International Journal of Modern Studies in Mechanical Engineering (IJMSME)
Volume 10, Issue 1, 2024, PP 20-35
ISSN 2454-9711 (Online)
DOI: https://doi.org/10.20431/2454-9711.1001003
www.arcjournals.org

Enhancing Proactive Maintenance of Critical Equipment by Integrating Digital Twins and Lean Six Sigma Approaches

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Abstract: *Proactive maintenance is a policy aimed at identifying the root cause of failure and correcting it before it causes other problems and leads to machinery failure and breakdown. Implementing this policy can enhance reliability, availability, maintainability, and safety (RAMS) at low cost. Digital Twin (DT) and Lean Six Sigma (LSS) are useful tools to enhance proactive maintenance. DT is a digital copy of a physical object whose applications will play a leading role in the future of smart manufacturing. DTs facilitate real-time monitoring and investigation, improve decision-making, and enhance performance. LSS is the industry's most recognized approach to process continuous improvement, focusing on eliminating waste, reducing variation, and improving process efficiency, effectiveness, and customer satisfaction. This study reviewed and analyzed the LSS methodology and the DT approach (DTs-LSS) to improve proactive maintenance management. It explored the fact that previous studies have paid limited attention to DTs-LSS. Furthermore, this study provides a comprehensive roadmap for future research initiatives aiming to utilize technology design teams' capabilities fully. To the authors' knowledge, this is the first time that the structure and tools of DTs and LSSs have been combined in a hybrid framework for enhancing proactive maintenance. Finally, this study's results will be valuable to professionals who want and aspire to implement technological design to achieve maintenance excellence.*

Keywords: *Proactive Maintenance, Fault Prediction, Digital Twin, Lean Six Sigma, Continuous Improvement*

1. INTRODUCTION

Proactive maintenance is a proactive policy that aims to identify, analyze, and correct the root cause of a failure before it causes further problems and leads to machinery failure. Implementing this policy can enhance reliability, availability, maintainability, and safety (RAMS), [11]. As depicted in Figure 1, a digital twin (DT) is a digital version of a physical object or system. It can successfully model a virtual object from its physical counterpart. The main function of a DT is to provide a two-way data flow between the virtual and physical entity so that it can continuously upgrade and improve the physical counterpart, [5,6]. NASA first used the term digital twin in 2010, which was described as "an integrated, multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physics models, sensor updates, fleet history, etc., to simulate the life of its flying twin." [32,38]. Michael Graves was the first to propose the term DT, [12,37]. Recently, DT has been utilized in various manufacturing fields, and it is promoting positive developments in these fields, [16,19]. Kritzinger, [23] recognized three levels of DT integration, namely digital model, digital shadow, and digital twin, as shown in Figure 2. Attaran, [3] mentioned the main DT applications in manufacturing, as presented in Figure 3. Many diagnostic tools are available to identify and analyze the root causes of failures. Failure Mode Effects and Criticality Analysis (FMECA) is the most common diagnostic method, which consists of two analyses; the Failure Mode and Effects Analysis (FMEA) and the Criticality Analysis (CA), [11,18,37,40,43]. DT enables maintenance management to accurately identify equipment status, proactively predict faults, and enhance reliability, [1,2,4]. DT contains a set of adaptive models that can emulate the behavior of a physical system in a virtual system, obtaining real-time data to update itself along its life cycle, [3,39]. Figure 4 shows an equivalent representation of the general architecture of DT, [56].

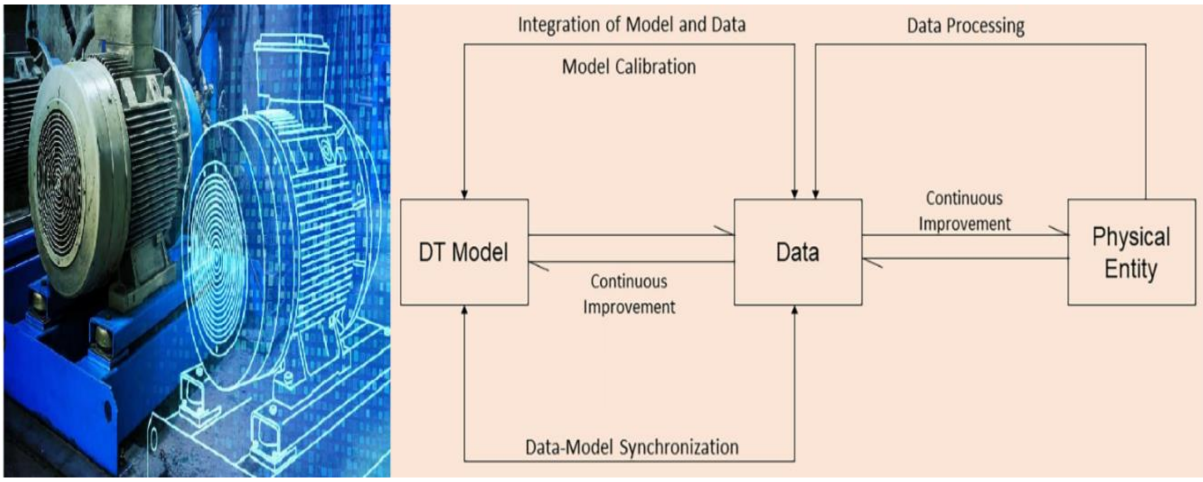

Fig1. Digitaltwin illustration.

