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Enhancing maintenance management of critical equipment using digital twin

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Abstract

Digital twin (DT) technology develops virtual models of objects digitally, simulating their behavior in the real world based on data. Recent advances in DT have greatly facilitated the development of predictive maintenance for critical equipment, enabling accurate identification of equipment conditions, proactive prediction of faults, and enhanced reliability. This research aims to explore the previous studies on DT for proactive maintenance applications of critical equipment. The literature review shows the importance of DT in maintenance management for improving equipment RAMS (reliability, availability, maintainability, and safety). Finally, the findings of this study will be valuable to professionals who desire and aspire to implement DT to achieve maintenance excellence.

Keywords: Manufacturing; Maintenance; Fault prediction; Digital twin; Machine learning; Continuous improvement

1 Introduction

A digital twin (DT) is a digital copy or virtual representation of an object that is designed to accurately reflect a physical object, (refer to Figure 1). It is updated from real-time data and uses simulation, machine learning and reasoning to help make decisions. It was first suggested by Michael Graves, (Grieves, 2014). Subsequently, DT was described as an integrated entity of a physical product, a virtual description of that product, and the data connections between them. Recently, DT has been applied in various manufacturing areas, and it is promoting positive developments in these areas., (Jones et al., 2020).

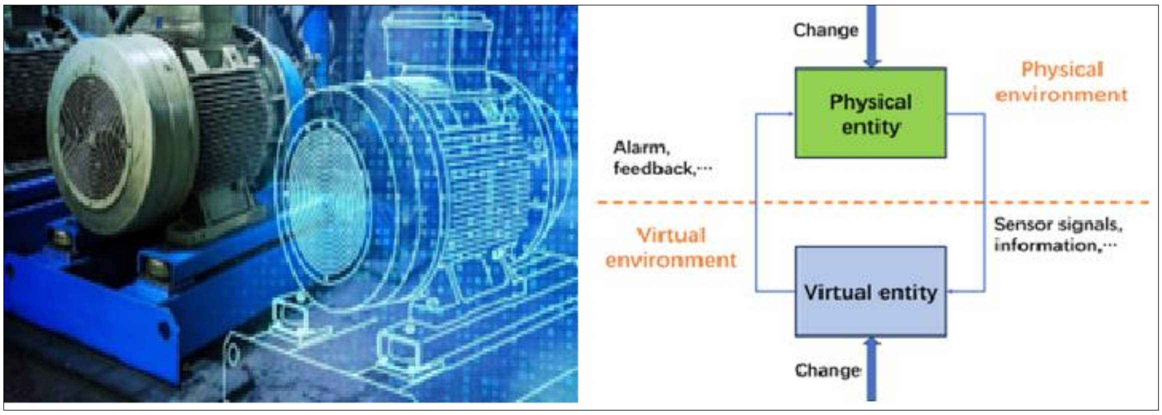

Figure 1 An illustration of a Digital Twin

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In the manufacturing industry, equipment repair and maintenance are a very important link. The maintenance method is to regularly check the health of the equipment, repair equipment failures, and prevent secondary damage and downtime, which directly affects the operating time and work efficiency. More and more sophisticated diagnostic methodologies are available to determine the root causes of machine failure. The failure mode effects and criticality analysis (FMECA) is the most common diagnostic methodology. The FMECA consists of two analyses; the Failure Mode and Effects Analysis (FMEA) and the Criticality Analysis (CA). This methodology enables the identification of known and potential failure modes, their causes and effects, the prioritization of the identified failure modes, and the planning of the corrective actions for the corresponding failure modes (Spreafico et al., 2017).

However, diagnostics, which is conducted when a fault has already occurred, is a reactive process for maintenance decisions and cannot prevent downtime as well as a corresponding expense from happening, (Jay et al., 2014). The DT application adopts a proactive approach to equipment management services by integrating real-time equipment sensor data such as temperature and vibration with environmental data, to update the DT model and prevent unplanned downtime. DT enables maintenance management to accurately identify equipment status, proactively predict faults, and enhance reliability, (Aivaliotis et al., 2019).

