Vol. 03, Iss. 4 (2025) 404-410, DOI: 10.61552/JME.2025.04.004

JME

Journal of Materials and Engineering

www.jme.aspur.rs

Research article

Predictive Maintenance in the Era of Industry 5.0: Challenges and Opportunities

Houssem Hosni[a,*]

[a]*Capgemini Engineering, France.*

Keywords:

Predictive maintenance
Industry 5.0
Internet of things
Artificial intelligence
Digital twins

* Corresponding author:

Houssem Hosni
E-mail : hosny.houssem@gmail.com

Received: 12 September 2024
Revised: 13 October 2024
Accepted: 22 November 2024

A B S T R A C T

As the industrial landscape evolves, integrating advanced maintenance strategies becomes essential for sustainable and efficient operations. In this paper we investigate predictive maintenance as aligned towards the concept of Industry 5.0 for industrial systems administration. First, we provide the definitions of predictive maintenance and Industry 5.0 to set the stage for an understanding of their synergy. The main objectives of this research are to identify some of the key technologies that support predictive maintenance, such as the Internet of Things, artificial intelligence and digital twins for advanced data analysis and informed decisions being made. We also speak to the technical challenges of integrating these technologies, and organizational barriers including resistance to change within companies. The article looks at how digital transformation can open opportunities, illustrated with concrete case studies that show it can be used to great effect in different sectors. We then, present future perspectives that will guide businesses to employ predictive maintenance for improving their operational performance in the industry 5.0.

1. INTRODUCTION TO PREDICTIVE MAINTENANCE AND INDUSTRY 5.0

Industry 5.0 is the new industrial stage with the main concern of cooperation between man and machine [1]. Unlike Industry 4.0 focusing on simplicity and robotization, Industry 5.0 considers human manipulations that establish a synergy with high technologies [2]. This model is based on three fundamental principles: Humanity, resilience and technological integration [3]. Systems built with resilience allow for change and disruption, returning humanity to the position of bringing workers back to the center, acknowledging their creativity and expertise in the industrial process [3].

Industry 5.0 emphasizes the departure from an era in which digital technology simply automates processes via a change to an era where industrial experience is humanized through digital technology [1]. It is an industry of close cooperative effort between humans and intelligent systems resulting in the best outcome by working together. As we enter the new stage, this is driven by technology, the Internet of Things (IoT) for example, artificial intelligence and collaborative robots (or 'co-bots') the ability to respond as quickly as possible and tailor to the changing desires of consumers and businesses in such a fast-moving market [2]. In Industry 5.0, the role of machines is no longer limited to carrying out tasks: making production more flexible and more human centered, they adapt their actions according to human needs and interactions [3].

A turning point in practices of the industry is this transition from an industrial and perfectly individual practice to a digital and collaborative one [1]. And companies are embracing interlinked platforms and intelligent architectures to enable real time decision making that takes place via the processing of very large amounts of data by machines [2]. The development of 'digital twins' to simulate and predict how systems behave based on continuous operational data, reinforce this process [4]. The changes we want to implement don't just want to be more efficient with systems, but have people still at the center of process, with collaborative tools that empower humans, not replace them [3].

That's where predictive maintenance becomes useful. Predictive maintenance anticipates breakdowns before they even occur based on random data collected continuously by machine sensors [2,3] Unlike reactive or programmed maintenance, which triggers once a problem has already occurred, or according to a fixed schedule, predictive maintenance leverages advanced analytics to improve operational efficiency [1]. We consider machine learning models that can learn in real time to interpret operational data and detect anomalies and warning signs of failure. In an industrial environment, this approach reduces the unscheduled downtime and increases equipment reliability, a valuable feature since a minute of unscheduled downtime in an industrial environment often can translate into a significant loss of productivity and revenue [5-7].

This new paradigm is also characterized by the emergence of predictive maintenance as a key element. It's using real time data to predict an equipment failure before it happens. An approach of active this allows businesses to reduce unplanned downtime and optimize operating costs. An example of IoT sensors: in this case, IoT sends information from a machine to constantly monitor temperature variations or any abnormal vibrations, for instance. By combining these technologies, companies can add longevity to their equipment as well as improve their energy efficiency [8-10].