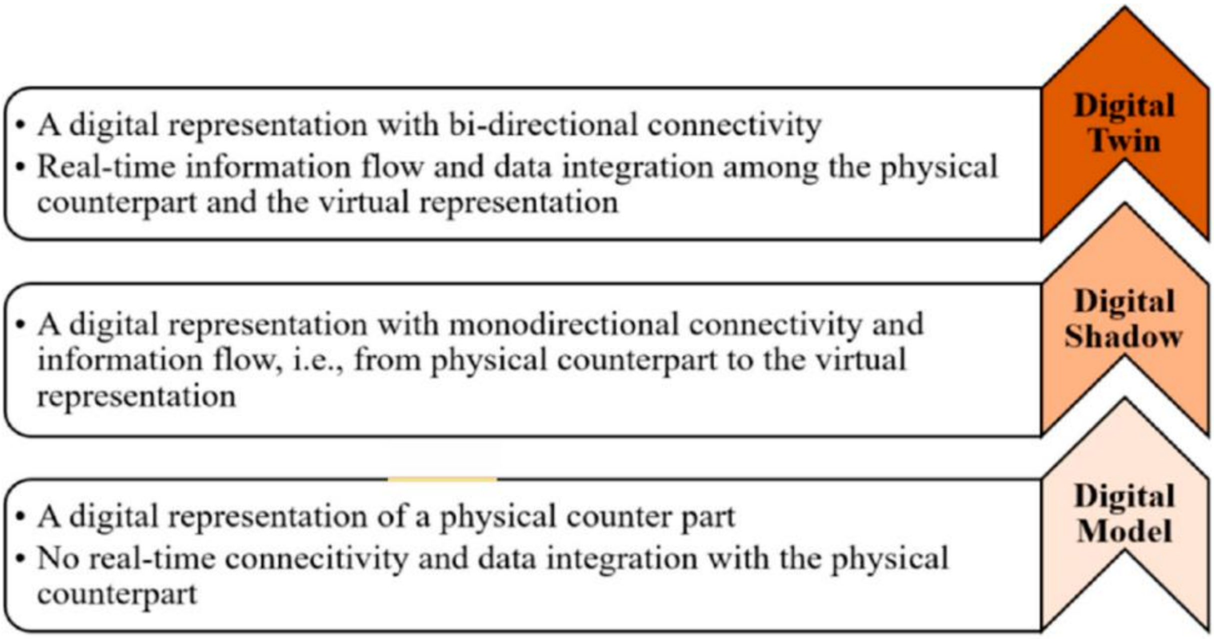

Fig2. *Digital twin Levels of integration.*

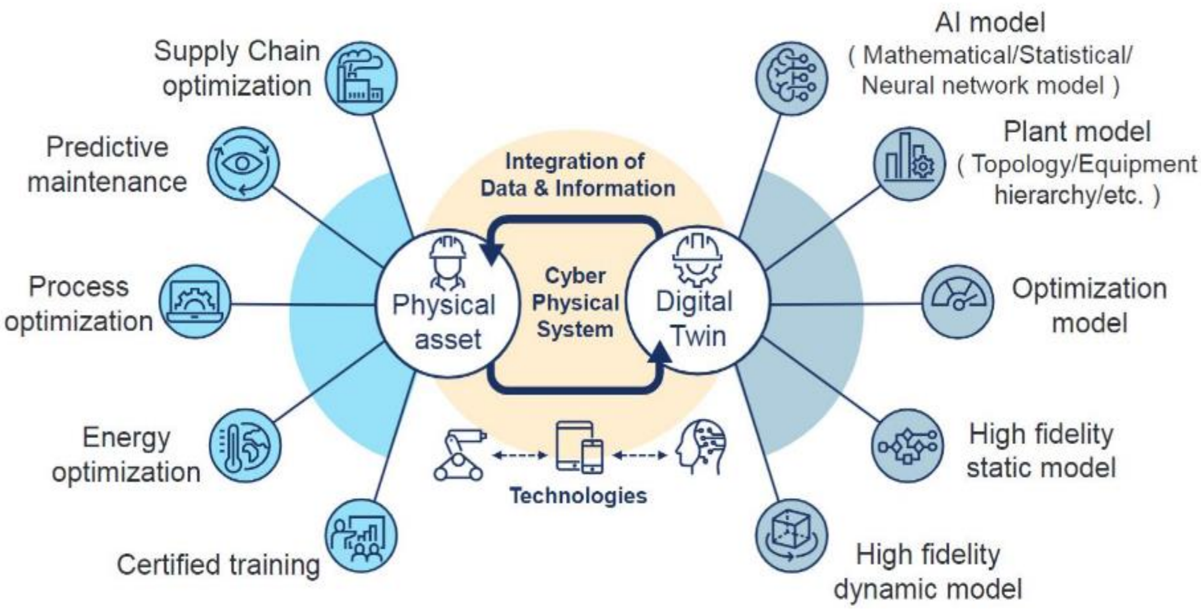

Fig3. *Digital twin applications in manufacturing.*

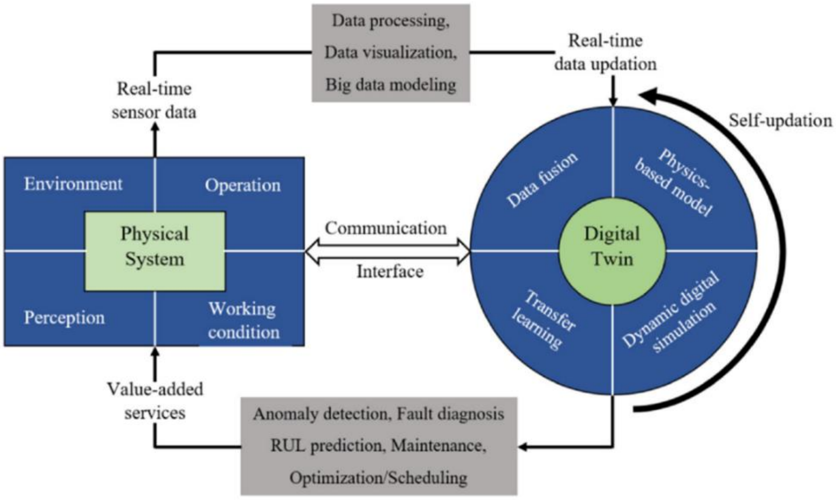

Fig4. *Equivalent representation of the general architecture of DT.*

Organizations constantly seek ways to enhance operations efficiency, reduce costs, and improve competitiveness. In this effort, Lean Six Sigma (LSS) tools provide structured approaches to streamline operations and improve efficiency and effectiveness. The main objectives of LSS are to improve process quality, improve production rate, reduce delivery time, reduce production cost, and improve customer satisfaction. DMAIC is a specific framework for process continuous improvement within LSS that includes, (D) defining the problems and objectives, (M) measuring the current situation, (A) analyzing the problem's root causes, (I) implementing a workable solution (I), and (C) controlling the process to ensure and maintain the continuous improvement. Figure 5 shows the most popular LSS tools. By using these tools and techniques, the organization can improve business processes, [70,71].

