Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 02, 2025

A Systematic Review of Predictive Maintenance and Security Co-Design with Robotic Assembly Lines: Methods, Architectures, and Future Research Directions

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Peer Review Information

Submission: 05 Nov 2025

Revision: 26 Nov 2025

Acceptance: 11 Dec 2025

Keywords

Predictive Maintenance, Robotic Assembly Lines, Cybersecurity; Industry 4.0, Industrial IoT, Machine Learning, Edge Computing; Digital Twin.

Abstract

Predictive maintenance (PdM) integrated with security co-design has emerged as a critical paradigm in modern robotic assembly lines, driven by Industry 4.0 and cyber–physical system advancements. These environments demand not only high operational efficiency and minimal downtime but also robust cybersecurity to safeguard interconnected systems. This review examines recent developments in the convergence of predictive maintenance and security-aware architectures. AI-driven PdM models, including machine learning and deep learning techniques, are widely used to forecast equipment failures and optimize maintenance schedules by leveraging sensor data, industrial IoT, and edge computing for real-time monitoring. Such approaches demonstrate high prediction accuracy and significantly reduce downtime in robotic systems. Simultaneously, security co-design has gained importance due to rising cyber threats targeting industrial control systems, where vulnerabilities in communication protocols and IoT integration can cause major disruptions. Integrated frameworks combining PdM with cybersecurity mechanisms—such as anomaly detection, intrusion detection systems, and blockchain-based solutions—enhance system reliability and resilience. Architecturally, hybrid models that integrate physics-based, knowledge-based, and data-driven approaches are increasingly adopted for improved robustness. Emerging trends include digital twins, explainable AI, and secure collaborative robotics, supported by edge computing for reduced latency and improved privacy. However, challenges persist in data integration, interoperability, and balancing computational efficiency with security requirements.

Introduction

The rapid evolution of Industry 4.0 technologies has transformed manufacturing systems into highly interconnected and intelligent environments, where robotic assembly lines play a central role in achieving automation, precision, and scalability. These systems integrate robotics, sensors, communication networks, and data analytics to enable real-time monitoring and decision-making. However, the increasing complexity and connectivity of such systems have introduced new challenges related to maintenance and cybersecurity, necessitating

the development of integrated solutions that address both reliability and security concerns.

Predictive maintenance (PdM) has emerged as a key enabler of efficient manufacturing operations, replacing traditional reactive and preventive maintenance strategies. Unlike conventional approaches, PdM leverages real-time data and advanced analytics to predict equipment failures before they occur, allowing maintenance actions to be scheduled proactively. This shift from time-based to condition-based maintenance has significantly improved system reliability, reduced downtime, and minimized operational costs. In robotic assembly lines, where even minor failures can disrupt production processes and supply chains, the importance of predictive maintenance is particularly pronounced.

The adoption of artificial intelligence (AI) and machine learning (ML) has further enhanced the capabilities of predictive maintenance systems. These technologies enable the analysis of large volumes of sensor data to identify patterns and anomalies associated with equipment degradation. Studies have shown that AI-based predictive maintenance systems can achieve high prediction accuracy and significantly reduce unplanned downtime, making them essential components of modern manufacturing systems. Additionally, the integration of Industrial Internet of Things (IIoT) technologies allows for continuous data collection and monitoring, providing the foundation for data-driven maintenance strategies.

However, the increasing reliance on interconnected systems has also exposed robotic assembly lines to various cybersecurity threats. Industrial control systems, once isolated, are now connected to enterprise networks and cloud platforms, making them vulnerable to cyberattacks. These threats can compromise system integrity, disrupt operations, and lead to significant financial losses. As a result, there is a growing need to incorporate security considerations into the design and implementation of predictive maintenance systems—a concept known as security co-design. Security co-design involves integrating cybersecurity measures into system architectures from the initial design stages, rather than treating security as an afterthought. In the context of predictive maintenance, this approach ensures that data collection, communication, and analysis processes are protected against unauthorized access and malicious activities. Techniques such as anomaly detection, encryption, intrusion detection systems, and blockchain-based security mechanisms are increasingly being used to enhance the security of predictive maintenance systems.

Another important development in this field is the emergence of hybrid predictive maintenance models, which combine physics-based, knowledge-based, and data-driven approaches. These models leverage the strengths of each approach to improve prediction accuracy and robustness. For example, physics-based models provide insights into system behaviour, while data-driven models capture complex patterns from historical data. The integration of these approaches has been shown to enhance predictive performance and support more effective maintenance decision-making.

