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Enhancing predictive maintenance in lean manufacturing for continuous process improvement using digital twin technology

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Abstract

The latest advancement in digital technologies has greatly revolutionized modern manufacturing processes, particularly through the adoption of Lean Manufacturing initiatives aimed at minimizing wastage and enhancing operational efficiency. Predictive Maintenance (PM) being one of the primary drivers of transformation in lean manufacturing by reducing equipment downtime and optimizing asset performance. The lack of failure data is one of the biggest obstacles to PM deployment because traditional maintenance methods are used to maintain equipment after they break down. In order to address the issue of data scarcity, this study investigates the use of Digital Twin (DT) technology, which creates a virtual duplicate of the physical item and enables real-time monitoring utilizing sensors and Internet of Things devices for predictive analysis. IoT and data analytics are well complemented by digital twin technology, giving the manufacturer access to real-time information about the state of the machines while they are operating. This connectivity allows them to predict future asset failures accurately and strategically schedule maintenance activities in advance. The findings presented in this paper demonstrate that digital twin applications can reduce maintenance costs by 35% and machine uptime by 98%. It also presents case studies of DT application across different industries, and comparative study of positive impacts achieved through DT adoption. Cumulatively, the study highlights DT's transformational capability to facilitate lean initiatives and demands further investigation into integrations of emerging technology for process improvement.

Keywords: Lean Manufacturing; Continuous Process Improvement; Digital Twin; Predictive Maintenance; Digital Transformation

1. Introduction

For manufacturing companies to achieve an optimum economic success-especially being in a global market where competitive advantage needs to be maximized, their operations have to be streamlined. Continuous improvements should be made to realize manufacturing excellence that sustains economic growth. Reduction of waste from manufacturing processes, therefore, is vital, and hence implementation of lean-manufacturing principles is key to achieving this [1, 2]. Lean manufacturing has often been described as a philosophy based on continuous improvement. It pursues the implementation of processes that guarantee high quality, safety, and improvement in the productive activities of workers, while simultaneously decreasing the costs of production and lead times [3]. This approach focuses on minimizing product costs throughout the entire production lifecycle, whether during design, fabrication, or manufacturing, by leveraging insights from previous business evaluations. Through optimizing expenses and materials during the design phase, organizations can achieve greater efficiency in management. A critical step in this process

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involves identifying and eliminating all forms of production waste [4, 5]. Lean manufacturing is an integrated manufacturing method that aims to minimize operational interruption while optimizing industry resource use. by employing streamlined processes to cut down on material waste, operating expenses, and manufacturing cycle time. The lean idea has gained popularity in industry management over the past ten years. According to earlier research, industries who adopted the lean approach produced better and more superior results than their rivals in terms of both cost and quality [6, 7, 8]. This lean method is a long-term growth plan that incorporates multiple practices that demand a high level of commitment from top management, rather than just being a cost-cutting or inventory-cutting tactic [9]. As a result of pressure from local and international firms, organizations move from the traditional manufacturing systems to lean systems. Changing into lean system is associated with barriers and challenges that are required to be handled for the implementation of this change successfully [10, 11]. For system maintenance, the effective adoption of a lean system hinges on crucial factors such as organizational management, adequate financial resources, technical skills and expertise, and a corporate culture geared towards operational efficiency. In these, predictive maintenance integrated into the framework of Lean further improves equipment reliability and downtime, thus supporting the philosophy of continuous improvement as harnessed in the lean manufacturing concept [12, 13]. Lean thinking on the process of maintenance is one critical productivity success factor toward reaching strategic organizational objectives in the high competitiveness markets [14]. Predictive Maintenance fits into lean approach in manufacturing very well by utilizing data-driven tools and techniques that predict equipment failures, and hence minimize unplanned downtime, thereby optimizing asset usage. This proactive approach supports the lean goal of maintaining streamlined operations and enhancing production efficiency, so facilities can meet customer demand consistently with minimum amount of waste [15, 16]. The lean system is an integrated long-term growth approach which extends beyond mere cost reduction. It focuses on sustained and continuous improvement, integrating various best practices that must be implemented and supported by top management if the approach is to succeed [17]. Going lean is the only way to survive in today's competitive market, where an immense need to transform from a traditional manufacturing system to a lean system is essential for staying relevant but comes with challenges, including overcoming cultural and operational barriers [18]. Critical success factors for implementing lean strategy include strong management interest and a corporate culture that prioritizes efficiency and embraces continuous improvement in operation [19]. Lean manufacturing will become even more dynamic when combined with predictive maintenance because it utilizes real-time, precise information to proactively identify potential inefficiencies and equipment failures. Predictive maintenance enhances the lean principle by reducing downtime, optimizing asset performance, and eliminating processes that waste resources and add no value. The integration of PM in lean principles will lead to increased productivity and profitability, operational efficiency, innovation and continuous improvement throughout the organization. Relied on by genuine and reliable data, lean manufacturing coupled with predictive maintenance ensures that firms stay agile, resilient, and well-equipped in handling future challenges and demands [21, 22]. One fundamental strategy for creating a more dependable, profitable, and sustainable industrial sector is predictive maintenance. However, because maintenance is usually done only after equipment breaks down, one of the major obstacles to creating predictive maintenance systems is the scarcity of failure data [23]. By developing a virtual model of actual equipment, this study seeks to present the integration of Digital Twin technology as a solution to the problem of failure data availability. This will generate valuable operational data in real-time, including asset degradation trends, which will be used to inform predictive maintenance algorithms [24, 25].