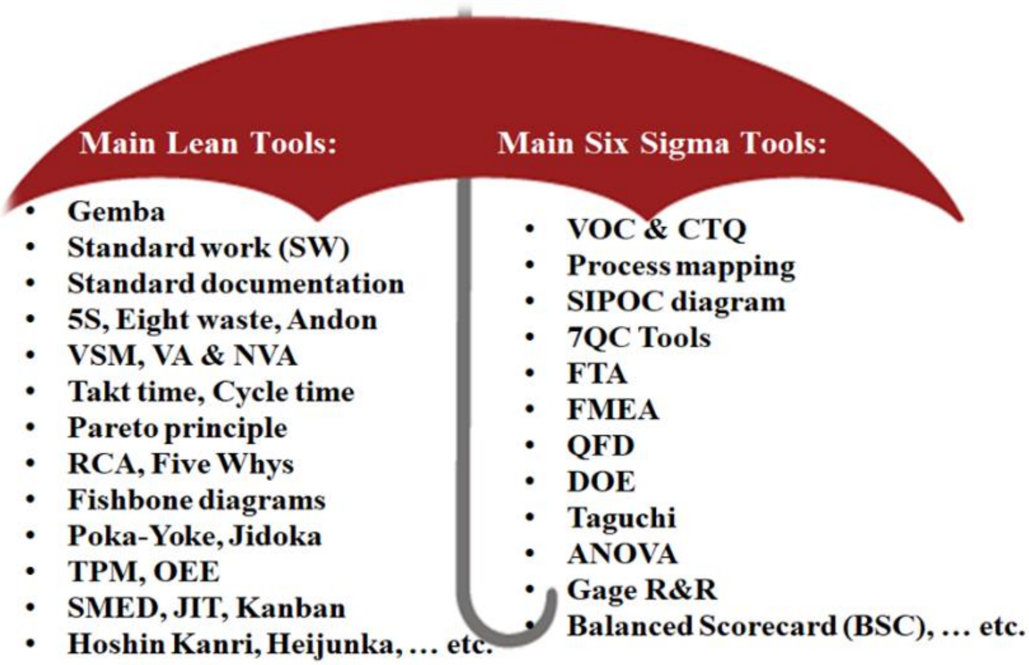

Fig5. *Main LSS tools in maintenance operations, [70,71].*

This study focuses on the performance and applications of DTs and LSS in proactive maintenance policies and the importance of maintenance management for improving equipment RAMS (reliability, availability, maintainability, and safety).

After this introduction, this paper is organized as follows: In Section 2, the literature review is carried out. In Section 3, the research gap is identified. Section 4 includes the frameworks for proactive maintenance. Finally, Section 5 focuses on conclusions and future directions.

2. Literature Review

Firstly, the DT technique and its applications in proactive maintenance are reviewed. Then the literature on LSS technology and its applications in proactive maintenance are investigated.

2.1. Review of Digital Twins in Proactive Maintenance

Digital twins (DT) can provide a real-time response to the manufacturing system and increase flexibility and reliability, [13]. According to Hu, [16] Figure 6 illustrates some of the key milestones in the development of DT. In 2016, Siemens used DT devices in Industry 4.0, resulting in a tremendous growth in related publications.

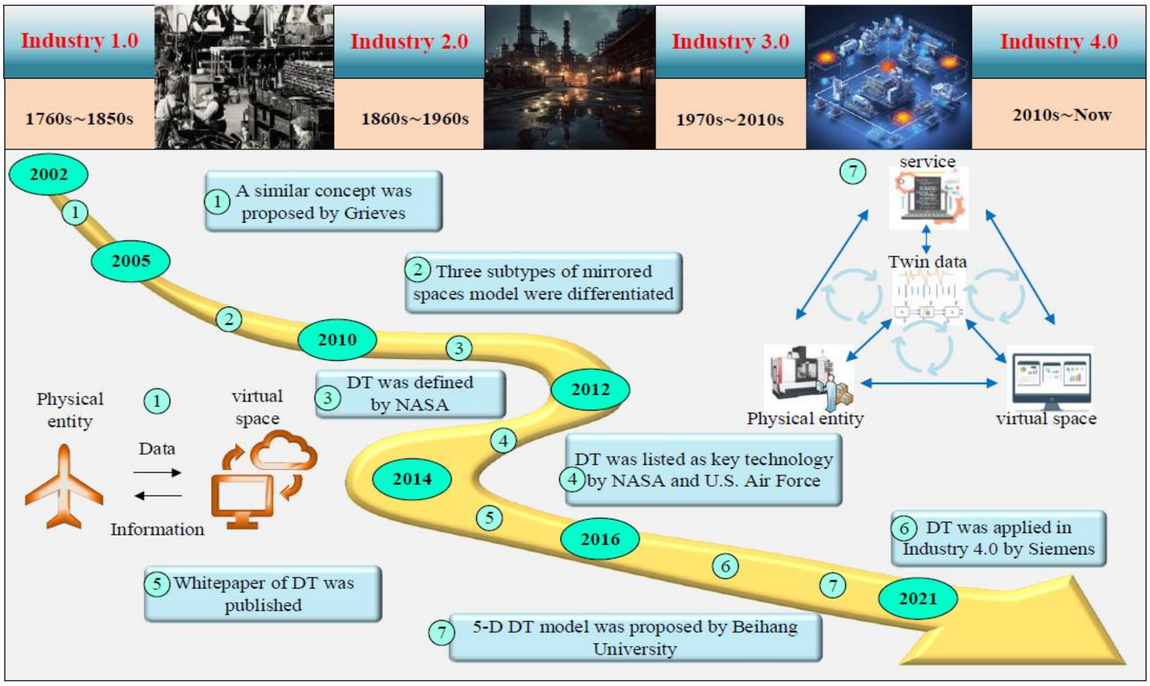

Fig6. *The milestones of DT development, [16].*

Proactive maintenance can reduce failure risks, improve system uptime, extend the equipment life, and lower process downtime losses. DT can model individual equipment or processes to identify variations that indicate the need for preventive maintenance. The goal is to estimate, predict, detect, or diagnose the condition of the component for more effective maintenance. This can prevent costly failures before a serious problem occurs. They can also determine if better materials or processes can be used or help improve cycle times, load levels, and tool calibrations, [20,46]. The application of DTs enables the monitoring of the condition and prediction of abnormal conditions in machine tools. This greatly enhances the safe and efficient operation of mechanical process systems. Parameter optimization plays a crucial role in the optimization of the operation process. Traditional parameter optimization methods rely on manual experience and often involve high levels of uncertainty. DT operation process facilitates the suppression of errors and the optimization of operating parameters, thus laying the foundation for achieving high-quality and high-level operation, [16].

