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Research Article

# Digital Twins for Improving Proactive Maintenance Management

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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. A digital twin (DT) is a digital copy of a physical object and its applications will play a leading role in the future of smart manufacturing. DT concept is increasingly appearing in industrial applications including proactive maintenance, enabling accurate identification of equipment condition, proactive prediction of faults, and enhanced reliability. This review paper focuses on the performance and applications of different aspects of DTs in proactive maintenance polices. The review of literature focused on the applications of DT in maintenance management for improving equipment RAMS. The literature review shows that the application of DT techniques in proactive maintenance remains very important for managing the maintenance of critical equipment and production systems. Several DT frameworks for proactive maintenance have been discussed. Furthermore, this study provides a comprehensive roadmap for future research initiatives aiming to fully utilize the capabilities of technology design teams. Finally, the results of this study will be of value to professionals who want and aspire to implement technological design to achieve maintenance excellence.

## Keywords

Manufacturing, Simulation, Maintenance, Fault Prediction, Digital Twin, Machine Learning, 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

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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), [18, 40, 11, 37, 43]. DT enables maintenance management to accurately identify equipment status, proactively predict faults, and enhance reliability, [1, 2, 4, 26, 47]. 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, [39, 3]. Figure 4 shows an equivalent representation of the general architecture of DT, [55].