Nevertheless, much remains yet to be done to bring predictive maintenance into Industry 5.0. Technology integration issues and management of increasing volume of data is a problem that companies address. Major obstacle to success of these systems based on this data is the lack of qualified people to analyze it. What's more, as machines become more complex, it is necessary to train staff on an ongoing basis to capitalize on the new technologies [11-13].

Continuous optimization of resources is the context in which predictive maintenance is integrated into Industry 5.0. With rising production volumes and increasing complexity inherent to modern systems, breakdowns can be highly expensive in terms of production costs and environmental impact. On top of that, Industry 5.0 can't tolerate unplanned interruptions, because it wants to maximize efficiency while minimizing energy losses and waste. The inevitable need for better predictive models has inspired many researchers to explore more accurate ones by bringing together artificial intelligence and innovative data processing schemes to assist in predictive maintenance in current industrial environment [14-18].

The current problem of integrating these technologies on a large scale and in a smooth way is a fundamental problem facing industry. The implementation of predictive maintenance in different industrial installations with their own special features, but under constraints, gives rise to specific technical and organizational challenges. Say for example, the data is of varying quality and uniformity; making it impossible to build a predictive model that necessitates homogeneous and trustworthy data sets. For industries, they must also address the complexity of the infrastructure they are embedded in and the safeguarding of data that is so commonplace in a highly interconnected world [19-20].

The objectives of this research review are therefore to explore how predictive maintenance tools and methods can be refined to align with the expectations of Industry 5.0. This includes not only identifying the machine learning models best suited to handle large amounts of data in real time, but also exploring solutions that guarantee optimal interoperability between different systems. The paper also aims to establish frameworks for efficient and secure data management, enabling companies to exploit the full potential of predictive maintenance in advanced digital environments. Ultimately, the aim is to provide a roadmap or compendium for industries seeking to adopt intelligent and autonomous maintenance, capable of adapting to the dynamic requirements and sustainability goals of Industry 5.0.

This paper will be divided as follows: First, we will present predictive maintenance and industry 5.0, setting the stage, defining the problem and outlining research objectives. Then we'll look at the other key technologies enabling predictive maintenance, which include the Internet of Things, artificial intelligence, and digital twins. Also, we explore the challenges in implementing predictive maintenance within the framework of Industry 5.0; technical and organizational challenges will also be addressed. We then turn to look at what the opportunities in digital transformation are, followed by case studies and practical applications of predictive maintenance. Finally, we conclude with future perspectives and recommendations to businesses on their use of these innovative approaches.

2. KEY TECHNOLOGIES SUPPORTING PREDICTIVE MAINTENANCE

Several key technologies are required to support the roll out of predictive maintenance and are an essential part of making it as effective as possible. However, among these technologies, the Internet of Things (IoT), artificial intelligence (AI), and digital twins become main for being able to collect, analyze and interpret real time data to predict machine failure [8-10,20].

To implement the predictive maintenance, we need the Internet of Things. It allows the connections between machines and sensors, creating the possibility for collecting relevant information as to how equipment is performing and in condition. Temperature, vibrations and pressure levels are all critical data for diagnosis of latent issues that may evolved in major failures. As an example, the continuous status monitoring of machines in the industrial environments through IoT sensors provides real time operational information for operators to take informed decisions. With this proactive approach, not only is downtime reduced but operationally this reduces more down time by maintaining on point personnel while using concrete data to ensure specific maintenance [20,21].

The predictive maintenance is enabled with artificial intelligence, especially machine learning algorithms. Unlike traditional analytics where we sort through huge amounts of data to determine patterns, these algorithms crunch massive amounts of data generated by IoT sensors to spot patterns or abnormalities. For instance, Neural Networks can be trained to detect abnormal behaviors of machines, to forecast failures prior to their coming into existence. In addition, machine learning can increase the accuracy of predictive models by considering numerous contextual factors that can affect machine performance including environmental conditions and usage patterns. Such ability to continuously analyze and learn enables a precision in predictions that enables more responsive, efficient maintenance [8].