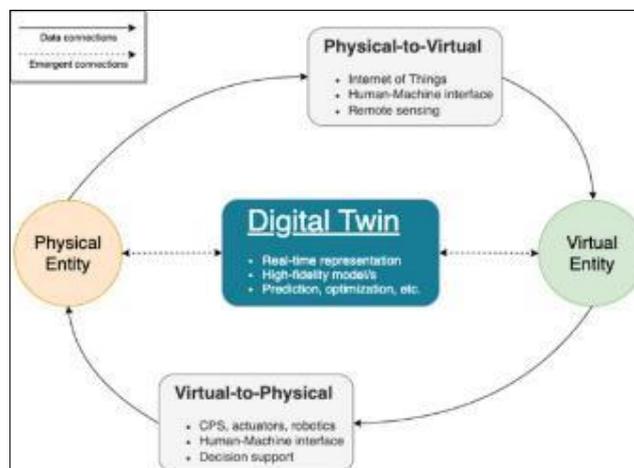


Figure 1 A Lean-Based Approach to Predictive Maintenance Using Digital Twin Technology [20]

2. Digital Twin Technology

2.1. Definition

The development of virtual copies of physical assets connected via real-time data transmission is known as digital twin (DT) technology. Applications like real-time monitoring, design verification, performance optimization, maintenance, and remote access management are made possible by the digital model's realistic representation of the physical counterpart's state and behavior [26]. It is an essential tool for data-driven decision-making, enabling complex system and process monitoring, lifecycle management, and simulation. Adoption of digital twins, an emerging technology, is growing across several industries, including smart cities, healthcare, automotive systems, and industrial applications. A thorough examination of digital twin technology is given in this systematic study, which also highlights its use in various application areas and important engineering disciplines [27, 28]. Dr. Michael Grieves first proposed the idea in 2002, defining a digital twin as a virtual information construct that fully describes and represents a physical asset, from the micro atomic level to the macro geometrical level [29]. Although the concept has recently gained significant momentum in both academic and industrial contexts, its roots go back much further. He added that any information that may be obtained by looking at a physical thing may equally be available through its digital equivalent. According to this definition, a Digital Twin system is made up of three primary components: a digital counterpart, a physical model, and a system that allows data to flow in real time between them [30]. The critical aspect of this framework emphasizes a full interfacing between the physical and virtual systems or entities in a back-and-forth flow. That is, all data available on the physical entity should also be accessible via its digital counterpart. In this respect, DTs reflect the vigorous information interflow between the physical and digital objects of all processes, actions, and visualizations during their whole life cycle [31]. The foremost practice of digital twin concept was with Apollo 13 mission in 1970; it is often considered as the foundational example of DT application. The concept was first presented by Dr. Michael Grieve at the University of Michigan in 2003. The National Aeronautics and Space Administration (NASA) had a significant impact on its wider acceptance and industry usage. Its application was for aerospace vehicle health maintenance and assurance in the year 2011 which significantly contributed to the broader acknowledgement and adoption [32, 33].