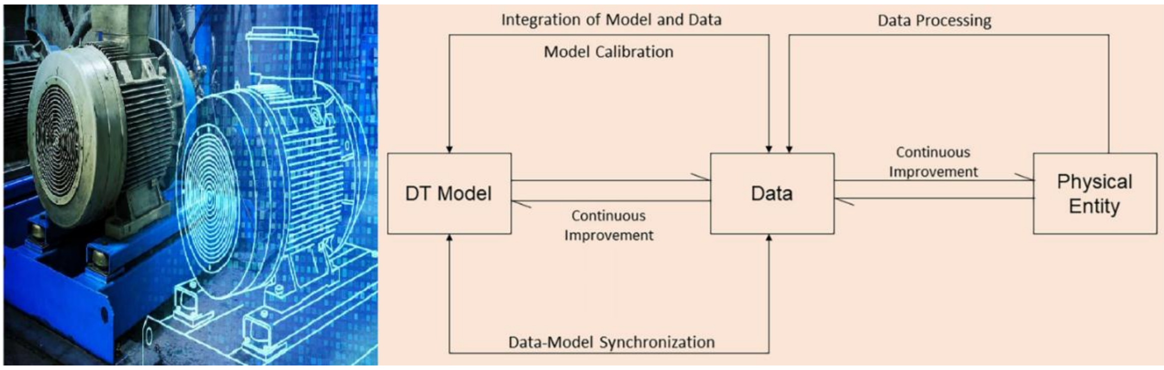


***Figure 1.*** *Digital twin illustration*

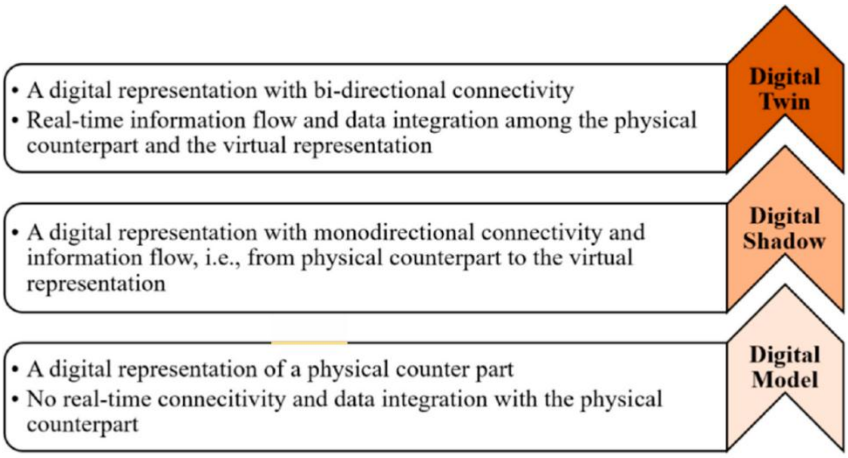


***Figure 2.*** *Digital twin Levels of integration.*

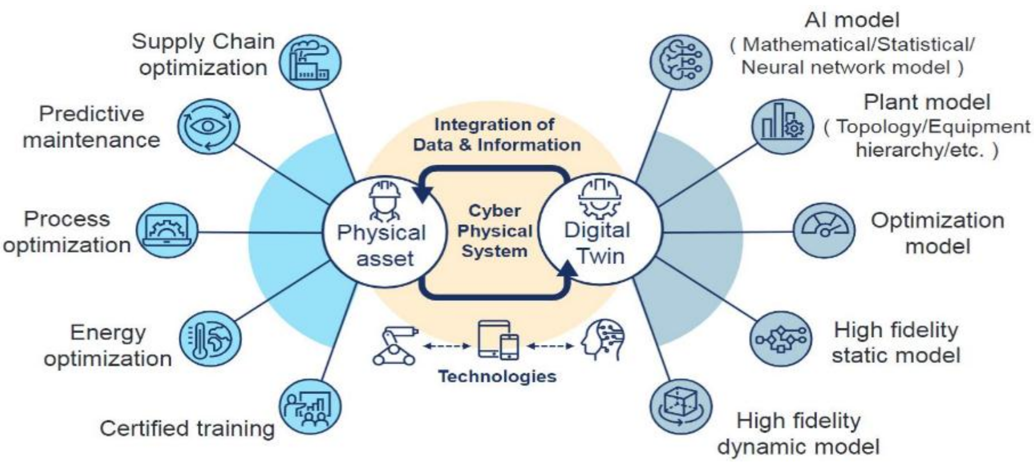


***Figure 3.*** *Digital twin applications in manufacturing.*

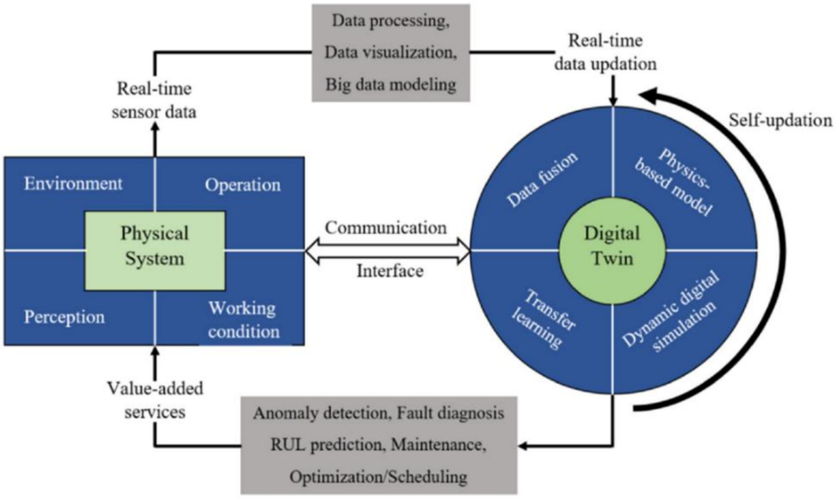


***Figure 4.*** *Equivalent representation of the general architecture of DT.*

This study focuses on the performance and applications of DTs in proactive maintenance policies and the importance of DT in maintenance management for improving equipment RAMS (reliability, availability, maintainability, and safety). This study is an extension of a previously published paper, [10].

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 DT framework for proactive maintenance. Finally, Section 5 focuses on conclusions and future directions.

## 2. Literature Review

Digital twins (DT) can provide a real-time response to the manufacturing system and increase flexibility and reliability, [13]. According to Hu, [16] Figure 5 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.