Digital twins are considerably a leap forward in predictive maintenance. First, they build virtual replicas of physical systems for companies to simulate and optimize the functioning of their equipment. Therefore, this simulation is an effective means of forecasting behavioral response of the equipment under different conditions, thereby, aiding in maintenance planning. So, taking an example, companies can test maintenance scenarios for instance in virtual environment, and this will limit the risks of interventions in the real world. With the integration of these virtual models with real-time data from IoT sensors these virtual models can solve predictive maintenance problems that not only are more efficient but are also safer [4-7].

Integration of these technologies into a predictive maintenance framework provides a high didactic basis for improving industrial systems. Research indicates that companies substituting IoT and AI for predictive maintenance can save 10% to 30%

in operational costs, improving their operational availability. But this synergy involving IoT, AI and digital twins doesn't run away with just cost reductions; sustainability benefits include minimizing waste, and more optimally using resources [1,21].

The pillars of predictive maintenance include IoT, artificial intelligence and digital twins. Through integration, companies can transform the nature of their industrial operations, moving maintenance from relatively inefficient but overly responsive to problems to efficient, yet proactive and reactive coverage of modern challenges.

3. CHALLENGES IN IMPLEMENTING PREDICTIVE MAINTENANCE IN INDUSTRY 5.0

Many problems that hinder the effectiveness of predictive maintenance in Industry 5.0 are discussed. Data interoperability, integration, and lack of data standardization pose the technical challenges, as collecting and using data from different sources are difficult for many companies. That fragmentation makes it hard to integrate data collected from IoT devices and other sensors and can cause predictive analytics to be less accurate. Additionally, with the volume of the data being generated, existing IT infrastructures are not able to cope and new capabilities for advanced analytics and machine learning are needed which many companies find difficult to implement [8,9].

Cybersecurity is another huge technical issue. Threats of cyber malware target connected devices and cloud computing used heavily for predictive maintenance. Often these technologies aren't adopted due to a lack of robust security measures from organizations which can act as a deterrent. Further, the complexity of machine learning models can be a barrier since, in some cases, the machine learning models are out of the reach of the knowledge of the firms to develop or maintain the system adequately [11,22,23].

The implementation of predictive maintenance also involves the presence of organizational barriers. Organizations are replete with resistance to change because workers may fear their job is being removed or that their workload will increase. But managing this resistance takes strong leadership combined with the expenditure of resources in support of workforce training.

Additionally, matching predictive maintenance strategies to the overall business objectives is difficult. The problem is that many organizations struggle to show the return on investment for predictive maintenance initiatives, which makes it difficult to secure buy in at the stakeholder level and gets money reallocated for these projects. Making it even more complicated is the need for cross departmental collaboration as the successful predictive maintenance implementation necessitates input from IT, operations and management. Both the effectiveness and sustainability of predictive maintenance initiatives in the context of Industry 5.0 depend on overcoming these technical and organizational challenges to be successful [24,25].

4. OPPORTUNITIES OFFERED BY DIGITAL TRANSFORMATION

Digital transformation offers many open doors for organizations, including better operations efficiency and customer care. Through the power of technology such as IoT, AI and data analytics, organizations can design processes more streamlined and take data driven decisions. For example, IoT devices enable real-time monitoring yielding low maintenance schedules, little downtime. It not only improves productivity but also minimizes operations costs.

With the integration of AI and machine learning, AI can interpret better data providing predictive analytics that look to see what the market and customers may need before it happens. This brings an improvement in offerings and services based on a customer's preference, which means customer loyalty and satisfaction. The automation also reduces man involvement by reducing errors and increasing throughput.

Digital transformation, however, here encourages collaboration and knowledge sharing among departments or within departments, so silos are broken down and there's an environment of innovation. This shift to digital platforms improves speed of implementing decisions and greater communication with stakeholders, improving the overall agility of the organization as well. But a digital transformation requires a strategic approach to ensure the technology plays to business goals. That means companies are going to have to put some money back into training their workforce to adapt to new systems and processes. Also, sensitive data must be protected from a likely breach by robust cybersecurity measures. It means that the opportunities of digital transformation can bring about a competitive advantage that made organizations more resilient and responsive to the market dynamics.