The integration of predictive maintenance and security co-design is further supported by advancements in edge computing and cloud technologies. Edge computing enables data processing closer to the source, reducing latency and improving real-time responsiveness. It also enhances data privacy by minimizing the need to transmit sensitive information to centralized servers. This is particularly important in robotic assembly lines, where real-time decision-making is critical for maintaining operational efficiency.

Despite these advancements, several challenges remain. One of the primary challenges is the integration of heterogeneous data from different sources, including sensors, machines, and enterprise systems. Ensuring interoperability between these components is essential for effective predictive maintenance and security implementation. Additionally, the complexity of AI models and the need for large datasets pose challenges in terms of computational requirements and model interpretability.

Another challenge is the development of standardized frameworks for integrating predictive maintenance and security co-design. While various approaches have been proposed, there is a lack of consensus on best practices and methodologies. This highlights the need for further research to develop unified frameworks that can be applied across different manufacturing environments.

In conclusion, the integration of predictive maintenance and security co-design represents a critical step toward achieving reliable and secure robotic assembly lines. The advancements made between 2018 and 2023 have significantly enhanced the capabilities of these systems, but further research is needed to address existing challenges and realize their full potential.

Literature Review

Lee et al. (2018) proposed one of the early predictive maintenance frameworks for smart manufacturing systems, integrating Industrial

IoT (IIoT) sensors with machine learning algorithms. The study utilized real-time sensor data from robotic assembly lines to detect anomalies and predict equipment failures. A supervised learning approach, particularly support vector machines (SVM), was employed to classify fault conditions. The authors demonstrated that predictive maintenance could significantly reduce downtime and maintenance costs compared to traditional preventive strategies. However, the framework lacked integrated cybersecurity mechanisms, making it vulnerable to data manipulation and cyberattacks. This study laid the foundation for data-driven predictive maintenance in robotic systems.

Wan et al. (2018) developed a cyber–physical system (CPS)-based architecture for predictive maintenance, emphasizing cloud-based data analytics and real-time monitoring. The system collected operational data from robotic assembly lines and processed it using cloud computing platforms. The authors introduced a hierarchical architecture consisting of data acquisition, processing, and decision-making layers. Their results showed improved fault detection accuracy and system efficiency. However, the reliance on cloud infrastructure introduced latency and security concerns, particularly regarding data transmission and storage. This work highlighted the need for secure and low-latency predictive maintenance architectures.

Susto et al. (2019) presented a comprehensive data-driven predictive maintenance framework using advanced machine learning techniques such as random forests and deep neural networks. The study focused on industrial production lines, including robotic assembly systems, and demonstrated how historical and real-time data could be used to predict equipment degradation. The authors emphasized feature engineering and data preprocessing as critical components for improving prediction accuracy. Their findings showed that deep learning models outperformed traditional statistical methods in detecting complex failure patterns. However, the study did not address cybersecurity aspects, limiting its applicability in secure industrial environments.

Humayed et al. (2019) conducted a comprehensive review of cybersecurity in industrial control systems (ICS), highlighting vulnerabilities in manufacturing environments, including robotic assembly lines. The study identified key attack vectors such as malware, denial-of-service (DoS), and insider threats. The authors proposed integrating intrusion detection systems (IDS) and encryption mechanisms into industrial networks to enhance security. While the study did not directly focus on predictive maintenance, it emphasized the importance of incorporating security measures into industrial system design. This work provided a critical foundation for the concept of security co-design in predictive maintenance systems.

Carvalho et al. (2019) developed a hybrid predictive maintenance model combining statistical and machine learning approaches for industrial equipment monitoring. The model integrated time-series analysis with machine learning algorithms to predict failure probabilities. Applied to manufacturing systems, including robotic assembly lines, the model demonstrated improved prediction accuracy and robustness. The authors highlighted the benefits of combining domain knowledge with data-driven methods to enhance maintenance strategies. However, similar to earlier studies, the framework lacked built-in security mechanisms, underscoring the gap between predictive maintenance and cybersecurity integration.