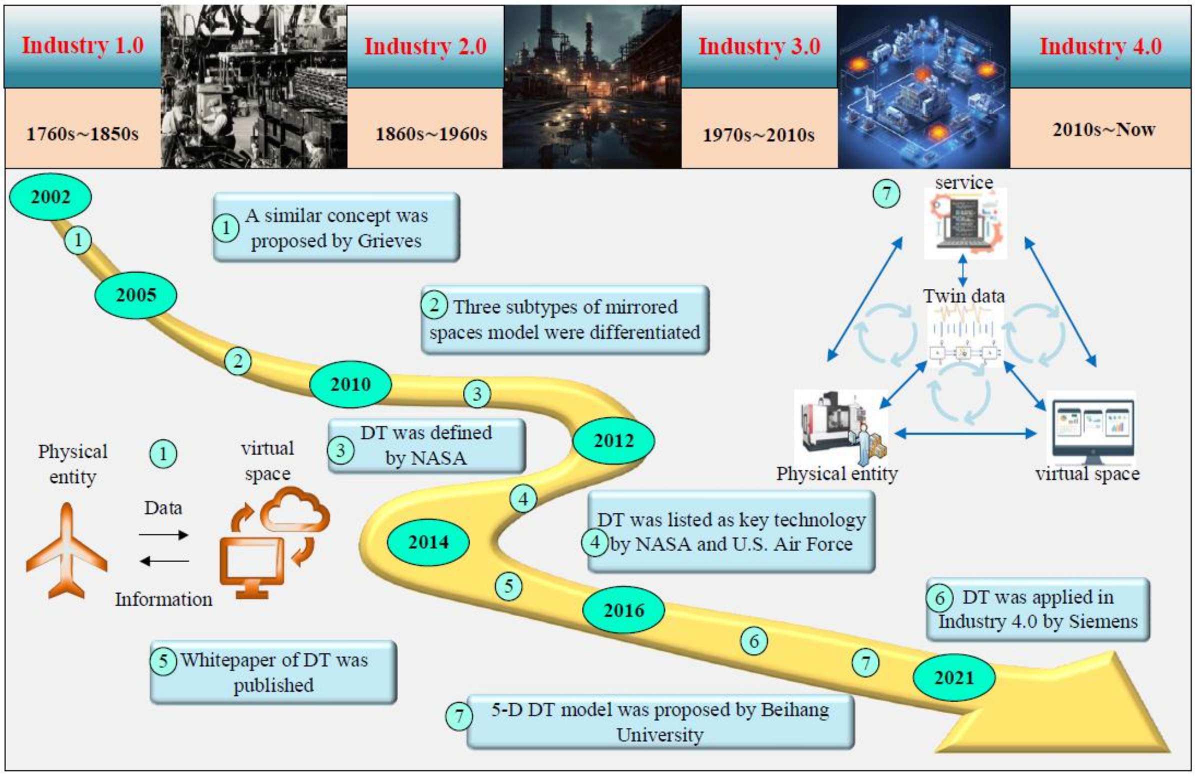


***Figure 5.*** *The milestones of DT development.*

Proactive maintenance can reduce failure risks, improve system uptime, extend the equipment life, and lower process down time 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, 49]. 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 |
|---|---|
| Before 2017 | - |
| 2017 | [42] |
| 2018 | [44] |
| 2019 | [2, 41, 34, 52] |
| 2020 | [7, 14, 25] |
| 2021 | [27, 31, 35, 48, 50, 51, 58] |
| 2022 | [10, 15, 22, 30, 45, 55, 56] |
| 2023 | [25, 28, 36, 46, 48, 54, 57] |
| August 2024 | [8, 17, 21, 24, 53] |

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, [52] 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, [50] 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, [51] 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, [51] 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, [57] 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, [54] 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, [53] 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.

