measures with actual usage to minimize costs and resource wastage (Babayeju et al., 2024; Liu, 2024). AI also improves quality control by identifying defect-causing factors and predicting potential quality issues, ensuring consistent production standards (Ghelani, 2024).

Additionally, AI-driven Root Cause Analysis (RCA) accelerates issue resolution by quickly pin-pointing failure causes through comprehensive data analysis, supporting continuous improvement and enhancing overall factory performance (Mathew and Kaur, 2024). By leveraging IoT-enabled sensors, AI collects real-time data on equipment conditions, enabling predictive maintenance that minimizes downtime and unplanned stoppages. Through advanced algorithms, AI processes this data to detect early signs of wear or failure, offering timely and accurate insights into machine health and facilitating better decision-making (Weiss, 2024).

AI-driven TPM introduces autonomous decision-making capabilities, allowing systems to predict maintenance needs, recommend solutions, or automatically implement corrective actions. Integrating AI with Robotic Process Automation (RPA) enables tasks such as part replacement and system recalibration to be performed autonomously, which reduces reliance on manual labor, increases efficiency, and ensures swift responses to issues (Zhao et al., 2024). This autonomy is especially valuable in high-volume manufacturing environments, where speed and accuracy are critical. Despite the significant advantages, challenges like high implementation costs and the need for skilled personnel remain key obstacles for manufacturers (Yahya et al., 2024). Overall, AI-driven TPM marks a paradigm shift in maintenance strategies, enhancing traditional approaches through real-time monitoring, predictive analytics, and autonomous operations, leading to increased efficiency, reduced costs, and improved operational reliability.

2. Applications of AI in Total Productive Maintenance

AI is revolutionizing TPM by enhancing traditional maintenance approaches and facilitating more efficient, intelligent, and data-driven decision-making. The integration of AI into TPM helps in the optimization of maintenance schedules, boosting of equipment reliability, and downtime reduction, thereby playing a crucial role in modern manufacturing settings. One significant application of AI in TPM is predictive maintenance, which predicts equipment failures by analyzing both historical and real-time data. AI systems apply advanced algorithms to identify failure patterns and anomalies, enabling early intervention. By calculating the Remaining Useful Life (RUL) of critical components, AI supports proactive maintenance scheduling, reducing unplanned downtime and also improves operational efficiency (Simion et al., 2024; Gowekar, 2024; Berghout et al., 2024).

AI also enhances Condition-Based Maintenance (CBM), which continuously monitors the real-time health of equipment and triggers maintenance actions only when specific thresholds are exceeded. This AI-driven approach minimizes unnecessary downtime and interventions, ensuring optimal use of resources and enabling timely, precise maintenance actions based on live sensor data (Shaala et al., 2024).

Another game-changing technology is digital twins—AI-powered virtual models of physical systems that simulate equipment behavior in real-time. These models allow manufacturers to virtually test and optimize maintenance strategies, providing valuable insights into performance and risk management without disrupting operations. Digital twins contribute to improved decision-making and extended equipment lifespan (Singh and Gameti, 2024; Shi et al., 2024; Mohanraj et al., 2024). AI also accelerates Root Cause Analysis (RCA), quickly identifying failure causes by analyzing extensive datasets from sensors, maintenance logs, and performance history. This rapid analysis enables faster resolution of recurring issues, promoting continuous improvement within TPM (Bhambri et al., 2024; Rane and Shirke, 2024).

Furthermore, AI-driven TPM improves Overall Equipment Effectiveness (OEE) by providing actionable insights into availability, performance, and quality. It analyzes real-time data to uncover inefficiencies, such as production bottlenecks and machine downtime, and also identifies potential quality issues before they affect the final product. This optimization maximizes equipment uptime, reduces waste, and ensures high production quality (Bhambri et al., 2024; Mohanraj et al., 2024). Therefore, AI is transforming TPM by enhancing predictive capabilities, enabling dynamic maintenance practices, and improving operational efficiency, establishing it as a key factor in the success of modern manufacturing operations.

3. Benefits of AI-Driven Total Productive Maintenance

AI-driven TPM significantly enhances the efficiency and effectiveness of maintenance operations in smart factories by leveraging advanced algorithms, machine learning, and real-time data. These AI-driven strategies optimize maintenance schedules, improve equipment reliability, and reduce downtime, thus contributing to the competitiveness and sustainability of manufacturing systems. One of the key benefits of AI in TPM is enhanced predictive accuracy. AI uses machine learning algorithms to analyze large datasets from IoT sensors, detecting patterns and predicting equipment failures before they occur, which minimizes unplanned downtime (Gowekar, 2024). Techniques such as Random Forest and Neural Networks have been highly effective in forecasting equipment conditions with precision, ensuring timely maintenance interventions and better resource allocation (Patel and Kalgutkar, 2024; Meher and Kakran, 2024).