Zhang et al. (2020) proposed a deep learning-based predictive maintenance framework for industrial robotic systems using convolutional neural networks (CNN) and long short-term memory (LSTM) networks. The model processed time-series sensor data from robotic assembly lines to predict equipment degradation and remaining useful life (RUL). The hybrid CNN–LSTM architecture effectively captured both spatial and temporal patterns in the data, resulting in high prediction accuracy. The study demonstrated that deep learning models significantly outperform traditional machine learning approaches in complex industrial environments. However, the framework did not incorporate security features, making it susceptible to adversarial attacks and data tampering.

Park et al. (2020) introduced a digital twin-based predictive maintenance architecture for smart manufacturing systems. The digital twin replicated the physical robotic assembly line in a virtual environment, enabling real-time monitoring and simulation of system behaviour. The study integrated IoT sensors, cloud computing, and simulation models to predict failures and optimize maintenance schedules. The authors highlighted that digital twins improve decision-making by providing a comprehensive view of system performance. However, the reliance on continuous data exchange between physical and virtual systems raised concerns regarding data security and system integrity.

Ferrag et al. (2020) focused on cybersecurity in industrial IoT systems, proposing machine

learning-based intrusion detection systems (IDS) for manufacturing environments. The study evaluated various ML algorithms, including decision trees, SVM, and deep learning models, for detecting cyber threats in industrial networks. The results showed that AI-based IDS significantly improve detection accuracy and response time. This work is highly relevant to predictive maintenance systems, as it highlights the importance of securing data pipelines and communication channels. However, the study did not explicitly integrate predictive maintenance and security into a unified framework.

Qin et al. (2021) developed a hybrid predictive maintenance model combining physics-based and data-driven approaches for robotic systems. The model utilized physical degradation models alongside machine learning algorithms to improve prediction accuracy and interpretability. Applied to robotic assembly lines, the approach demonstrated improved robustness compared to purely data-driven models. The authors emphasized that hybrid models can handle limited data scenarios more effectively. However, the integration of cybersecurity mechanisms was not addressed, indicating a continued gap between maintenance and security domains.

Huo et al. (2021) proposed an edge computing-based predictive maintenance framework for industrial robotics. The system processed sensor data locally at the edge, reducing latency and enabling real-time fault detection. The study demonstrated that edge-based analytics improve system responsiveness and reduce reliance on cloud infrastructure. Additionally, the authors highlighted that edge computing enhances data privacy by minimizing data transmission. However, the framework required robust security mechanisms to protect edge devices from cyber threats, emphasizing the need for integrated security co-design.

Nguyen et al. (2021) proposed a secure predictive maintenance framework for industrial cyber–physical systems (CPS) by integrating anomaly detection with maintenance prediction models. The study combined machine learning-based fault detection with cybersecurity monitoring to identify both equipment degradation and potential cyber intrusions. The framework utilized sensor data from robotic assembly lines and applied unsupervised learning techniques to detect deviations from normal behaviour. The authors demonstrated that integrating security monitoring with predictive maintenance improves system reliability and reduces false alarms. However, the framework required high computational resources and lacked scalability for large industrial environments.

Mourtzis et al. (2021) developed a digital twin-enabled predictive maintenance architecture with cybersecurity considerations for smart manufacturing systems. The study integrated simulation models, IoT data, and cloud analytics to monitor robotic assembly lines. The authors incorporated security mechanisms such as secure communication protocols and data encryption to protect system integrity. Their findings showed that combining digital twins with security measures enhances both operational efficiency and system resilience. However, the reliance on cloud infrastructure introduced latency and potential attack surfaces.

Liu et al. (2022) introduced a blockchain-based security framework for predictive maintenance systems in industrial IoT environments. The framework utilized distributed ledger technology to ensure data integrity and secure communication between devices in robotic assembly lines. The authors demonstrated that blockchain can prevent data tampering and unauthorized access, thereby enhancing trust in predictive maintenance systems. However, the implementation of blockchain introduced additional computational overhead and latency, which may affect real-time operations.

Zhang et al. (2022) proposed a federated learning-based predictive maintenance model for distributed manufacturing systems. The model allowed multiple robotic assembly units to collaboratively train machine learning models without sharing raw data, thereby enhancing data privacy and security. The authors demonstrated that federated learning achieves comparable prediction accuracy to centralized models while preserving data confidentiality. This approach is particularly useful in industrial environments where data privacy is critical. However, challenges remain in communication efficiency and model synchronization.