## 3. Research Gap Analysis

The literature review shows that the application of DT 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 concept of proactive maintenance. Moreover, implementing DT technology, for maintenance activities in a production plant, requires creating a DT for each machine. 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. Digital Twin Frameworks for 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 6 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 7 shows the DT data analysis process for building a successful DT.

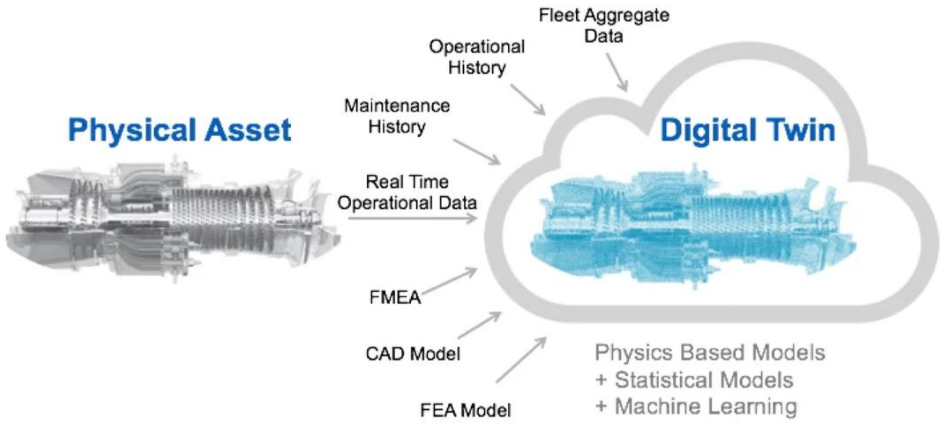


***Figure 6.*** *DT model in maintenance.*

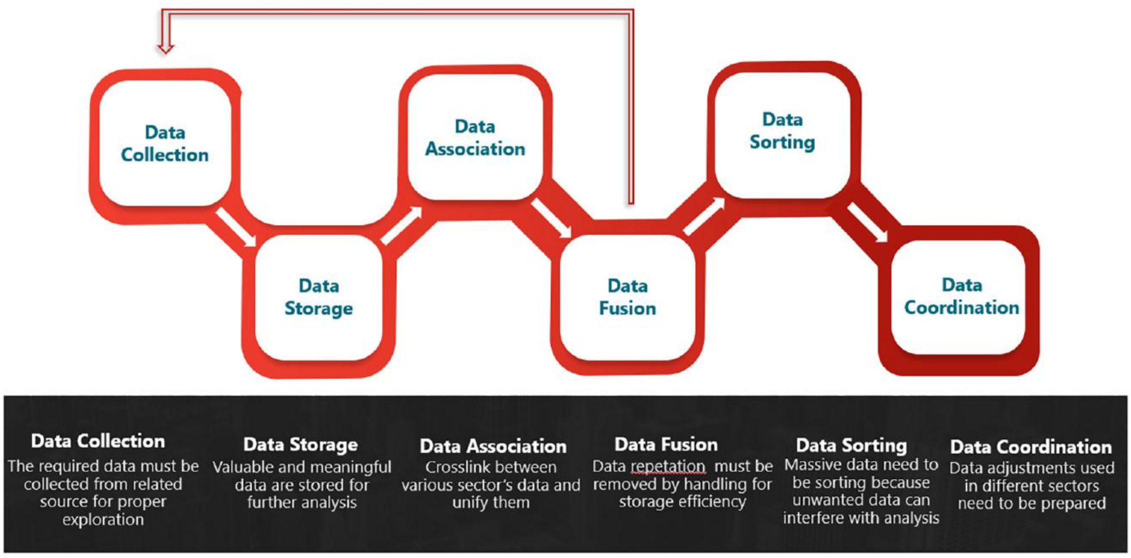


***Figure 7.*** *DTs Data analysis process, [5].*

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 8 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 9 shows COBie components.