DT represents the innovation that has spurred evolution and adaptation in the aerospace industry. For instance, employing DT for an aircraft or rocket ship is believed to enhance global tracking accuracy by 147%. In a recent survey, 75% of Air Force executives favored DT solutions for their industry. DT enables engineers to ensure the safety of the aircraft by looking into the potential aircraft's problem before any danger. For example, Boeing, the world's largest aerospace company, uses DT solutions to improve the safety of the parts and systems used to manufacture commercial and military airplanes. DTs of specific aircraft models enable technicians to use augmented reality (AR) overlaying the DT data on the real plane, facilitating faster and more accurate inspections and improving maintenance efficiency. As a result, Boeing has achieved a 40 percent improvement in the quality of the parts and systems, [29,50]. According to GE Research, [9] GE's DT technology is revolutionizing how the aviation industry handles maintenance. Predicting engine wear, such as the blade wear on the GE90, saves airlines millions of dollars in costs and prevents aircraft from landing unexpectedly, especially in areas with sand, a major contributor to the problem.

According to Pinello [33], the European Space Agency (ESA) also adopted the DT approach for its ExoMars mission. They built Amalia, a physical and DT of the Rosalind Franklin rover. This duo serves a vital purpose: anticipating and solving potential problems before they occur on the Martian surface. Overall, using both physical and DTs significantly increases mission success by minimizing risks and improving rover performance.

DTs have been increasingly used in condition monitoring and fault diagnosis (CMFD) in recent years. Table (1) shows the survey of DTs in maintenance over the past years. The details of these studies are explained in the next section.

Table 1. *Survey of DTs in Proactive Maintenance, (2017 to August 2024).*

Period	#	References
2017	2	[40,42]
2018	3	[23,44,50]
2019	7	[1,2,29,34,41,43,53]
2020	4	[7,14,19,25]
2021	10	[13,20,27,31,35,37,47,48,51,52]
2022	9	[10,15,22,30,32,45,56,57,59]
2023	12	[4,6,9,26,28,33,36,39,46,48,55,58]
August 2024	10	[3,5,8,11,16,17,21,24,49,54]

Tao, [42] adopted the concept of a DTs workshop, providing theoretical support for industry applications by discussing its characteristics, composition, operating mechanism, and key technologies. Tao, [44] suggested a five-dimension DT model for complex systems to improve the accuracy of prognosis.

Qiao, [34] developed a data-driven model for DT, together with a hybrid model prediction method based on deep learning that creates a prediction technique for enhanced machining tool condition prediction. Xu, [53] studied a two-stage DT-assisted method based on deep migration learning. This method identifies potential problems that may not have been considered during the design phase and uses deep neural network-based diagnostic models for fault diagnosis. Aivaliotis, [2] presented a methodology to calculate the Remaining Useful Life (RUL) of machinery equipment by utilizing physics-based simulation models and the DT concept, to enable predictive maintenance for manufacturing resources using Prognostics and health management (PHM) techniques.

Luo, [25] suggested a hybrid DT model that consists of model-based DTs and data-driven DTs to take into consideration the environmental variations in the life cycle of the tool. To realize reliable predictive maintenance of CNC machine tools, a hybrid approach driven by DT is studied. Xia, [51] developed a DT model for machinery fault diagnosis where the DT is built by establishing the simulation model which can be updated through the real-time data collected from the physical asset. The proposed DT is validated through a case study of triplex pump fault diagnosis. Xiong, [52] investigated the predictive maintenance model of an aero-engine driven by DTs. Through the consistent evaluation of virtual data assets and real data assets, the effectiveness of the model is verified. Experimental results show that when the dataset used to train the model is 80%, the model prediction has high accuracy. Wang, [48] developed a DT model including a geometric model, physical model, behavior model, and rule model to perform fault prediction of the autoclave to generate simulated data to address the problem of insufficient data for fault prediction. The effectiveness of the proposed model is verified through result analysis. Olatunji, [31] discussed an overview of the application of DT technology in the fault diagnosis and condition monitoring of wind turbine mechanical components. Qin, [35] proposed a DT model of life-cycle rolling bearing driven by the data-model combination. By comparing the obtained DT result with the signal measured in the time domain and frequency domain, the effectiveness of the developed model is verified.

Refer to Xiong, [52] DTs solutions are widely used in the aerospace industry for aircraft maintenance and tracking, weight monitoring, accurate determination of weather conditions, flight time measurement, catastrophic failure analysis, safety and security management, and failure detection. Moghadam and Nejad, [30] presented a DT-based condition monitoring and fault diagnosis (CMFD) approach for offshore drivetrain systems, where the DT in the study includes a torsional dynamic model, online measurements, and fatigue damage estimation. The remaining useful life of the drivetrain can be estimated by means of the DT. Kim, [22] utilized various environmental information to design a predictive model for offshore WT power generation based on DT. The proposed system enables an accurate representation of the offshore WT power generation and makes contributions to the safety of the power system. Hosamo, [15] suggested a DT predictive maintenance framework for air handling units (AHU) to overcome the limitations of facility maintenance management (FMM) systems now in use in buildings. The proposed framework was tested in a real-world case study.

Zhong, [58] reviewed the increasing research interest in DTs-based predictive maintenance in the manufacturing industry. The predictive maintenance approaches based on DTs are introduced. Wang, [48] proposed a real-time planetary gear fault diagnosis method by combining the atom search optimization-support vector machine and DTs which can significantly improve the operation of wind turbines. Reimann, [36] developed a DT model of a wind turbine. The model was evaluated in simulations using real measurement data of the wind speed from a research wind turbine. Luo, [25] suggested a DT system for wind turbine blades, which can construct a DT in virtual space that is completely equivalent to the wind turbine blades, reflecting in real time the operational data and status of the wind turbine blades, and realizing online monitoring and predictive maintenance of the wind turbine blades. Van-Dinter, [46] conducted domain analysis to model key features and synthesize relevant literature. A case study on fault diagnosis using DFDD in a vehicle body-side production line is presented. The results demonstrate the superiority and applicability of the proposed method. Yang, [55] developed a complex fault diagnosis method using DT by combining virtual and real data. Field data from an offshore platform in the South China Sea were used to demonstrate the effect of the suggested method. The results indicate that the proposed method is very effective for complex faults of production control systems.