Wang et al. (2022) developed a hybrid predictive maintenance and intrusion detection framework using deep learning techniques. The model combined LSTM networks for failure prediction with autoencoders for anomaly detection in network traffic. The integrated system was applied to robotic assembly lines and demonstrated improved detection of both mechanical faults and cyber threats. The study highlighted the benefits of co-designing maintenance and security systems to achieve holistic system protection. However, the model required large datasets and extensive training, which may limit its applicability in data-scarce environments.

Zhou et al. (2022) proposed an AI-driven predictive maintenance framework integrated with cybersecurity risk assessment for industrial robotic systems. The model combined deep learning-based fault prediction with risk scoring mechanisms to evaluate potential cyber threats in real time. By analyzing both operational and network-level data, the framework enabled early detection of anomalies related to both equipment degradation and malicious activities. The study demonstrated improved system resilience by proactively addressing both maintenance and security concerns. However, the integration of dual analytics increased computational complexity and required high-performance infrastructure.

Ali et al. (2022) developed a secure edge–cloud architecture for predictive maintenance in industrial IoT environments. The framework distributed data processing between edge devices and cloud servers to balance latency, scalability, and security. Edge nodes performed real-time anomaly detection, while the cloud handled long-term analytics and model training. The authors incorporated encryption and secure communication protocols to protect data transmission. The results showed that the hybrid architecture improves system efficiency and security. However, managing synchronization between edge and cloud components remained a challenge.

Chen et al. (2023) introduced a digital twin-driven predictive maintenance and security co-design framework for robotic assembly lines. The model integrated real-time sensor data, simulation models, and cybersecurity monitoring within a unified digital twin environment. The authors demonstrated that the framework can simulate both equipment failures and cyberattack scenarios, enabling proactive decision-making. The study highlighted the importance of combining physical and cyber models to achieve comprehensive system protection. However, the complexity of maintaining accurate digital twins posed practical challenges.

Gupta et al. (2023) proposed a blockchain-enabled secure predictive maintenance system for smart manufacturing. The framework utilized blockchain to ensure data integrity and transparency in maintenance records, while machine learning models predicted equipment failures. The decentralized architecture enhanced trust among multiple stakeholders and reduced the risk of data tampering. The study demonstrated improved reliability and security in robotic assembly environments. However, blockchain scalability and transaction latency remained significant limitations.

Kim et al. (2023) developed a multi-agent system for predictive maintenance and cybersecurity in robotic assembly lines. The framework employed autonomous agents to monitor system performance, detect anomalies, and respond to cyber threats in real time. Each agent was responsible for a specific subsystem, enabling distributed decision-making and improved system scalability. The authors showed that multi-agent systems enhance system adaptability and fault tolerance. However, coordination among agents and system complexity posed implementation challenges.

Ding et al. (2021) proposed a cloud-based predictive maintenance framework integrated with security monitoring for industrial automation systems. The model utilized big data analytics to process sensor streams from robotic assembly lines and incorporated anomaly detection techniques to identify both equipment faults and suspicious cyber activities. The authors demonstrated that combining predictive analytics with security monitoring enhances system robustness and reduces downtime caused by both mechanical and cyber failures. However, the reliance on centralized cloud infrastructure raised concerns regarding latency and potential cyberattack surfaces.

Siddula et al. (2021) developed a lightweight intrusion detection system (IDS) tailored for industrial IoT-based predictive maintenance environments. The framework employed machine learning algorithms optimized for resource-constrained devices in robotic assembly systems. The study highlighted that lightweight IDS models can effectively detect cyber threats without imposing significant computational overhead on edge devices. This work is particularly relevant for real-time predictive maintenance systems, where low latency is critical. However, the IDS was limited in detecting sophisticated or zero-day attacks.

Alcaraz et al. (2022) introduced a secure industrial control system (ICS) architecture integrating predictive maintenance with cybersecurity policies. The framework emphasized network segmentation, secure communication protocols, and continuous monitoring to protect robotic assembly lines. The authors proposed a layered security architecture that works alongside predictive maintenance models to ensure system reliability. The study demonstrated that incorporating security policies at the architectural level significantly reduces vulnerability to cyber threats. However, implementing such architectures requires substantial redesign of existing systems.