This research aims to provide a literature review regarding the concept of DT for proactive maintenance strategies of critical equipment for improving equipment RAMS (reliability, availability, maintainability, and safety), and achieving maintenance excellence. The paper is structured as follows: Section 2 presents a literature review. In Section 3, research gap identification takes place. Section 4, includes a DT Framework for Proactive Maintenance. Finally, Section 5 highlights the conclusion and future work.

2 Literature Review

Digital twin (DT) is one of the most promising enabling technologies for realizing smart manufacturing. DT can provide a real-time response of the manufacturing system and increase flexibility and reliability, (He et al., 2021).

Preventive maintenance focuses on predicting when to schedule maintenance for a component or system to reduce cost and increase machine uptime. Predictive maintenance allows the organization to prevent problems without incurring the cost of unnecessary frequent maintenance (Kang et al, 2021). As a result, predictive maintenance in manufacturing could extend the life of aging assets, improve uptime, reduce quality risks, and reduce costs. DT can model individual equipment or manufacturing processes to identify variances that indicate the need for preventive repairs or maintenance. The aim is to estimate, predict, detect, or diagnose the condition of a component or a system for maintenance more effectively. This would prevent costly failure before a serious problem occurs. They can also determine if better materials or processes can be utilized or help optimize cycle times, load levels, and tool calibration (van Dinter et al. 2022).

According to (Miskinis, 2019), 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 favoured 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. That would include retesting the airframes, testing its engine, or doing further security checks to enhance the efficiency of dealing with any threat. In addition, DT solutions enable aviation engineers to operate effectively and reduce testing costs by maintaining and repairing aircraft when they are not within physical proximity. 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 (Woodrow III, 2018). General Electric's (GE) DT technology is revolutionizing how the aerospace industry approaches maintenance. Predicting engine wear and tear, like blade spallation in the GE90 engine, saves airlines millions in costs and prevents aircraft from being grounded unexpectedly, especially in regions with sand, a major contributing factor to this issue.

In recent years, DTs are increasingly used in the field of condition monitoring and fault diagnosis (CMFD). This study aims to provide a literature review of all DT-CMFD papers that were in specialized journals to explore the most popular topics published in this field. While the literature search was limited to English language only. Table (1) shows the survey of DT-CMFD papers over the past years. The details of these studies are explained in the next section.

Table 1 A comprehensive survey of digital twins in maintenance, (2017 to 2022)

Period	#	References
Before 2017	0	-
2017	1	Tao et al., (2017)
2018	1	Tao et al., (2018)
2019	4	Tao et al., (2019), Qiao et al., (2019), Xu et al., (2019), Aivaliotis et al., (2019 b)
2020	3	Luo et al., (2020), Heim et al., (2020), Errandonea et al., (2020)
2021	5	Xia et al., (2021), Xiong et al., (2021), Wang et al., (2021), Olatunji et al. (2021), Mihai et al., (2021)
2022	5	Xiong et al., (2022), Moghadam and Nejad, (2022), Kim, (2022), Van Dinter et al., (2022), Hosamo et al., (2022)

Tao et al. (2017) proposed the concept of a DT workshop, providing theoretical support for manufacturing applications by discussing its characteristics, composition, operation mechanism, and key technologies. To further promote the application of DTs in various domains. Tao et al. (2018) proposed a five-dimension DT model for complex equipment to improve the accuracy of prognosis. A general DT for complex equipment is first constructed, then a new method using DT-driven PHM is proposed, making effective use of the interaction mechanism and fused data of DT. A case study of a WT is used to illustrate the effectiveness of the proposed method. Tao et al. (2019) extended the existing three-dimensional DT model to propose a five-dimensional DT model.