Inturi, [17] reported a review study focusing on the definitions, methods, applications, and performance of different aspects of DTs in the context of transportation and industrial machinery. This review summarizes how individual aspects of DTs are extremely useful for lifelong design, manufacturing, or decision-making. Liu, [24] developed an innovative DT-based anomaly detection framework for real-time tool condition monitoring (TCM). The "data flow connections" involve real-time measured vibration data and machine tool numerical controller (NC) signals providing real-time information on machine tool dynamics and various machining processes. Experimental studies have demonstrated the effectiveness of the proposed method, especially for complicated machining processes. Gao, [8] discussed the concept of post-disaster recovery for power DTs systems to study rational approaches to enhance the post-disaster monitoring capability of such systems after significant disasters. The results indicate that the proposed branch-and-limit algorithm greatly enhances the monitoring capabilities of the resource-constrained power system, thus enhancing its stability and emergency response mechanisms. Xue, [54] developed a DT-driven fault diagnosis method for CNC machine tools. By using the spindle of a CNC machine as an example, the deterioration of spindle stiffness during operation is effectively diagnosed, which confirms the effectiveness and applicability of the proposed method. Karkaria, [21] discussed a DT framework for predictive maintenance of long-term physical systems. Using tire health monitoring as an application, they demonstrate how the DT framework can be used to enhance the safety and efficiency of automobiles. The proposed framework effectively embodies a physical system, leveraging big data and machine learning for predictive maintenance, model updates, and decision-making. Finally, Wang, [49] developed a novel intelligent state evaluation and maintenance arrangement (iSEMA) system based on DT, which can accurately evaluate the state of wind turbines, detect faults in the early stage, and provide useful information or warnings to operators and help them to efficiently arrange maintenance tasks.

2.2. Review of Lean Six Sigma in Proactive Maintenance

LSS tools have been increasingly used in proactive maintenance in recent years. Table (2) shows the survey of LSS tools in maintenance over the past years. For example, Al Farihi,et al., [60] proposed a lean maintenance methodology in an automotive company to reduce machine breakdown and maintenance downtime and improve process efficiency. Several steps were used to solve the problem: root cause analysis, determining the TPM pillars applied, RCM, and realization of TPM pillars. Trubetskaya et al., [78] developed an LSS-DMAIC framework for optimizing maintenance shutdown performance in the industry. They presented a case study applying the proposed model to Ireland's largest dairy processing site to optimize the annual maintenance shutdown. The objective was to deliver a 30% reduction in the duration of the overhaul, enabling an extension of the processing season. Gomaa, [70,71] discussed the importance of LSS tools in proactive maintenance management. LSS critical failure factors (CFFs) in project management were discussed. A generic LSS-MM framework was proposed and validated with a case study conducted in a petrochemical company in Egypt. A case study of a feedwater pump station in a steam system has been used to illustrate the proposed framework. Results indicated that the proposed methodology is successful in identifying the critical equipment and improving maintenance efficiency and effectiveness. For example, overall equipment effectiveness (OEE) improved from 50% to 68%, the sigma level improved from 2.53 to 2.88, and maintenance process efficiency improved from 62.3% to 69.7 %. Imanov et al., [73] conducted a Six Sigma DMAIC framework for the identification of its applicability in the development of a maintenance task card for an engine replacement on the Boeing 747-8 using PM, and the essential results can be summarized as follows: Engine replacement maintenance task cards decreased by 18 items, Total saving man hours on engine replacement consist of 68 h., and Total saving man hours on equipment removal and installation consist of 48 h.

Table 2. Survey of LSS in Proactive Maintenance, (2014 to August 2024).

Period	#	References
2014	1	[80]
2015	1	[61]
2016	0	-
2017	2	[69,81]
2018	2	[62,76]
2019	0	-
2020	5	[65,66,67,72,75]
2021	1	[73]
2022	2	[64,74]
2023	6	[60,68,70,77,78,79]
August 2024	2	[63,71]

3. Research Gap Analysis

The literature review shows that the application of DT and LSS techniques in proactive maintenance remains very important for managing the maintenance of critical equipment to improve equipment RAMS (reliability, availability, maintainability, and safety) and achieve maintenance excellence. However, there is still a need for a common platform based on creating a physical model via a common methodology. This is a requirement for implementing the DT and LSS concept of proactive maintenance.

Moreover, implementing DT technology, for maintenance activities in a production plant, requires creating a DT for each machine. Furthermore, to the authors' knowledge, there is no research demonstrating that the structure and tools of DTs and LSS have been combined into a hybrid framework. Finally, a more detailed review of the literature should also be conducted to identify further gaps, which will be addressed within the framework of constructing and fine-tuning the proposed model.

4. Proposed Frameworks for Improving Proactive Maintenance

Firstly, the DT framework is proposed to improve proactive maintenance. Then the LSS framework is suggested to enhance proactive maintenance.

4.1. DTs Frameworks for Improving Proactive Maintenance

As mentioned earlier, manufacturing maintenance costs and downtime losses are very high in different sectors, which justifies the investment in creating DTs to optimize maintenance activities. Figure 7 shows a DT model in maintenance, [10]. According to Dihan [5], data analysis is the technology driver of a successful DT system. Since data is the fundamental difference between a successful and unsuccessful system, proper guidance of data structure should be given due attention. Figure 8 shows the DT data analysis process for building a successful DT.