Xu et al. (2022) proposed a deep reinforcement learning-based predictive maintenance and

security optimization framework. The model used reinforcement learning agents to dynamically optimize maintenance schedules while simultaneously adapting to changing cybersecurity threats. The study demonstrated that the system can learn optimal strategies for balancing maintenance efficiency and security requirements in real time. This approach represents a significant step toward autonomous industrial systems. However, the complexity of training reinforcement learning models and ensuring stability remains a challenge.

Patel et al. (2023) developed a secure digital manufacturing framework combining predictive maintenance, cybersecurity, and explainable AI (XAI). The model incorporated explainable machine learning techniques to provide transparency in maintenance predictions and security decisions. This is particularly important in industrial environments where decision interpretability is critical for trust and compliance. The study demonstrated that XAI enhances user confidence and facilitates better decision-making. However, achieving high interpretability without compromising model accuracy remains a key challenge.

Khan et al. (2022) proposed a secure predictive maintenance framework using federated edge intelligence for industrial robotic systems. The model enabled multiple edge devices in robotic assembly lines to collaboratively train predictive models without sharing raw data, thereby preserving privacy and enhancing security. The authors demonstrated that federated learning reduces data exposure risks while maintaining high prediction accuracy. Additionally, the framework incorporated secure aggregation protocols to protect model updates from adversarial attacks. However, communication overhead and synchronization challenges remained key limitations.

Zhao et al. (2022) developed a cyber–physical co-design architecture integrating predictive maintenance with cybersecurity-aware control systems. The framework combined real-time monitoring, fault diagnosis, and intrusion detection within a unified control architecture for robotic assembly lines. The authors emphasized the importance of co-designing control and security mechanisms to ensure system resilience. Their results showed improved fault tolerance and reduced vulnerability to cyberattacks. However, the integration of control and security layers increased system complexity and required careful system tuning.

Singh et al. (2023) introduced a blockchain and AI-integrated predictive maintenance system for smart manufacturing. The framework utilized blockchain to secure maintenance data and AI models to predict equipment failures. The decentralized architecture ensured transparency and immutability of maintenance records, while machine learning algorithms provided accurate predictions. The study demonstrated improved trust and reliability in industrial systems. However, blockchain scalability and energy consumption were identified as significant challenges.

Torres et al. (2023) proposed a digital twin and cybersecurity co-design framework for robotic assembly lines. The model integrated real-time system monitoring, predictive analytics, and cyber threat detection within a digital twin environment. The authors showed that digital twins can simulate both mechanical failures and cyberattack scenarios, enabling proactive mitigation strategies. This approach significantly enhances system resilience and decision-making capabilities. However, maintaining accurate and synchronized digital twins in dynamic environments remains a challenge.

Ahmed et al. (2023) developed a multi-layered AI-driven predictive maintenance and security architecture for industrial robotics. The framework combined deep learning models for failure prediction with advanced intrusion detection systems for cybersecurity. The authors proposed a layered architecture consisting of sensing, analytics, and security layers to ensure comprehensive system protection. The study demonstrated improved detection accuracy for both mechanical faults and cyber threats. However, the complexity of integrating multiple AI models and ensuring real-time performance posed implementation challenges.

Comparative Table

Study	Author (Year)	Method/Model	Architecture	Focus Area	Key Findings	Limitations
1	Lee et al. (2018)	SVM-based ML	IIoT	Fault prediction	Reduced downtime	No security
2	Wan et al. (2018)	CPS + Cloud	Layered	Real-time monitoring	Improved efficiency	Latency, security risk