Qiao et al. (2019) presented 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. First, a five-dimensional digital twin model is introduced that highlights the performance of the data analytics in model construction. Next, a deep learning technique, termed Deep Stacked GRU, is demonstrated that enables system identification and prediction. Experimental studies using vibration data measured on the milling machine tool have shown the effectiveness of the presented digital twin model for tool wear prediction. Xu et al. (2019) proposed 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. By employing deep migratory learning, previously trained diagnostic models can be migrated from virtual space to physical space for real-time monitoring and predictive maintenance. This ensures diagnostic accuracy and prevents unnecessary delays.

Aivaliotis et al., (2019 b) 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. The resources and the properties of them are first modeled in a digital environment able to simulate the real machine's behavior. Data are gathered by machines' controllers and external sensors to be used for the synchronous tuning of the digital models and their simulation. The outcome of the simulation is then used to assess the resource's condition and to calculate RUL. In this way, the condition and the status of the machines can be monitored and predicted as a result from the simulation of physics-based models, without invasive techniques of common predictive maintenance solutions. A case study is presented where the proposed methodology is validated by predicting the RUL of an industrial robot.

To realize a more reliable real-time tool condition monitoring (TCM) approach, Luo et al. (2020) proposed 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 tool, a hybrid approach driven by DT is studied. This approach is DT model-based and DT data-driven hybrid. With the proposed framework, a hybrid predictive maintenance algorithm based on DT model and DT data is researched. At last, a case study on cutting tool life prediction is conducted. The result shows that the proposed method is feasible and more accurate than single approach. Heim et al. (2020) provided several methods to describe the remaining useful life of a given part for aircraft maintenance through two separate aircraft data sets. Then it shows how to combine these results with the digital twin model to help design a sufficiently stable supply chain and maintenance strategy.

Xia et al. (2021) proposed 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. The experimental results demonstrate that the proposed method achieves intelligent fault diagnosis with a limited amount of measured data and outperforms other state-of-the-art data-driven methods. Xiong et al. (2021) studied the predictive maintenance framework of an aero-engine driven by digital twin, and mined the implicit digital twin model. 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 data set used for model training is 80%, the model prediction has high accuracy. Wang et al. (2021) proposed a DT model including a geometric model, physical model, behaviour model and rule model to conduct fault prediction of the autoclave to generate simulated data to address the issue of insufficient data for fault prediction. The characteristics of autoclaves under different conditions are analyzed and presented with specific parameters. The data in normal and faulty conditions are simulated by using the DT model. Both the simulated data and extracted historical data are applied to enhance fault prediction. A convolutional neural network for fault prediction will be trained with the generated data which matches the feature of the autoclave in faulty conditions. The effectiveness of the proposed method is verified through result analysis. Olatunji et al. (2021) provided an overview of the application of digital twin technology in the fault diagnosis and condition monitoring of wind turbine mechanical components. The frequently used tools for digital twins and enabling technologies are identified and briefly analyzed while the common mode of failure in wind turbine components were highlighted. The benefits and challenges associated with the application of this technology are discussed. Qin et al. (2021) proposed a DT model of life-cycle rolling bearing driven by the data-model combination. With the measured signals and the bearing fault dynamic model, the time-varying defect size is estimated, and the evolution law of bearing defect during the life cycle is revealed by a back propagation neural network. Then, the excitations of evolutionary defects are introduced into the bearing dynamic model, so as to form a life-cycle bearing dynamic model in the virtual space. Finally, the simulation data in the virtual space is mapped into the corresponding data in the physical space via an improved CycleGAN neural network with smooth cycle consistency loss. By comparing the obtained digital twin result with the measured signal in the time domain and frequency-domain, the effectiveness of the proposed model is verified.