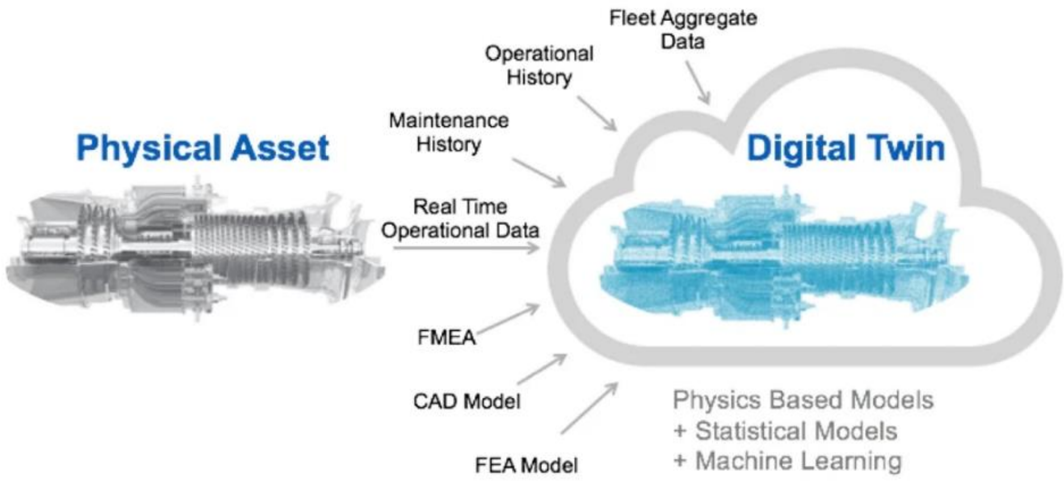

Fig7. *DT model in maintenance.*

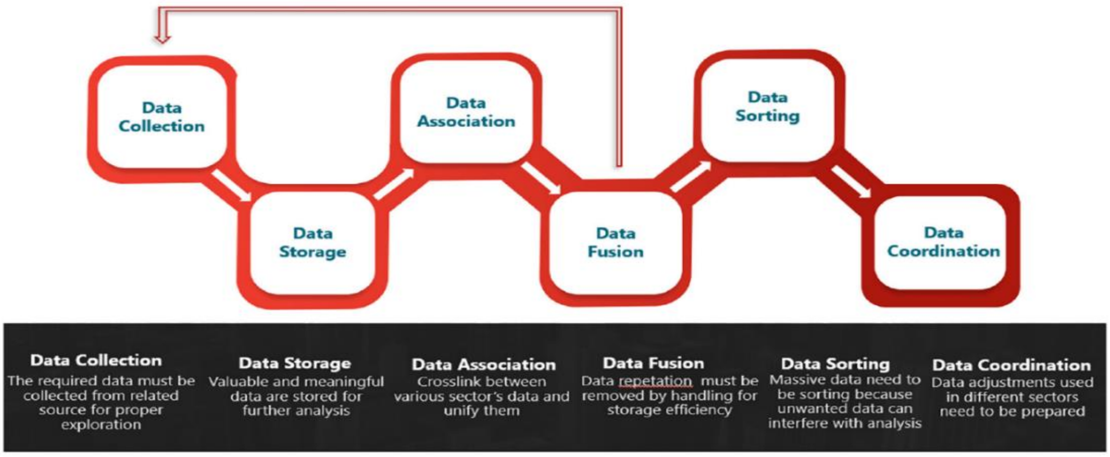

Fig8. *DTs Data analysis process, [5].*

Hosamo, [15] suggested a DT predictive maintenance framework for air handling units (AHU). The proposed framework utilizes DT technology for fault detection and diagnostics and predicts the condition of the building components so that the facility management staff can make better decisions at the right time. Figure 9 shows the principle of a DT in proactive maintenance. The proposed framework includes three main steps, Data acquisition, predictive maintenance process, and BIM model for information visualization and monitoring. Spatial information can be obtained from the BIM model. The BIM model was integrated with predictive maintenance results to support decision-making by developing a plug-in extension for Autodesk Revit using C sharp so that the FM team can easily understand the data. The three main levels of this framework will be explained in detail in the following sections. For facility management, COBie (Construction Operations Building Information Exchange) and Industrial Foundation Classes (IFC) are information exchange specifications for the lifetime capture and transfer of information. Figure 10 shows COBie components.