2.2. Evolution of Digital Twin Technology

While there are several definitions of DT technology both from academia and industry, the advantages coming with DT technology are well acknowledged. DT technology enhances manufacturing processes by a reduction in operational costs and time, boosting system productivity, supporting decision-making, allowing remote monitoring, making the working environment safer, and promoting sustainability. In recent years, the manufacturing sector has adopted them more quickly due to these advantages. According to Grand View Research, the global DT technology market is expected to increase dramatically from its 2020 valuation of USD 5.04 billion to USD 86.09 billion by 2028, with a compound annual growth rate (CAGR) of 42.7% between 2021 and 2028. This significant expansion highlights how DT is revolutionizing the industrial sector and how important it is to the advancement of industry 4.0 projects [34, 35]. With partial fuel from the COVID-19 pandemic, Digital Twin has reached high demand for its technologies. Lockdowns resulting from the pandemic creating disruptions in supply chains, shortage of workforces, and requirements for remote or contactless operations, emphasizing more the importance of digitization and advanced processes that require minimal human touch or intervention. A Gartner survey shows that 21% of companies currently utilize digital twin technology for remote asset monitoring, particularly in environment where physical checks at the site are difficult or risky, such as checking patients in a hospital or operations in mining areas to enhance safety for operators [36, 37]. DT adoption spans across various digitally transforming sectors, like Aerospace, Manufacturing, Healthcare, Energy, Automotive, and Agriculture. At the initial stage, DT were primarily focused on system simulation, monitoring, and operational control, its scope has significantly increased toward design optimization, system validation, predictive maintenance. According to Juniper Research journal manufacturing would have the largest share of DT deployment by 2028, with 34%, followed by energy at 18% [38]. Notably, the aerospace and aviation sector were the first to adopt the use of digital twin technology [39]. The majority of DT applications in this industry seek to improve aircraft and spacecraft performance and reliability, anticipate and address maintenance problems, and ultimately make the crew's mission safer. Digital twins were first created in the aerospace industry to optimize the functioning and dependability of spacecraft and aircraft [40, 41].

2.3. A Data-Driven Framework for Predictive Maintenance through Digital Twin-Enabled IoT and AI Analytics

This paper describes how Digital Twin will integrate with IoT and AI to extend the activities of predictive maintenance procedures. The framework proposes system efficiency improvement due to IoT enabled monitoring and AI driven fault prediction using real-time analytics [42]. The digital copy of the physical assets operational data are being harnessed through an IoT sensors embedded in the equipment, machinery, or infrastructure [43]. These sensors continuously collect vast amounts of data like temperature, pressure, vibration and other operational parameters. This influx data

creates a Big Data which needs to be processed and analyzed using an AI algorithm to generate a comprehensive, real-time interpretation of the asset's performance and operational condition from the complex datasets generated from the IoT devices [44, 45].

3. Addressing Predictive Maintenance Systems through the Application of a Decision Trees

Through a thorough analysis of the literature, this study investigates the application of machine learning and artificial intelligence to predictive maintenance. Results show that convolutional neural networks (CNNs) can be used to identify patterns for anomaly detection, while decision trees are commonly used for classification and regression [46]. Artificial neural networks (ANNs) can also be applied to address complex maintenance problems. However, there are issues of overfitting and lack of interpretability. The study suggests that employing hybrid models can address the demands for readability and accuracy, citing the necessity for domain-specific evaluation and continuous model refinement for an accurate prediction [47].

3.1. Importance of PM in Maintaining Lean Principles

Predictive maintenance (PM) aligns with lean manufacturing objectives in reducing waste and optimizing value in production. PM, by means of data-driven visibility, minimizes unscheduled downtime, maximizes the use of resources, and optimizes equipment life cycle for uninterrupted process operation. Similar to lean concepts, beneath removing non-value-added activity, PM does not perform redundant maintenance and discourages surplus spare parts inventory. This integration increases productivity, reduces costs, and simplifies sustainability with reduced energy use and material waste. PM efficiently supports lean manufacturing in driving reliability, efficiency, and value in the manufacturing process and parts [48].

3.2. Challenges in Implementing PM in Lean Environments

The research pointed out that it is hard to maintain Lean principles without a fundamental change in culture and a coherent strategic vision towards data management. The second main issues are employee resistance to change, technological incompetence, and a lack of managerial assistance. Before launching Lean transformation initiatives, firms can determine their readiness and competence by accurately identifying the impediments [49]. In addition to managerial and cultural issues, Lean also requires operation efficiency, and Predictive Maintenance (PM) fits the bill. Predictive Maintenance follows Lean philosophy by reducing downtime, waste, and free production operation flow. Through data analysis using digital twin, feedback from the IoT sensors, and machine learning algorithms, PM provides information on the condition of equipment, enabling organizations to prevent surprise failures and reduce maintenance costs. This progressive approach allows for overall business stability so that firms can roll out Lean programs in a sustainable manner [50].