Refer to (Xiong et al., 2022), DT solutions are widely embraced in the aerospace industry for aircraft maintenance, tracking, weight monitoring, an accurate stipulation of weather conditions, measurement of flight time, catastrophic malfunction analysis, safety, and security management, and defect detection. Moghadam and Nejad (2022) presented a digital twin-based CMFD approach for offshore WT 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 (2022) 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 et al., (2022) proposed a DT predictive maintenance framework of air handling units (AHU) to overcome the limitations of facility maintenance management (FMM) systems now in use in buildings. DT technology, which is still at an initial stage in the facility management industry, use Building Information Modeling (BIM), Internet of things (IoT) and semantic technologies to create a better maintenance strategy for building facilities. Three modules are implemented to perform a predictive maintenance framework: operating fault detection in AHU based on the APAR (Air Handling Unit Performance Assessment Rules) method, condition prediction using machine learning techniques, and maintenance planning. Furthermore, the proposed framework was tested in a real-world case study with data between August 2019 and October 2021 for an educational building in Norway to validate that the method was feasible. Inspection information and previous maintenance records are also obtained through the FM system. The results demonstrate that the continually updated data combined with APAR and machine learning algorithms can detect faults and predict the future state of Air Handling Unit (AHU) components, which may assist in maintenance scheduling. Removing the detected operating faults resulted in annual energy savings of several thousand dollars due to eliminating the identified operating faults.

3 Research Gap Analysis

In summary, the literature review shows that the application of DT in maintenance management techniques remains a very important proactive technology for managing the maintenance of critical equipment to improve equipment RAMS (reliability, availability, maintainability, and safety) and achieve maintenance excellence. However, a general platform based on the creation of a physical model via a common methodology, is still missing. There is not any common line for the development and implementation of the DT concept. This is a requirement for the implementation of the DT concept for maintenance. More specifically, the implementation of the DT technology, for maintenance activities in a production plant, requires the creation of the DT for each machine. Due to the great variety of machines included in a production plant, a common framework for the creation of the digital twin, using specific tools, should be defined. Finally, a more detailed literature review should also take place for the identification of more gaps, which will be addressed in the proposed model creation and tuning framework., (Aivaliotis et al., 2019 a).

4 Digital Twin Framework for Proactive Maintenance

As mentioned before, in different sectors of manufacturing maintenance costs are very high, which justifies the investment in creating DTs to optimize maintenance activities. Figure (2) shows a DT model in maintenance.

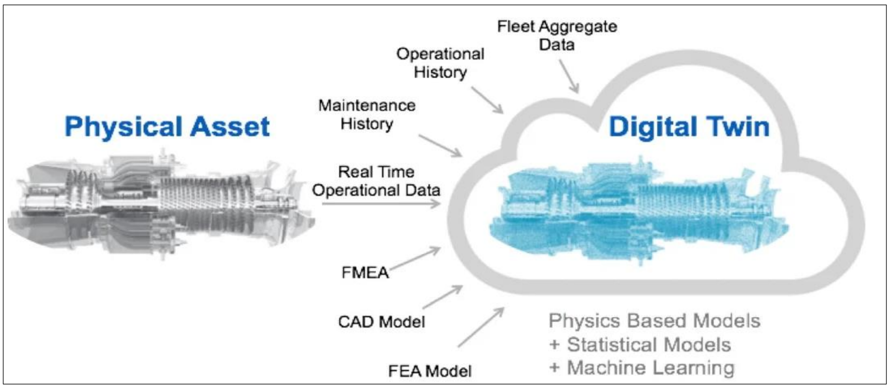

Figure 2 DT model in maintenance

Hosamo et al., (2022) proposed a DT predictive maintenance framework of air handling units (AHU) to overcome the limitations of facility maintenance management (FMM) systems now in use in buildings. Figure (3) shows the principle of a DT in maintenance. The proposed framework utilizes Digital Twin 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. This framework is based on our developed method by integrating the new technologies, particularly BIM, IoT, semantic metadata and expert rules, and ML. The 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 (4) shows COBie components.