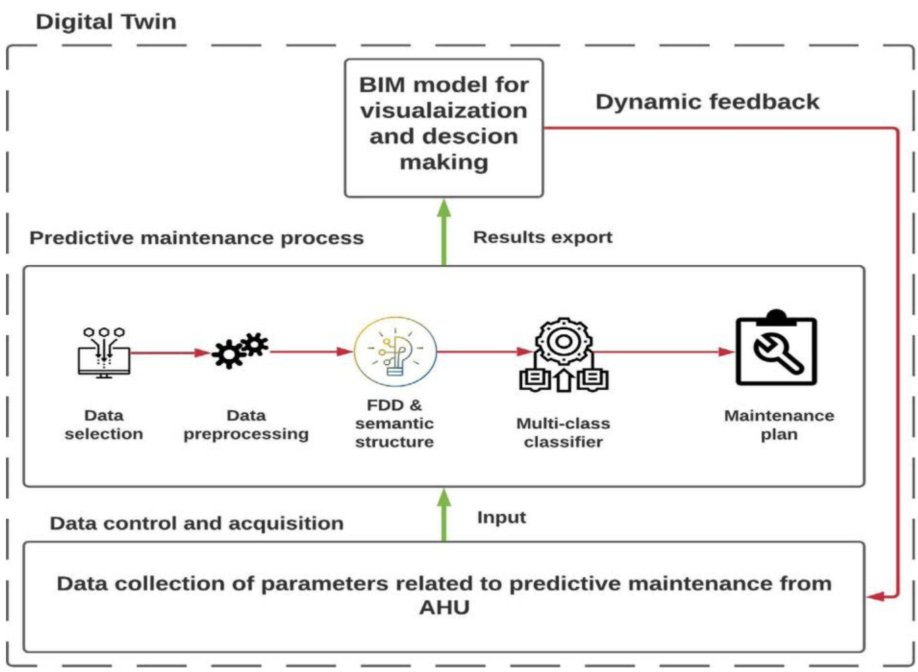

Fig9. *DT predictive maintenance framework, [15].*

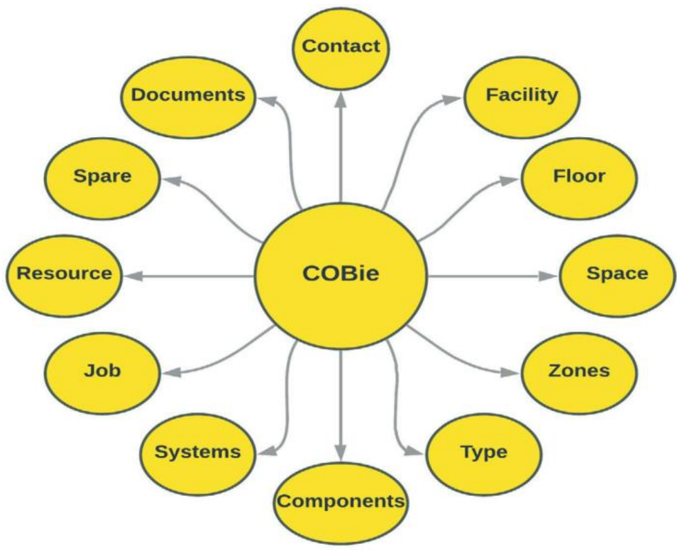

Fig10. *Standard COBie components, [15].*

Mihai et al., [27] developed a framework that aims to achieve optimized predictive maintenance by leveraging predominantly time-indexed streaming sensor data, along with configuration data coming from the digital twin of the Cyber-Physical Factory. The developed framework is illustrated in Figure 11, which consists of: the data acquisition block, the pre-processing block, the database, the time-series anomaly detection block, the RUL predictor block, and the monitoring dashboard.

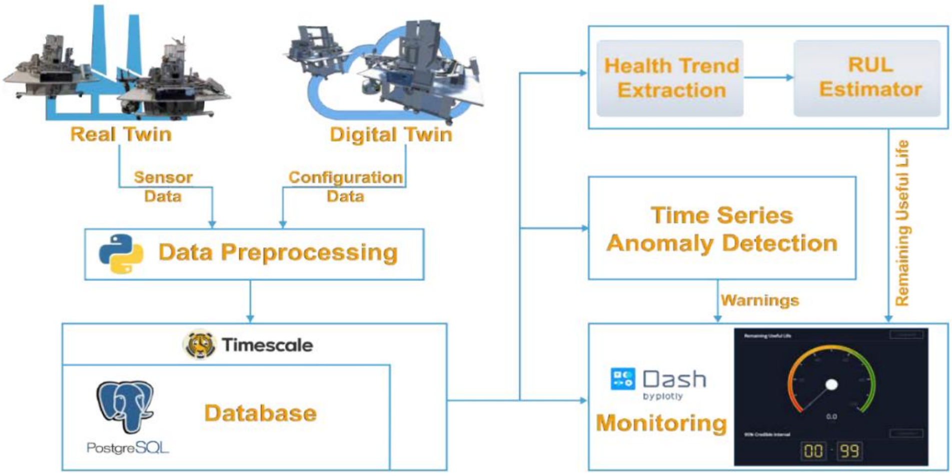

Fig11. *A Digital Twin Framework for Predictive Maintenance, [27].*

Karkaria, [21] introduced a DT framework for proactive maintenance of long-term physical systems. Figure 12 shows the tire health DT framework demonstrating the flow of information, and important components of DT like offline training, model update, and decision making. As shown in this figure, the digital twin begins with the offline training of the Tire Health Temporal Fusion Transformer (TFT) model in Step 1, leveraging historical datasets which has operating parameters (T !) - conditions under which the tire operates, usage parameters (U !) - how the tire is used, and state parameters (M !) - the current condition of the tire. Additionally, within our digital twin framework, we get our dataset with inputs derived from a physics-based Tire Design Finite Element Method (FEM) integrating physical insights with measured data. Incorporating a physics-based Tire Design Finite Element Method (FEM) is crucial to accurately understand the tire's physics-based state, ensuring a comprehensive analysis of its condition through the integration of physical principles with observed data. Then the Tire Health TFT model, a critical component of the Tire Health Digital Twin, facilitates real-time predictions of the damage state. A continuous quantity, named as Remaining Casing Potential (RCP), is considered as the damage state parameter). RCP serves as a key indicator of tire endurance damage, allowing for proactive maintenance decisions. The predictions by the Tire Health TFT model are subsequently compared with real-world instances of tire damage. This comparison allows us to quantify the discrepancy, effectively measuring the difference between the model's predictions and the actual tire damage data in Step 2. We utilize observed discrepancies to refine our Tire Health TFT model. It is important to highlight that, following an update, our model evolves into a hybrid version. Despite this transformation, we continue to refer to it as the Tire Health TFT model for consistency and clarity in our discussion in this paper. Then the updated Tire Health TFT model, with the Tire State Decision Algorithm in Step 3, informs timely tire replacement decisions. Thus, our tire health digital twin has the surrogate model, which is updated in real-time, and aids in making predictive maintenance decisions.

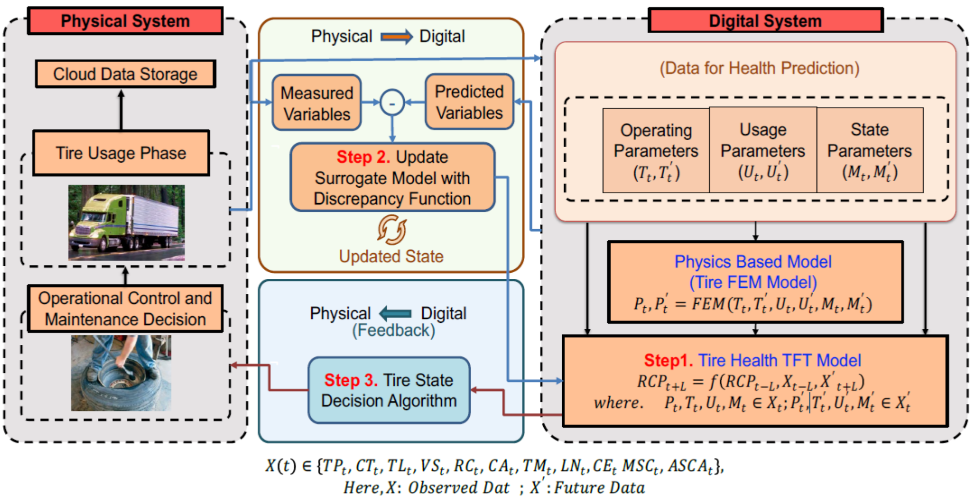

***Fig12.** Tire health digital twin framework, [21].*

4.2. LSS Frameworks for Enhancing Proactive Maintenance

Trubetskaya et al., [78] developed an LSS framework for improving maintenance operations. Figure 13 illustrates a graphic of the DMAIC, TAM, and LSS-DMAIC approaches and how they could be visualized to complement each other. These are important to consider in the further DMAIC-TAM methodology enhancements as three distinct tools working towards a common goal. On the other hand, Gomaa, [70,71] proposed a general framework for LSS to improve maintenance processes and validated it through a case study conducted in a petrochemical company, as shown in Table (3), [60,62,64,70,71,78].