Table 1 Comparative Analysis of Relevant Literatures

Paper References	Objectives	Results	Findings	Implementation Result
[51]	Analyze performance and maintenance needs of industrial machines Highlight practical issues and propose solutions for digital twin implementation	Successful detection of maintenance needs in 33 out of 47 cases. One false alarm occurred during the evaluation period.	Digital twins effectively detect maintenance needs in machines. Common errors arise from human interactions and parameter changes.	This paper explores the application of digital twins for predictive maintenance in industrial processes. The evaluation of the method shows promising results in detecting maintenance needs.
[52]	Implement Digital Twin for Predictive Maintenance in manufacturing.	Analyzed frequencies and deviations between healthy and faulty cases. Identified candidate mode shapes for further study.	Developed a sensor network for monitoring asset health.	The paper presents a novel methodology for developing Digital Twins for Predictive Maintenance. The case study shows the steps involved in applying

	Test Autoencoder model on real industry example.		Analyzed stiffness effects on vibration for fault detection.	the learning phase to a tangible asset.
[53]	Explore the history and definitions of digital twin. Highlight applications in predictive maintenance and hybrid frameworks.	Development of digital twins for digital manufacturing Novel dependency/constraint-aware ML models for DM	New digital twin models for making decisions offer a representation of a physical assets with a virtual model.	Digital manufacturing capabilities are being improved by advancements in constraint aware machine learning and digital twin technology. These developments help to lower energy usage, maximize maintenance, enhance product quality, and raise production efficiency.
[54]	Analyze advantages of digital twin in manufacturing systems. Talk about the difficulties in modifying part manufacture with digital twins.	The paper presents the goals of the IoT and Twins implementation in projects. The paper discusses the reference architecture and platform functionalities of the IoT Twins project.	The IoT and Twins integration project aims to develop hybrid digital twins. This collaboration enables predictive maintenance through distributed digital twins.	The paper presents the IoT and Twins application in a project aims at building a platform for developing hybrid digital twins in industrial settings. The platform allows manufacturers to deploy digital twins close to data sources and utilize cloud resources for intensive computational tasks.
[55]	Review digital twin integration in design-manufacturing-maintenance. Highlight challenges and prospects for digital twin applications.	Definition of process digital twins and their elements. Integration of AI and simulation technologies for supply chain optimization.	Digital twins use AI and simulation to optimize supply chains. Key challenges include data, modeling, and real-time synchronization.	Digital twins can help optimize manufacturing and supply chain performance. Simulation and machine learning are key tools for creating digital twins.
[56]	Propose a technical system integrating machine learning with digital twins. Construct a full life cycle digital twin for complex equipment.	Identified four distinct contributors of process-oriented digital twin application. Demonstrated cases in mould and blade machining.	Four levels of machine tool digital twins defined. Implementation strategy enhances NC machining process planning.	Defines four levels of predictive process-oriented digital twins. Enhance NC machining process planning with digital twins.
[57]	Develop Digital Twins for Predictive Maintenance. Analyze component stiffness and vibration for health detection.	The proposed steps to consider in the modeling of an anomaly detection system state mapping and state change efficiently and accurately.	Proposed procedures enable real-time state mapping and anomaly detection.	The proposed method helps in real-time mapping and state changes of manufacturing process.