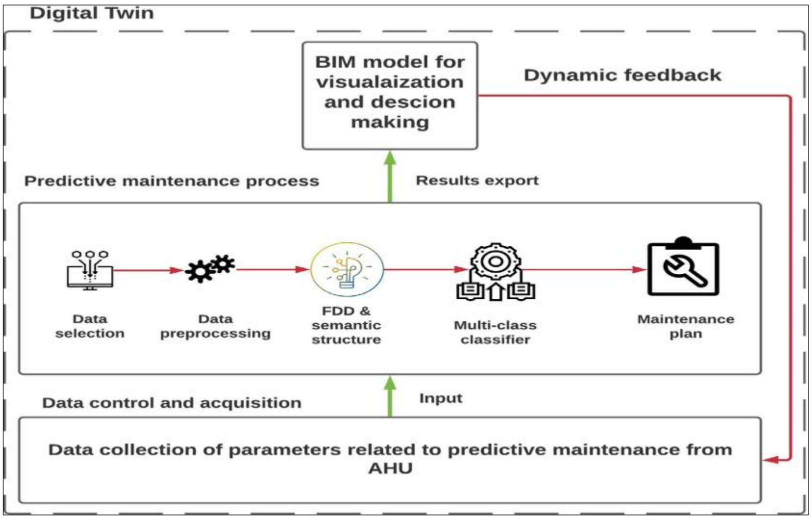

Figure 3 DT predictive maintenance framework, Hosamo et al., (2022)

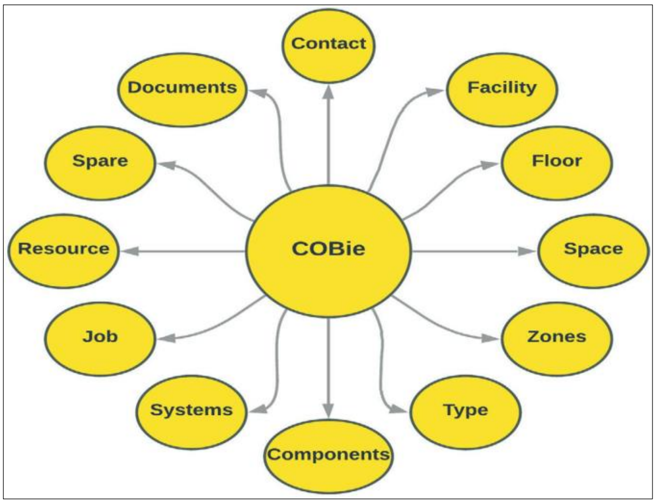

Figure 4 Standard COBie components, Hosamo et al., (2022)

Mihai et al., (2021) introduced 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 proposed framework is illustrated in Figure (5), and 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.

- Data Acquisition Block: The data acquisition block extracts information from both the real twin, and the digital twin. The types of data needed for the purpose of Predictive Maintenance are:
  - Sensor data - acquired from the Cyber-Physical Factory, the sensor data consists of time-indexed sensor readings from the PT100 temperature sensor installed in the baking station, the power monitor attached to the second island, as well as boolean flags readings from the capacitive position indicating sensors. The proposed framework communicates to the physical asset via the OPC UA protocol for timely machine-to-machine communication of the streaming data. _ Configuration data - acquired from the digital twin of the CP-Lab, it consists of meta-data that describes the configuration of the order, as well as the current load of the second island. It is important for the later stages of data analytics that the working regime of the smart factory be monitored in real-time, so that the power sensor data, which describes the power consumption of all the four stations installed on the second island, can be scaled and normalized to reflect the power consumption of the heating station.
- Data preprocessing Block: The data preprocessing block normalizes the data if necessary, then it inserts it into the database.
- Database Block: The database of the system consists of the relational PostgreSQL, which was optimized for time-series analysis through the TimescaleDB extension, allowing fast inserts of high-rate streaming data.
- Time series Anomaly Detection: This block deals with identifying odd behaviour in the time-series sensor data, with respect to the expected behaviour based on the configuration data coming from the digital twin. The anomaly detection block's responsibilities are also to detect outliers, changepoints, and transmit warnings with various levels of urgency based on the found anomalies.
- RUL Predictor Block: The Remaining Useful Life Predictor block is functionally split into two subsystems:
  - Health Trend Extraction - deals with analyzing the sensor and configuration data to extract a health trend. In order to qualify for the use of Predictive Maintenance, the extracted health trend must fulfill (as much as possible) certain conditions: it must be a function of time, it has to be monotonically increasing (or decreasing) over time, and, preferably, it has to be an injection. Popular methods that combine features, depending on whether they can be modelled linearly or not, are Principal Component Analysis (PCA) and Isomap.
  - RUL Estimator - extracts the Remaining Useful Life of the component, based on the current health status indicated by the health trend. A Machine Learning model is fit to the Health Trend, and it is updated for every coming sample. The Machine Learning algorithm that predicts the RUL will be chosen based on the characteristics of the health trend. In many cases, the RUL extraction can boil down to a simple curve fitting and regression technique, if the health trend respects the aforementioned conditions of monotonicity and dependence on time. However, if it does not, multiple other options can be applied, like Recurrent Neural Networks (RNNs), Long Short Term Memory