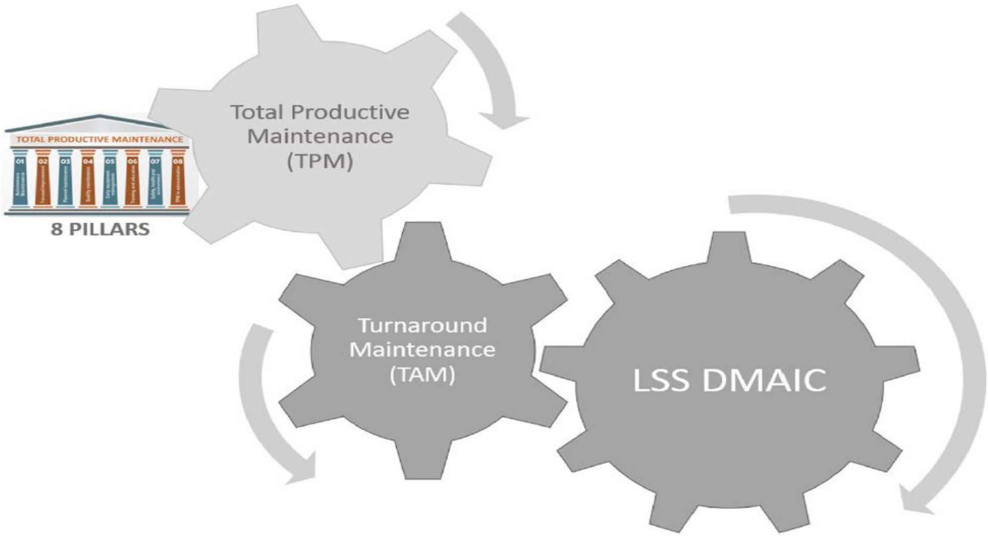

Fig13. *Visualize DMAIC, TAM, and TPM approaches that complement each other, [78].*

Table3. *Proposed LSS Roadmap for improving maintenance operations.*

Approach	Maintenance objectives	Main LSS Tools
Current Situation Analysis	- Maintenance process description - Maintenance KPIs dashboard	• Process mapping (process layout, process flow chart, and SIPOC diagram) • Voice of the customer (VOC) • Maintenance performance evaluation • Leading and lagging KPIs • Benchmarking • Performance gap analysis • KPIs dashboard • Define the problem statement • Establish the objectives and targets • Responsibility matrix (RACI) • Prepare a Project Charter • Construct LSS-DMAIC framework
Kaizen Approach	- Improving maintenance Staff's culture & productivity - Enhancing maintenance resource productivity	• Visual control (5S) • Standardize work (SW) • Root cause failure analysis (RCFA) • Mistake proofing (Poka-yoka)
Lean Approach	- Improving maintenance process value-added - Reducing maintenance process wastes	• Total productive maintenance (TPM) • Overall equipment effectiveness (OEE) • Value-added time analysis • Value stream mapping (VSM) • Lean waste analysis (8 wastes) • Just in time (JIT) • Breakdown structure analysis

Approach	Maintenance objectives	Main LSS Tools
		• Networking and Gantt chart
Six Sigma Approach	- Reducing equipment failures - Reducing equipment variance	• Critical to quality (CTQ) analysis • Sigma-level analysis • SQC for failure analysis • Pareto analysis of main failures • Root cause failure analysis (RCFA) • Cause and effect diagram (Fishbone) • Failure mode effect analysis (FMEA) • Equipment reliability analysis • Reliability centered maintenance (RCM)

5. Conclusion and Further Work

Proactive maintenance is a policy that aims to identify the root cause of a failure and correct it before it causes further problems and leads to machinery failure. Implementing this policy can enhance reliability, availability, maintainability, and safety (RAMS). This paper focuses on reviewing the applications of digital twins (DT) and Lean Six Sigma (LSS) in proactive maintenance. DT can be used as a data-driven digital concept or technology to effectively address critical equipment maintenance issues. DT enables maintenance management to accurately determine equipment status, proactively predict faults, and enhance reliability. LSS is the industry's most recognized approach to continuous improvement, focusing on eliminating waste, reducing variation, and improving process efficiency, effectiveness, and customer satisfaction. The application of DT and LSS technologies remains a critical proactive technology for critical equipment to improve equipment RAMS and achieve maintenance excellence. Several DT and LSS frameworks for proactive maintenance have been discussed. Furthermore, this study provides a comprehensive roadmap for future research initiatives aiming to utilize technology design teams' capabilities fully. To the authors' knowledge, this is the first time that the structure and tools of DTs and LSSs have been combined in a hybrid framework.

In future activities, the author plans to integrate and implement DT methodology and Lean Six Sigma approach into a more general maintenance management framework for critical equipment whose main role will be to assess and improve the health status of machines, improve reliability, and plan maintenance activities.

Abbreviations

ATM	Turnaround maintenance
CMFD	Condition monitoring and fault diagnosis
DT	Digital twins
LSS	Lean six sigma
RAMS	Reliability, availability, maintainability, and safety

6. Conflicts of Interest

The authors declare no conflicts of interest

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Citation: *Attia Hussien Gomaa. Enhancing Proactive Maintenance of Critical Equipment by Integrating Digital Twins and Lean Six Sigma Approaches. International Journal of Modern Studies in Mechanical Engineering (IJMSME)", 10(1), pp.20-35, DOI: https://doi.org/10.20431/2454-9711.1001003.*