[58]	Introducing theoretical aspects of Digital Twin in smart manufacturing. Analyze application areas of Digital Twin in modern industry.	The layout of cellular manufacturing facilities is optimized by digital twin simulation. Improve operational performance with productivity optimization.	Digital twin simulation efficiently optimizes the design of facility layouts. The improved layout increased productivity and reduced waste significantly.	Digital twin simulation optimizes facility layout for improved efficiency. Identifies bottlenecks and enhances production process flexibility.
[59]	Investigate machine learning for steel industry predictive maintenance. Determine the key sensors for anomaly detection and real-time monitoring.	In contrast to conventional DES employing past data, the connected digital twin uses real-time solutions. Additionally, within 15 minutes of a supply change, it allowed the DES to notify operators of possible long-term consequences.	DES with live data provides more accurate predictions. Connected digital twin reacts to production trends effectively.	Real-time connected DES improves short-term predictions and operational adjustments.
[60]	Implement predictive maintenance for manufacturing equipment. Reduce downtime and increase equipment availability through data-driven techniques.	Introduces components and steps for implementing Digital Twin. Applies signal processing techniques in milling process case study.	Steps for successful Digital Twin implementation identified. Signal processing techniques enhance data quality for decision making.	Emphasizes understanding process mechanisms for Digital Twin development. Highlights the importance of data analytics in manufacturing processes.
[61]	Build a platform for hybrid digital twins development. Enable distributed digital twins for predictive maintenance.	Development of a hybrid predictive maintenance system using virtual commissioning models. Successful implementation in a bottleneck process of electric engine production.	Provides predictive maintenance insights for production risk management.	Predictive maintenance insights based on anomaly detection and cycle time analysis.
[62]	Optimize preventive maintenance using historical and real-time data. Develop a cloud-based framework for remote control.	Framework feasibility verified by self-balancing pump manufacturing case. Upgraded pump tested, proving effectiveness of integrated framework.	Improved overall profit by 13.26% through optimization model. Enhanced dynamic equipment resource operation in smart manufacturing.	Enhances production efficiency and reduces resource waste. Supports quick market response for manufacturing enterprises.
[63]	Propose a modeling framework integrating AI and machine tool expertise. Enhance adaptability and accuracy of digital	Functional information exchange for virtual commissioning confirmed. Digital twin integration enhances production system design.	Digital twin architecture and interoperable data model explained. Integrated monitoring system case studies presented for	A digital twin architecture and system for integrate control monitoring are presented in the study; field engineers, designers, and layout engineers can collaborate with the system.

	twins in manufacturing.		automotive parts makers.	
[64]	Implement Digital Twin technologies in food processing companies. Analyze performance improvement through various implementation stages.	Digital twin technology improves flexible production management significantly. Reduced debugging faults by 70% using virtual debugging.	Proposes digitalization framework for selecting DT sophistication level. Aligns business value and technological capabilities for successful DT deployment.	Help practitioners select appropriate DT sophistication levels. Aligns technology capabilities with strategic business needs.
[65]	Develop real-time maintenance policy optimization model for manufacturing systems. Analyze energy efficiency and the environmental impact of maintenance strategies.	Ant Colony Optimization algorithm outperforms immune and genetic algorithms. Stable deadlines achieved by predicting reliability parameters.	Integration of simulation, optimization, and prediction enhances production flexibility. ACO algorithm achieves efficient scheduling with low computation time.	Stable deadlines achieved by predicting resource reliability parameters. Quick reaction to disruptions enabled by smart factory construction.
[66]	Study steps for successful Digital Twin implementation. Signal processing and information extraction from data acquisition.	The proposed technique achieves a prediction accuracy of 91% for tool conditions.	Seamless switching between original and alternative production plans.	A distributed MES architecture for Industry 4.0 is suggested in the article. For effective production, the design incorporates AI-powered real time replanning capabilities.
[67]	Increase business value for RMC plants and customers.	Two out of three ML algorithms effective in predicting anomalies. Results suggest implementing algorithms to enhance safety for employees.	PNN algorithm achieved maximum prediction accuracy of 91%. Developed DT model effectively predicts tool conditions using sensory data.	Five machine learning algorithms' accuracy was confirmed by the research study. The developed DT model accurately predicts tool conditions based on sensory data.
[68]	Propose a novel implementation framework for digital twins. Facilitate intelligent manufacturing through container technology and cloud services.	Striking the ideal balance between model interpretability, computational economy, and predictive accuracy. This allows for real-time fault notifications and the optimization of maintenance schedules.	Two out of three algorithms effectively predict anomalies. Enhances safety for employees in industrial plants.	Enhances anomaly detection in industrial systems. Improves safety for employees in plants.
[69]	Explain digital twin architecture and system development.	KSPMI automates predictive analytics in Industry 4.0 using hybrid AI. KSPMI uses statistical and symbolic AI for predictive maintenance tasks.	CNN-LSTM improves predictive accuracy over regular LSTM. The average F-Score increased from 93.34% to 97.48%.	The proposed hybrid CNN-LSTM model improves prediction accuracy in PM.