networks (LSTMs), Support Vector Regression (SVR), etc., depending on the characteristics of the pre-processed data. It is worth mentioning that, even though it is preferred that the RUL be a function of time, it can also be expressed in ”cycles” or ”orders”. For example, the output of the RUL Estimator block can indicate that the machine would fail in a certain number of cycles, if a given sequence of order configurations is to be serviced after the moment of prediction.

- Monitoring Block: The Monitoring Block is a web application built with Dash, which displays continuous comprehensive information about the current state of the real asset.
- It also presents controls that can be communicated back to the physical twin for engineered process optimization.

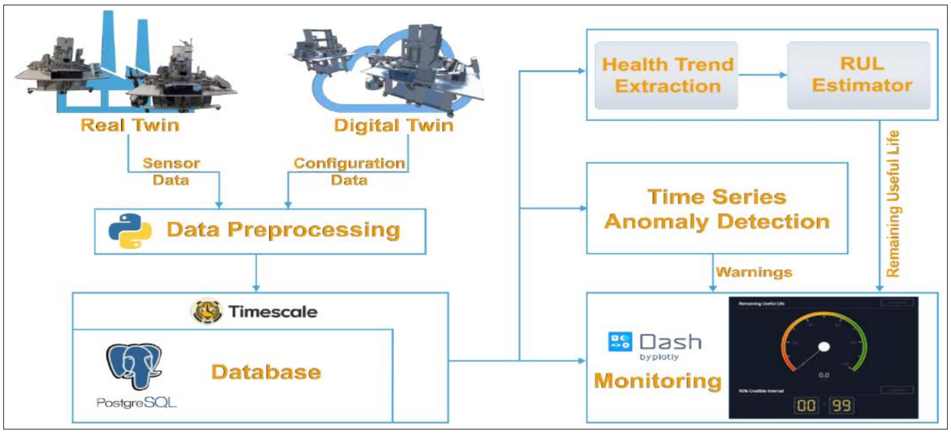

Figure 5 A Digital Twin Framework for Predictive Maintenance, Mihai et al., (2021)

5 Conclusion

Digital twin (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. This paper is based on a review of the use of DT in maintenance management, and then, the latest applications of DT in different application areas of MM are presented. The application of DT technologies remains a critical proactive technology for critical equipment to improve equipment RAMS (reliability, availability, maintainability, and safety) and achieve maintenance excellence. Furthermore, the findings of this study will be valuable to professionals who desire and aspire to implement digital twins to achieve maintenance excellence.

Further Work

In future activities, the author plans to integrate DT methodology and Lean Six Sigma (LSS) 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. Finally, a more detailed literature review should also take place for the identification of more gaps, which will be addressed in the proposed model creation and tuning framework.

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