5. CASE STUDIES AND PRACTICAL APPLICATIONS OF PREDICTIVE MAINTENANCE

Predictive maintenance is taking centerstage in Industry 5.0, how companies run their operations. Its practical application and the benefits that result is illustrated with several case studies.

Several studies have been made to the integration of artificial intelligence, machine learning and the Internet of Things (IoT) and digital twins to optimize predictive maintenance in different industrial environments. Specifically, it focuses on pre-processing data to enhance analysis [26], using machine learning combined with IoT for robust applications [27] and advanced use of AI to predict failure in industrial systems [28], and digital twins in industrial vacuum process reviews how virtual modelling facilitates maintenance by simulating operations to mitigate failure before it occurs [4,29].

Several papers in the automotive scene also demonstrate how predictive maintenance revolutionized the automotive industry with machine learning assisting in predictive maintenance. It demonstrates use cases for this approach to predict failures before they happen and therefore decrease downtime and maintenance costs [30-32].

In Health Care insurance an application of advanced artificial intelligence techniques shows its importance to improve predictive maintenance. In the paper [33], the authors describe other AI models that would predict healthcare system failure, giving concrete case studies that might optimize operations, save money, and improve quality of care. With AI, a proactive approach not only preempts service interruptions but optimizes resource utilization, which represents a major reform of the sector.

A variety of machine learning studies in the building installations sector show how predictive maintenance is revolutionizing machine learning. In this article [34], the examples where this approach can detect anomalies and predict failures in building management systems are mentioned. Not only does it cut downtime through better operational efficiency, it also improves maintenance costs from reactive to proactive by moving from a reactive to a proactive maintenance management approach. Using real time signals and historical data, facility managers can extend the life of equipment while keeping the facility comfortable for the occupants.

In other studies, the implementation of predictive maintenance has been studied in the mining sector. Consequently, in paper [35], for instance, the authors have chosen to concentrate on grinding mills. This study demonstrates the application of advanced data analytics and sensors to detect imminent failures of equipment before they occur. It also enhances maintenance costs optimization and reduces the unplanned downtime. The mining case study shows how this approach is changing maintenance practices, resulting in a tremendous productivity increase for the mining industry.

Several other case studies were done to analyze the use of machine learning for improving the predictive maintenance use in the oil and gas sector [36,37]. The conclusions of these studies show that advanced algorithms can not only detect anomalies and predict failures but minimize operations downtime. These use cases show how large these technologies are impacting operational efficiency and asset management in this critical industry.

6. FUTURE PERSPECTIVES AND RECOMMENDATIONS FOR BUSINESSES

Predictive maintenance in Industry 5.0 puts businesses at a strategic crossroads. Artificial intelligence, combined with digital twins, the Internet of Things and predictive maintenance has fused into one integrated solution able to predict failures and better pinpoint what can go wrong. This extends to self-learning systems that increase the predictability of parameters to their operating conditions as well as machine (actual machine) and environment (Environmental variation).

To be competitive, companies should keep their resources on the updating and continuous adjustment of interoperable and modular technologies that allow for little or no obstruction to the business. A key lever for optimizing maintenance decisions is the ability to establish sophisticated digital twins, reproducing not only equipment but also processes. For these simulations, the costs, reduced by the accurate predictive insight, is reduced as well as the unexpected downtime is reduced.

And in this context the key topic is cybersecurity, both for protecting sensitive sensor data but also for trustworthy prediction. Human capital management also gains a new dimension: Key to enable continuous data interpretation and AI tool configuration is to train the personnel in multidisciplinary skills. Finally, companies must form close working relationships with technology providers to get their hands on the cutting-edge innovations and best practices and to adopt open standards to ensure interoperability between complex maintenance systems.

REFERENCES

[1] M. Pech, J. Vrchota, and J. Bednář, "Predictive maintenance and intelligent sensors in smart factory," *Sensors*, vol. 21, no. 4, p. 1470, 2021.

[2] T. Zonta, C. A. Da Costa, R. R. da Rosa Righi, M. J. de Lima, E. S. da Trindade, and G. P. Li, "Predictive maintenance in the Industry 4.0: A systematic literature review," *Computers & Industrial Engineering*, vol. 150, p. 106889, 2020.