	Present case studies for integrated monitoring systems.			The model outperforms other PM works in terms of accuracy.
[70]	Put out a time-varying, self-learning digital twin system. Enhance production lines' intelligence monitoring and product quality.	This study presents a multi-objective optimization approach that integrates production scheduling with predictive maintenance planning. The model is solved using the Non-dominated Sorting Genetic Algorithm II.	DSS optimizes predictive maintenance using IoT and ML. Achieved high predictive performance and reduced service costs.	Optimizes maintenance schedules and reduces service costs. Provides real-time warnings about operational risks.
[71]	Provide a data-driven quality prediction framework and digital twin. Predicting quality in real time during die-casting operations.	The digital twin concept allows for the integration of design, manufacture, and maintenance throughout the lifecycle of a product. Information-physical framework for precise design, flawless production, and astute maintenance.	KSPMI automates predictive maintenance using hybrid AI technologies. Chronicle mining predicts machinery failures and their occurrences.	Use hybrid AI to automate predictive maintenance in industry 4.0. Improve the Cyber-Physical Systems decision-making process.

4. Advantages of Lean Manufacturing with Digital Twin Integration

Lean manufacturing optimizes efficiency through the use of digital twin technologies for predictive analysis, real-time monitoring, and process improvement. More thorough project management insights into process variability, resource allocation, and risk management are made possible by digital twins. This capability reduces waste, maximizes response to unpredictable behavior, hence enabling Lean philosophies of waste reduction and continuous improvement. It is a shared knowledge base that improves process design and maintenance efficacy across the course of a production system's life cycle. As it could run simulations of scenarios to optimize production scheduling and minimize downtime [72]. Data-driven decision-making makes the manufacturing process lean and responsive, saving cost, and ensuring product quality control.

Table 2 Predictive Maintenance in a Manufacturing Plant

Component	Issue Detected	Digital Twin Prediction	Action Taken
Robotic Arm	Excessive vibration	Possible motor failure in 2 weeks	Replace motor proactively
CNC Machine	High temperature fluctuation	Overheating due to clogged coolant	Clean and inspect coolant system
Conveyor Belt	Speed inconsistency	Wear and tear in rollers	Schedule part replacement

A manufacturing facility's employment of a digital twin for predictive maintenance is simulated in the table above. Sensors mounted on industrial systems and machines can continuously track performance and identify early indicators of equipment failure or deterioration. The digital twin receives this real-time data, models potential failures, anticipates maintenance needs, and suggests preventive actions to avoid sudden malfunctions. Implementation of DT also optimize material usage, tool monitoring, and production scheduling, minimizing operational expenses and downtime. With machine intelligence and AI-powered analytics, manufacturers can make knowledgeable choices, boost production efficiency, and guarantee sustainable manufacturing processes [73].

Table 3 Operational Metrics Comparison Between Conventional and DT-Driven Maintenance Systems

Parameter	Traditional Maintenance	Digital Twin-Based Predictive Maintenance
Machine Uptime (%)	85%	98%
Unplanned Downtime (hrs/month)	20	2
Maintenance Cost Reduction (%)	0%	35%

To determine the effectiveness of new maintenance methods, particularly lean manufacturing, traditional maintenance methods should be contrasted with high-technology, data-driven methods. A comparative review of pertinent research is provided in Table 3, which also shows important performance indicators that are prevalent under traditional and DT-based maintenance approaches, including machine uptime, unscheduled downtime, and maintenance cost savings. The information readily demonstrates the performance benefits of applying DT-based predictive maintenance in an industrial context.

5. Conclusion

This study has looked at the main intersection of Lean Manufacturing and Predictive Maintenance to ascertain the creative potential of using Digital Twin technology to overcome typical maintenance planning challenges, such as a lack of failure data. The Lean principles and their focus on eliminating waste and achieving the best possible operational performance complement the Predictive Maintenance strategies intended to take action proactively based on equipment health in real time. Through replacing the traditional, response-based maintenance practices with DT-supported predictive maintenance, a lean-driven, proactive, and fact-based approach to maintenance is attained. The synergy effect built with the integration of lean thinking with predictive maintenance enables continuous improvement, builds equipment reliability, and constructs the culture of operational excellence. According to the research, although the use of DT and predictive maintenance produces observable benefits including higher machine availability, lower maintenance costs, and enhanced manufacturing efficiency, it is difficult to get beyond organizational, technological, and cultural barriers. However, strategic alignment of real-time analytics, IoT, and AI within a framework of DT for manufacturing offers end-to-end visibility into business operations never seen before. As companies evolve to accommodate Industry 4.0 demands, the combination of digital twin technology with lean principles will be an important factor in the design of next-generation sustainable, agile, and resilient manufacturing systems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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