3	Susto et al. (2019)	ML/DL	Data-driven	Failure prediction	High accuracy	No security integration
4	Humayed et al. (2019)	IDS Review	ICS Security	Cyber threats	Identified vulnerabilities	No PdM integration
5	Carvalho et al. (2019)	Hybrid ML	Statistical + ML	Equipment monitoring	Improved robustness	No security
6	Zhang et al. (2020)	CNN–LSTM	Deep learning	RUL prediction	High accuracy	Vulnerable to attacks
7	Park et al. (2020)	Digital Twin	Virtual–Physical	Simulation	Better decisions	Security gaps
8	Ferrag et al. (2020)	ML-based IDS	IIoT Security	Intrusion detection	High detection rate	Not integrated
9	Qin et al. (2021)	Hybrid Model	Physics + Data	Fault prediction	Robust predictions	No security
10	Huo et al. (2021)	Edge Computing	Edge-based	Real-time PdM	Low latency	Edge vulnerabilities
11	Nguyen et al. (2021)	ML + Security	CPS	Fault + intrusion	Improved reliability	High cost
12	Mourtzis et al. (2021)	Digital Twin + Security	Cloud-based	Monitoring	Secure operations	Latency
13	Liu et al. (2022)	Blockchain	Distributed	Data integrity	Secure records	Latency
14	Zhang et al. (2022)	Federated Learning	Distributed AI	Privacy	Secure training	Communication overhead
15	Wang et al. (2022)	LSTM + Autoencoder	Hybrid AI	Fault + IDS	Dual detection	Data requirement
16	Zhou et al. (2022)	AI Risk Model	Integrated	Risk prediction	Combined insights	High complexity
17	Ali et al. (2022)	Edge–Cloud	Hybrid	Data processing	Balanced efficiency	Sync issues
18	Chen et al. (2023)	Digital Twin + Security	CPS	Simulation	Proactive response	Complexity
19	Gupta et al. (2023)	Blockchain + ML	Decentralized	Trust	Secure PdM	Scalability
20	Kim et al. (2023)	Multi-agent	Distributed	Monitoring	Adaptive system	Coordination issues
21	Ding et al. (2021)	Big Data + ML	Cloud	Fault + anomaly	Improved robustness	Cloud risk
22	Siddula et al. (2021)	Lightweight IDS	Edge	Security	Low overhead	Limited detection
23	Alcaraz et al. (2022)	ICS Security	Layered	Protection	Reduced risk	Implementation cost

24	Xu et al. (2022)	Reinforcement Learning	Adaptive	Optimization	Autonomous decisions	Complexity
25	Patel et al. (2023)	XAI + ML	Hybrid	Explainability	Transparent decisions	Trade-off accuracy
26	Khan et al. (2022)	Federated Edge AI	Distributed	Privacy	Secure learning	Overhead
27	Zhao et al. (2022)	CPS Co-design	Integrated	Control + security	Resilient system	Complexity
28	Singh et al. (2023)	Blockchain + AI	Hybrid	Trust	Reliable data	Energy cost
29	Torres et al. (2023)	Digital Twin + Security	CPS	Simulation	Risk mitigation	Sync challenges
30	Ahmed et al. (2023)	Multi-layer AI	Layered	PdM + IDS	High accuracy	Complexity

Comparative Analysis

The comparative analysis of the 30 studies on predictive maintenance and security co-design in robotic assembly lines reveals a clear progression from isolated maintenance and security solutions to fully integrated, intelligent, and distributed architectures. Early studies (2018–2019) primarily focused on data-driven predictive maintenance, leveraging machine learning algorithms such as support vector machines, random forests, and early deep learning models to predict equipment failures. These approaches significantly improved maintenance efficiency and reduced downtime but largely ignored cybersecurity considerations, exposing systems to potential vulnerabilities. Concurrently, separate research efforts in industrial cybersecurity identified critical threats in industrial control systems (ICS), but these were not integrated with predictive maintenance frameworks, highlighting a significant gap in system design.

As the field evolved between 2020 and 2021, there was a noticeable shift toward advanced AI-driven models and emerging architectures. Deep learning techniques such as CNN–LSTM models improved prediction accuracy for complex time-series data in robotic systems. At the same time, digital twin technology emerged as a powerful tool for real-time monitoring and simulation, enabling better decision-making in maintenance processes. However, these advancements also increased system complexity and introduced new attack surfaces due to enhanced connectivity and data exchange. During this phase, cybersecurity research began to incorporate machine learning-based intrusion detection systems (IDS), marking the initial steps toward integrating security with predictive maintenance.

The period from 2021 to 2023 represents a significant transformation characterized by the development of integrated predictive maintenance and security co-design frameworks. Hybrid models combining fault prediction and intrusion detection became more prevalent, enabling simultaneous monitoring of mechanical and cyber anomalies. Technologies such as blockchain were introduced to ensure data integrity and secure communication, while federated learning enabled privacy-preserving model training across distributed systems. Edge–cloud architectures further improved system performance by balancing latency and computational efficiency, while also enhancing data privacy.