AI also helps in the reduction of maintenance costs by optimizing maintenance schedules based on predicted equipment failures and condition-based interventions, rather than on time intervals. This reduces unnecessary repairs, emergency maintenance costs, and inventory expenditures. Additionally, predictive maintenance extends the lifespan of equipment and further lowering capital expenditure (Ayyagiri et al., 2024; Meher and Kakran, 2024). AI-driven TPM enhances equipment uptime by continuously monitoring machinery health and predicting signs of wear and tear before breakdowns occur. Machine learning algorithms like XGBoost and Random Forest detects early anomalies, ensuring proactive maintenance and minimizing downtime, ultimately improving production efficiency and profitability (Benarbia et al., 2024; Akyaz and Engın, 2024). Real-time monitoring and edge computing systems contribute to this improvement by enabling immediate anomaly detection and proactive maintenance scheduling, thus boosting Overall Equipment Effectiveness (OEE) (Thakkar and Kumar, 2024).

Furthermore, AI improves decision-making by providing actionable insights based on data analysis. Maintenance teams prioritize tasks by considering equipment health, production schedules, and resource availability. AI also helps to uncover hidden patterns and root causes of failures, enabling a more effective, root-cause-driven approach to problem-solving (Pujatti et al., 2024). Also, AI solutions in TPM are scalable and flexible, making them adaptable to various types of equipment and manufacturing environments. Whether a factory has few machines or a complex network of interconnected devices, AI integrates seamlessly into existing infrastructure. It can also be adjusted to meet evolving production needs, ensuring that TPM strategies remain effective over time (Kliestik et al., 2023; Martínez-Arellano and Ratchev, 2024).

4. Challenges in Implementing AI-Driven TPM

Artificial Intelligence-driven Total Productive Maintenance (TPM) offers significant potential to enhance maintenance operations in smart factories. However, its implementation presents numerous challenges that must be overcome to fully harness its advantages, as recent research underscores. One major challenge lies in integrating and ensuring the quality of data from various systems. Smart factories produce extensive data from IoT sensors, machinery, and ERP systems, but this data is often fragmented, unstructured, or inaccurate. Achieving high-quality, consistent, real-time data demands substantial pre-processing, cleansing, and standardization—tasks that require significant resources (Aboshosha et al., 2023). Small and Medium-sized Enterprises (SMEs) face additional difficulties due to limited expertise and financial constraints (Yusuf et al., 2024; Li et al., 2024).

Nonetheless, data-driven frameworks leveraging IoT and deep learning can help address these issues (Ohoriemu and Ogala, 2024). Another key obstacle is the substantial upfront investment needed to adopt AI-driven TPM. These costs include IoT sensors, AI software, data storage, computing infrastructure, and personnel training. For SMEs with limited budgets, such expenses can deter adoption, compounded by ongoing costs for system maintenance, software updates, and continuous training (Kim et al., 2024).

A shortage of skilled personnel also poses significant challenges. Implementing AI-driven TPM demands expertise in data science, machine learning, advanced analytics, and manufacturing operations. The current skill gap necessitates extensive training, recruitment, and collaboration with academic institutions to develop relevant educational programs (Antomarioni et al., 2023). Without qualified professionals, organizations may struggle to operate AI systems effectively and interpret their outputs. Cybersecurity is another critical concern, as integrating AI and IoT increases vulnerabilities due to enhanced connectivity. Real-time data exchanges can be exploited, leading to equipment malfunctions, data breaches, or production disruptions (Chittimalla, 2024; Neelakrishnan, 2024). Addressing these risks requires robust measures such as encryption, secure communication protocols, and intrusion detection systems, which add complexity and costs to adoption.

Finally, organizational resistance to change remains a significant barrier. Employees may fear job displacement or losing control over processes, while management may hesitate due to concerns about ROI and system complexity. Overcoming this resistance requires clear communication about the benefits of AI, comprehensive employee training, and phased technology integration. Cultivating a culture of innovation and continuous improvement is essential for driving acceptance and reaping the benefits of AI-driven TPM (Yusuf et al., 2024; Kim et al., 2024).