[3] A. Adel, "Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas," *Journal of Cloud Computing*, vol. 11, no. 1, p. 40, 2022.

[4] M. F. Yakhni et al., "Design of a digital twin for an industrial vacuum process: a predictive maintenance approach," *Machines*, vol. 10, no. 8, p. 686, 2022.

[5] P. P. Apte and C. J. Spanos, "The digital twin opportunity," *MIT Sloan Management Review*, vol. 63, no. 1, pp. 15-17, 2021.

[6] N. Crespi, A. T. Drobot, and R. Minerva, "The Digital Twin: What and Why?" in *The Digital Twin*, Cham: Springer International Publishing, 2023, pp. 3-20.

[7] P. Raj and C. Surianarayanan, "Digital twin: the industry use cases," in *Advances in Computers*, vol. 117, no. 1, pp. 285-320, Elsevier, 2020.

[8] A. Kanawaday and A. Sane, "Machine learning for predictive maintenance of industrial machines using IoT sensor data," in *2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS)*, pp. 87-90, IEEE, Nov. 2017.

[9] M. Pech, J. Vrchota, and J. Bednář, "Predictive maintenance and intelligent sensors in smart factory," *Sensors*, vol. 21, no. 4, p. 1470, 2021.

[10] M. Compare, P. Baraldi, and E. Zio, "Challenges to IoT-enabled predictive maintenance for industry 4.0," *IEEE Internet of Things Journal*, vol. 7, no. 5, pp. 4585-4597, 2019.

[11] M. C. Zizic, M. Mladineo, N. Gjeldum, and L. Celent, "From Industry 4.0 towards Industry 5.0: A review and analysis of paradigm shift for the people, organization and technology," *Energies*, vol. 15, p. 5221, 2022.

[12] B. Chander, S. Pal, D. De, and R. Buyya, "Artificial intelligence-based internet of things for industry 5.0," in *Artificial Intelligence-Based Internet of Things Systems*, pp. 3-45, 2022.

[13] B. Gladysz et al., "Current development on the Operator 4.0 and transition towards the Operator 5.0: A systematic literature review in light of Industry 5.0," *Journal of Manufacturing Systems*, vol. 70, pp. 160-185, 2023.

[14] D. P. Möller, H. Vakilzadian, and R. E. Haas, "From Industry 4.0 towards Industry 5.0," in *2022 IEEE International Conference on Electro Information Technology (eIT)*, pp. 61-68, IEEE, May 2022.

[15] X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang, "Industry 4.0 and Industry 5.0—Inception, conception and perception," *Journal of Manufacturing Systems*, vol. 61, pp. 530-535, 2021.

[16] S. Aheleroff, H. Huang, X. Xu, and R. Y. Zhong, "Toward sustainability and resilience with Industry 4.0 and Industry 5.0," *Frontiers in Manufacturing Technology*, vol. 2, p. 951643, 2022.

[17] S. Grabowska, S. Saniuk, and B. Gajdzik, "Industry 5.0: Improving humanization and sustainability of Industry 4.0," *Scientometrics*, vol. 127, no. 6, pp. 3117-3144, 2022.

[18] M. Ghobakhloo, H. A. Mahdiraji, M. Iranmanesh, and V. Jafari-Sadeghi, "From Industry 4.0 digital manufacturing to Industry 5.0 digital society: A roadmap toward human-centric, sustainable, and resilient production," *Information Systems Frontiers*, pp. 1-33, 2024.

[19] P. Nunes, J. Santos, and E. Rocha, "Challenges in predictive maintenance – A review," *CIRP Journal of Manufacturing Science and Technology*, vol. 40, pp. 53-67, 2023.

[20] R. van Dinter, B. Tekinerdogan, and C. Catal, "Predictive maintenance using digital twins: A systematic literature review," *Information and Software Technology*, vol. 151, p. 107008, 2022.

[21] M. Achouch, M. Dimitrova, K. Ziane, S. Sattarpanah Karganroudi, R. Dhouib, H. Ibrahim, and M. Adda, "On predictive maintenance in industry 4.0: Overview, models, and challenges," *Applied Sciences*, vol. 12, no. 16, p. 8081, 2022.