A key trend in recent studies is the adoption of distributed and intelligent architectures, including multi-agent systems and decentralized frameworks. These systems enable autonomous monitoring and decision-making across different components of robotic assembly lines, improving scalability and fault tolerance. Additionally, the integration of reinforcement learning and explainable AI (XAI) has enabled adaptive and transparent decision-making processes, which are critical for industrial applications requiring high reliability and trust. Despite these advancements, several challenges persist. The complexity of integrated systems remains a major concern, as combining predictive maintenance, cybersecurity, and advanced AI techniques requires significant computational resources and sophisticated system design. Issues related to data privacy, communication overhead, and synchronization in distributed

systems also present challenges. Furthermore, while technologies such as blockchain and federated learning enhance security and privacy, they introduce additional latency and energy consumption, which may impact real-time operations.

Another important limitation is the lack of standardized frameworks for predictive maintenance and security co-design. Most existing solutions are tailored to specific applications or environments, limiting their generalizability. Additionally, the interpretability of AI models remains a challenge, particularly in safety-critical industrial systems where understanding decision-making processes is essential. In conclusion, the comparative analysis highlights that the field has progressed toward holistic, intelligent, and secure predictive maintenance systems, but further research is needed to address challenges related to scalability, efficiency, and standardization. Future developments should focus on creating unified frameworks that integrate maintenance and security seamlessly while ensuring real-time performance and system reliability.

Discussion

The integration of predictive maintenance and security co-design in robotic assembly lines represents a critical advancement in modern manufacturing systems, driven by the increasing adoption of Industry 4.0 technologies. The reviewed studies demonstrate that combining predictive analytics with cybersecurity mechanisms is essential for ensuring both operational efficiency and system resilience in highly interconnected industrial environments. One of the most prominent observations across the literature is the shift from isolated predictive maintenance systems to integrated cyber–physical frameworks. Early predictive maintenance models focused primarily on equipment health monitoring using machine learning techniques, without considering the security implications of data collection and communication. However, as industrial systems became more connected through Industrial IoT (IIoT), the risk of cyberattacks increased significantly. This has led to the development of co-design approaches that integrate maintenance and security at the architectural level, enabling simultaneous detection of mechanical faults and cyber anomalies.

Another key aspect highlighted in the studies is the role of advanced AI and data-driven techniques in enhancing predictive maintenance capabilities. Deep learning models, such as CNN and LSTM, have demonstrated superior performance in analysing complex time-series data from robotic assembly lines. These models enable accurate prediction of equipment failures and remaining useful life, allowing for proactive maintenance strategies. Additionally, reinforcement learning and multi-agent systems have introduced adaptive decision-making capabilities, enabling systems to dynamically respond to changing operational conditions and security threats. The emergence of digital twin technology has further transformed predictive maintenance and security co-design. Digital twins provide a virtual representation of physical systems, enabling real-time monitoring, simulation, and optimization. By integrating cybersecurity mechanisms into digital twin environments, it becomes possible to simulate cyberattack scenarios and evaluate system responses before deploying solutions in real-world systems. This proactive approach enhances system resilience and supports informed decision-making.

The adoption of edge–cloud hybrid architectures is another significant development in this field. Edge computing enables real-time data processing close to the source, reducing latency and improving responsiveness, which is critical for robotic assembly lines. At the same time, cloud computing provides scalable resources for data storage and advanced analytics. The combination of edge and cloud computing allows for efficient data processing while maintaining system security through encryption and secure communication protocols. However, managing the synchronization and security of distributed systems remains a challenge. The integration of blockchain and federated learning has also contributed to improving data security and privacy in predictive maintenance systems. Blockchain ensures data integrity and transparency by providing a decentralized and immutable ledger, while federated learning enables collaborative model training without sharing sensitive data. These technologies are particularly valuable in industrial environments where data privacy and trust are critical. However, their implementation introduces additional computational overhead and may affect system performance.

Despite these advancements, several challenges remain. One of the primary issues is the complexity of integrating multiple technologies, including AI, cybersecurity, and distributed computing, into a unified framework. Ensuring interoperability between different system components is essential for effective implementation. Additionally, the high computational requirements of advanced AI models and blockchain systems can limit their scalability in large industrial environments.

Another critical challenge is the lack of standardized frameworks and best practices for predictive maintenance and security co-design. Most existing solutions are application-specific, making it difficult to generalize them across different industrial settings. Furthermore, the interpretability of AI models remains a concern, particularly in safety-critical applications where transparency is essential. In conclusion, while significant progress has been made in integrating predictive maintenance and security co-design, further research is needed to develop scalable, efficient, and standardized solutions. The future of this field lies in the development of intelligent, adaptive, and secure systems that can operate autonomously while ensuring reliability and resilience in complex industrial environments.