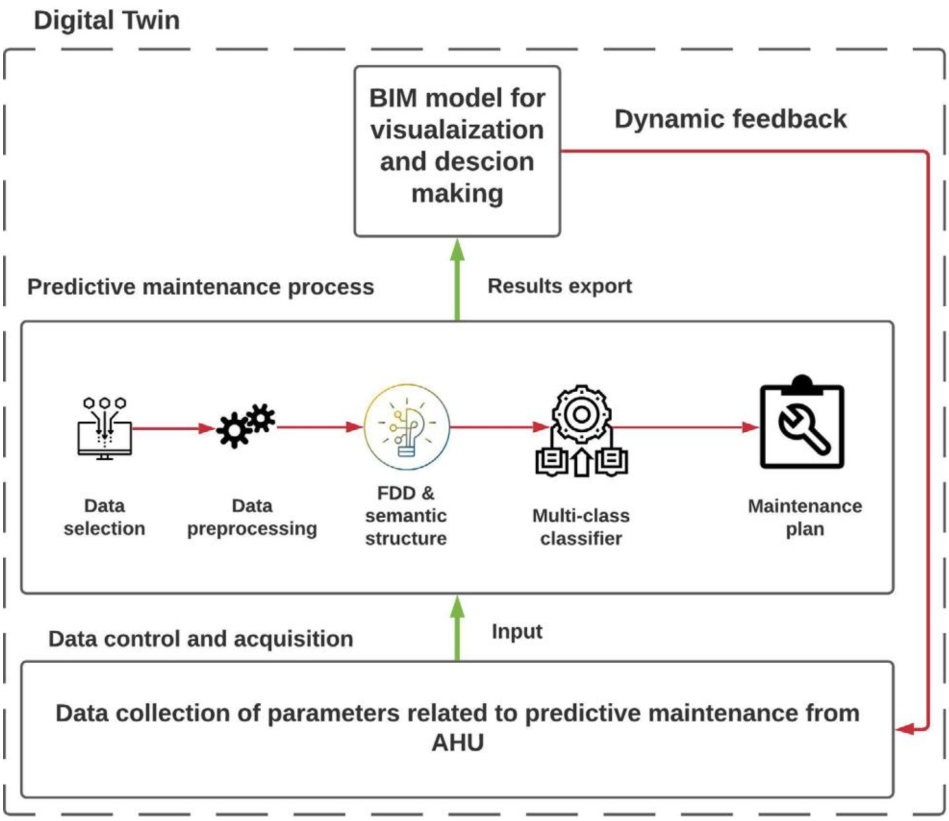


***Figure 8.*** *DT predictive maintenance framework, [15].*

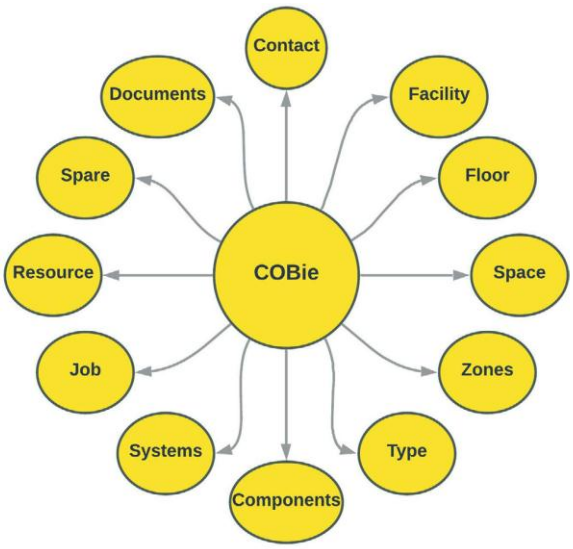


***Figure 9.*** *Standard COBie components, [15].*

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 10, 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.