[22] G. Czeczot, I. Rojek, D. Mikołajewski, and B. Sangho, "AI in IIoT management of cybersecurity for industry 4.0 and industry 5.0 purposes," *Electronics*, vol. 12, no. 18, p. 3800, 2023.

[23] M. Khan, A. Haleem, and M. Javaid, "Changes and improvements in Industry 5.0: A strategic approach to overcome the challenges of Industry 4.0," *Green Technologies and Sustainability*, vol. 1, no. 2, p. 100020, 2023.

[24] B. Van Oudenhoven, P. Van de Calseyde, R. Basten, and E. Demerouti, "Predictive maintenance for industry 5.0: Behavioural inquiries from a work system perspective," *International Journal of Production Research*, vol. 61, no. 22, pp. 7846-7865, 2023.

[25] G. M. Sang, L. Xu, and P. de Vrieze, "Supporting Predictive Maintenance in Virtual Factory," in *Smart and Sustainable Collaborative Networks 4.0: 22nd IFIP WG 5.5 Working Conference on Virtual Enterprises, PRO-VE 2021*, Saint-Étienne, France, Nov. 22-24, 2021, pp. 151-160. Springer International Publishing.

[26] E. T. Bekar, P. Nyqvist, and A. Skoogh, "An intelligent approach for data pre-processing and analysis in predictive maintenance with an industrial case study," *Advances in Mechanical Engineering*, vol. 12, no. 5, p. 1687814020919207, 2020.

[27] S. Elkateb, A. Métwalli, A. Shendy, and A. E. Abu-Elanien, "Machine learning and IoT–based predictive maintenance approach for industrial applications," *Alexandria Engineering Journal*, vol. 88, pp. 298-309, 2024.

[28] A. Abbas, "AI for predictive maintenance in industrial systems," *International Journal of Advanced Engineering Technologies and Innovations*, vol. 1, no. 1, pp. 31-51, 2024.

[29] H. Hosni, "Conception d'un jumeau numérique pour un procédé d'aspiration industrielle," Doctoral dissertation, La Rochelle University, 2022.

[30] A. Theissler, J. Pérez-Velázquez, M. Kettelgerdes, and G. Elger, "Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry," *Reliability Engineering & System Safety*, vol. 215, p. 107864, 2021.

[31] J. Fernandes, J. Reis, N. Melão, L. Teixeira, and M. Amorim, "The role of Industry 4.0 and BPMN in the arise of condition-based and predictive maintenance: A case study in the automotive industry," *Applied Sciences*, vol. 11, no. 8, p. 3438, 2021.

[32] R. Aravind, C. V. Shah, and M. D. Surabhi, "Machine learning applications in predictive maintenance for vehicles: Case studies," *International Journal of Engineering and Computer Science*, vol. 11, no. 11, 2022.

[33] B. P. Kasaraneni, "Advanced AI techniques for predictive maintenance in health insurance: Models, applications, and real-world case studies," *Distributed Learning and Broad Applications in Scientific Research*, vol. 5, pp. 513-546, 2019.

[34] Y. Bouabdallaoui, Z. Lafhaj, P. Yim, L. Ducoulombier, and B. Bennadji, "Predictive maintenance in building facilities: A machine learning-based approach," *Sensors*, vol. 21, no. 4, p. 1044, 2021.

[35] A. Rihi et al., "Predictive maintenance in mining industry: Grinding mill case study," *Procedia Computer Science*, vol. 207, pp. 2483-2492, 2022.

[36] D. D. Jambol, O. O. Sofoluwe, A. Ukato, and O. J. Ochulor, "Transforming equipment management in oil and gas with AI-driven predictive maintenance," *Computer Science & IT Research Journal*, vol. 5, no. 5, pp. 1090-1112, 2024.

[37] L. Saputelli, C. Palacios, and C. Bravo, "Case studies involving machine learning for predictive maintenance in oil and gas production operations," in *Machine Learning Applications in Subsurface Energy Resource Management*, pp. 313-336, CRC Press, 2022.