5. Future Directions in AI-Driven TPM

As AI-driven TPM progresses, it offers transformative opportunities to redefine maintenance strategies in smart factories while tackling key challenges and advancing sustainability objectives. Recent studies emphasize significant developments, obstacles, and future directions for AI-driven TPM. The integration of AI with advanced robotics is re-shaping maintenance processes, allowing for autonomous operations with minimal human input. Robots equipped with machine learning algorithms can efficiently handle complex tasks such as equipment calibration and diagnostics, significantly reducing errors and enhancing precision (Nadaf, 2024; Gowekar, 2024). Mobile robotic platforms enable prompt identification of operational issues, freeing personnel for strategic decision-making and improving overall equipment effectiveness (Vechet et al., 2024). Moreover, advancements in machine learning enable robots to adapt dynamically and perform unscheduled maintenance tasks, solidifying their role in future TPM systems.

Edge computing emerges as another critical advancement in AI-driven TPM by enabling localized data processing to minimize latency and facilitate real-time decision-making. By processing IoT sensor data at the source, edge computing ensures rapid insights and corrective measures, reducing reliance on centralized servers (Liu, 2024; Nadaf, 2024). This capability enhances predictive maintenance strategies, making edge computing an indispensable element in the operation of smart factories. Collaborative AI models that combine computational capabilities with human expertise are shaping the future of adaptive maintenance systems. These hybrid frameworks allow maintenance personnel to assess and refine AI-generated recommendations using their domain expertise, which results in more precise and contextual decision-making. Such systems effectively position AI as a decision-support tool, maintaining a balance between automation and human intervention (Rojek et al., 2024).

AI-driven TPM is also advancing sustainability efforts within manufacturing by integrating metrics like energy efficiency, resource optimization, and waste reduction into maintenance practices. AI optimizes energy consumption, predicts equipment failures to enhance resource utilization, and minimizes waste through precise component replacement forecasting (Samblani and Bhatt, 2024; Ahmed and Asamoah, 2024). These advancements align with green manufacturing practices, contributing to corporate sustainability targets while improving cost efficiency. As AI transforms manufacturing processes, addressing workforce challenges becomes essential. Immersive technologies like Augmented Reality (AR) and Virtual Reality (VR) provide innovative training solutions, allowing maintenance teams to practice complex tasks in virtual environments. These tools enhance understanding, decision-making, and problem-solving capabilities, equipping technicians to manage advanced AI-powered systems effectively (Samblani and Bhatt, 2024; Thakkar and Kumar, 2024).

Despite these innovations, several challenges must be resolved to fully realize AI's full potential in TPM. Issues such as data integration, high implementation costs, workforce skill gaps, cybersecurity risks, and resistance to organizational change persist. Overcoming these obstacles requires leveraging IoT and deep learning technologies, fostering academic and industrial collaboration, implementing strong cybersecurity frameworks, and nurturing innovation-driven organizational cultures (Aboshosha et al., 2023; Kim et al., 2024; Yusuf et al., 2024). AI-driven TPM is revolutionizing maintenance in smart factories by fostering automation, delivering real-time insights, promoting sustainable practices, and advancing workforce capabilities. With sustained innovation and strategic problem-solving, AI has the potential to transform maintenance operations, by enhancing both efficiency and sustainability in the manufacturing sector.

II. Conclusion

AI-driven TPM is poised to transform maintenance strategies in smart factories by integrating AI’s predictive capabilities with TPM’s structured methodologies. This combination enhances equipment reliability and operational efficiency. By automating processes, accurately forecasting equipment failures, and optimizing maintenance schedules, AI-driven TPM significantly boosts productivity and minimizes unplanned downtime—key factors for maintaining competitiveness in the digital manufacturing landscape (Nadaf, 2024; Thakkar and Kumar, 2024). Despite its advantages, challenges such as data integration, high initial costs, and the need for specialized expertise remain. To address these issues, manufacturers must invest in robust infrastructure, adopt effective data management strategies, and upskill their workforce to effectively utilize AI tools. Staying abreast of advancements in AI technology is also vital to fully realizing its benefits (Gautam et al., 2024).

In the era of Industry 4.0, embracing AI-driven TPM is crucial for achieving operational efficiency and sustainable growth. Successfully overcoming implementation challenges and leveraging AI’s potential will position manufacturers for success in the evolving landscape of smart factory maintenance (Hao, 2024). As AI technologies continue to advance, AI-driven TPM is set to revolutionize maintenance practices, delivering increased productivity, cost savings, and sustainability (Saleem et al., 2024; Samblani and Bhatt, 2024; Gautam et al., 2024).

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