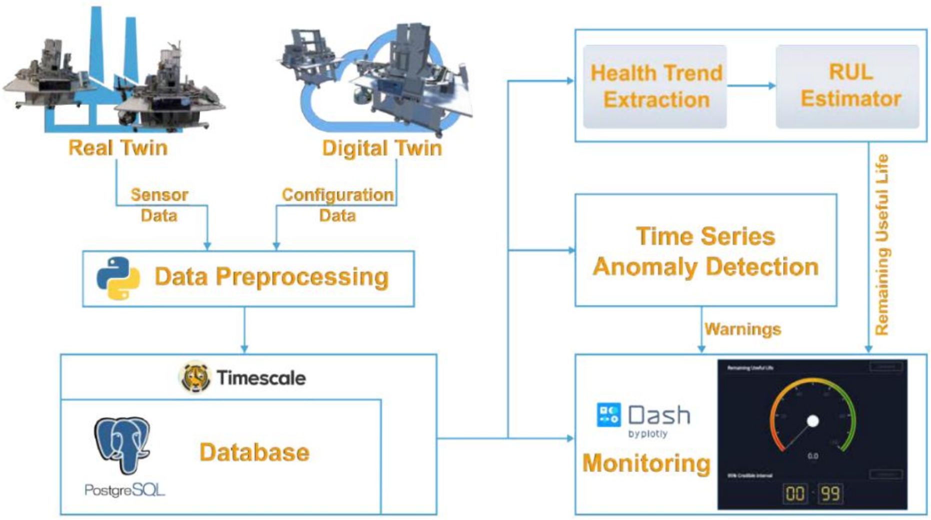


*Figure 10. A Digital Twin Framework for Predictive Maintenance. [27]*

Karkaria, [21] introduced a DT framework for proactive maintenance of long-term physical systems. Figure 11 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 damages. 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.

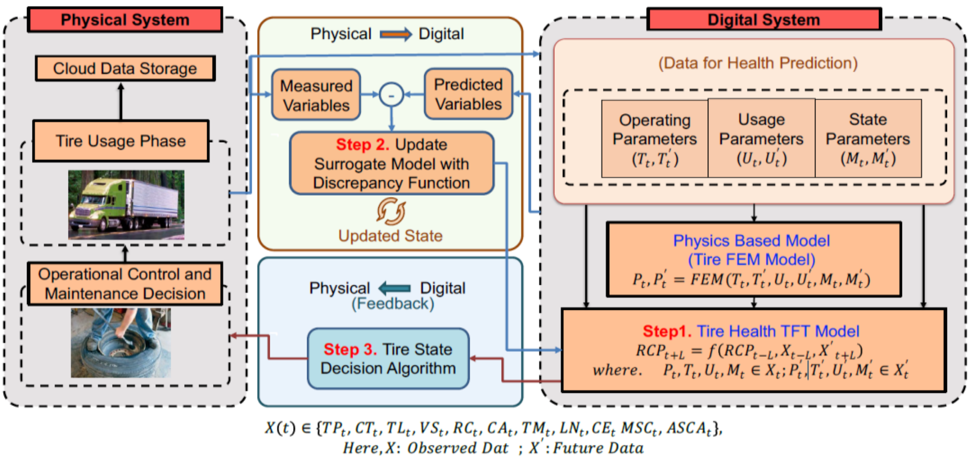


*Figure 11. Tire health digital twin framework, [21].*

## 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) 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. The application of DT technologies remains a critical proactive technology for critical equipment to improve equipment RAMS and achieve maintenance excellence. Several DT frameworks for proactive maintenance have been discussed. Furthermore, this study provides a comprehensive roadmap for future research initiatives aiming to fully utilize the capabilities of technology design teams.

In future activities, the author plans to integrate 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

| | |
|---|---|
| DT | Digital Twins |
| RAMS | Reliability, Availability, Maintainability, and Safety |

## Author Contributions

Attia Hussien Gomaa is the sole author. The author read and approved the final manuscript.

## Conflicts of Interest

The authors declare no conflicts of interest.

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