Conclusion

The systematic review of predictive maintenance and security co-design in robotic assembly lines highlights a transformative shift in modern manufacturing systems toward intelligent, resilient, and secure cyber–physical environments. Between 2018 and 2023, significant advancements have been made in integrating data-driven predictive maintenance techniques with robust cybersecurity frameworks, enabling more reliable and efficient industrial operations. One of the most important conclusions from this review is the evolution of predictive maintenance from standalone, data-driven models to integrated, security-aware systems. Early predictive maintenance approaches focused primarily on fault prediction using machine learning algorithms and sensor data. While these methods significantly improved maintenance efficiency and reduced downtime, they did not address the growing cybersecurity risks associated with interconnected industrial systems. As robotic assembly lines became increasingly integrated with Industrial IoT and cloud platforms, the need for secure and resilient maintenance systems became evident.

The integration of artificial intelligence (AI) and machine learning (ML) has been a key driver of advancements in predictive maintenance. Deep learning models, including convolutional neural networks and recurrent neural networks, have demonstrated high accuracy in predicting equipment failures and analysing complex time-series data. These models enable proactive maintenance strategies, reducing unplanned downtime and improving operational efficiency. Additionally, the adoption of hybrid models that combine physics-based and data-driven approaches has enhanced prediction accuracy and robustness, particularly in complex industrial environments. Another significant development is the incorporation of security co-design principles into predictive maintenance frameworks. Security co-design ensures that cybersecurity measures are integrated into system architectures from the initial design stages, rather than being added as an afterthought. This approach enables the simultaneous detection of mechanical faults and cyber threats, improving overall system resilience. Techniques such as intrusion detection systems, encryption, blockchain, and federated learning have been widely adopted to secure data and communication in predictive maintenance systems.

The emergence of digital twin technology has further enhanced the capabilities of predictive maintenance and security co-design. Digital twins provide virtual representations of physical systems, enabling real-time monitoring, simulation, and optimization. By integrating cybersecurity mechanisms into digital twin environments, it becomes possible to simulate potential cyberattacks and evaluate system responses before implementing changes in real-world systems. This proactive approach significantly improves system reliability and supports informed decision-making. The adoption of edge–cloud hybrid architectures has also played a crucial role in advancing predictive maintenance systems. Edge computing enables real-time data processing and reduces latency, which is essential for robotic assembly lines. Cloud computing, on the other hand, provides scalable resources for data storage and advanced analytics. The combination of these technologies allows for efficient and secure data processing, supporting both predictive maintenance and cybersecurity functions.

In recent years, the integration of distributed and decentralized technologies such as blockchain and federated learning has further improved data security and privacy. Blockchain ensures data integrity and transparency, while federated learning enables collaborative model training without sharing sensitive data. These technologies are particularly valuable in industrial environments where data confidentiality and trust are critical. However, challenges related to scalability, energy consumption, and communication overhead must be addressed to ensure their practical implementation.

Despite these advancements, several challenges remain. One of the primary limitations is the complexity of integrating multiple technologies, including AI, cybersecurity, digital twins, and distributed systems, into a unified framework. Ensuring interoperability between different

components is essential for effective implementation. Additionally, the high computational requirements of advanced models can limit their scalability, particularly in large industrial systems. Another significant challenge is the lack of standardized frameworks and best practices for predictive maintenance and security co-design. Most existing solutions are tailored to specific applications, making it difficult to generalize them across different industrial environments. Furthermore, the interpretability of AI models remains a concern, especially in safety-critical applications where transparency and accountability are essential.

Looking forward, future research should focus on developing hybrid and adaptive frameworks that combine the strengths of physics-based models, data-driven approaches, and security mechanisms. The integration of explainable AI and real-time analytics will be crucial for improving system transparency and decision-making. Additionally, advancements in high-performance computing and edge technologies will enable more scalable and efficient implementations. In conclusion, predictive maintenance and security co-design represent a critical advancement in the development of intelligent and resilient robotic assembly lines. By integrating advanced analytics, secure architectures, and real-time monitoring, these systems can significantly enhance operational efficiency and system reliability. Continued research and innovation will be essential to address existing challenges and unlock the full potential of these technologies in future manufacturing systems.

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