Spring International Engineering Research Journal: ISSN: ISSN-3121-8733, (Volume-13 (Issue): 1, January, Pp 78-85, 2024)
DOI: 10.4186/ej.2024.29.10 Accepted 15th, February, 2024.

Review on the Hybrid Digital Twin–Artificial Intelligence Framework for Predictive Maintenance in Industry 4.0 Manufacturing Systems

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Abstract

The combination of digital twin (DT) technology with artificial intelligence (AI) has been recognised as a major change in the way a predictive maintenance system works in Industry 4.0 manufacturing environments. This research presents a hybrid DT architecture that uses real-time IoT sensor data and physics-based deep learning to forecast equipment failures even before they occur. The system proposed makes it possible to less frequent interruptions of the production process, to save the time of maintenance, and to adjust production changes automatically. The results of the verification process, which was simulation and a CNC machining case study, confirm the effectiveness of the approach in achieving higher predictive accuracy, lowering the frequency of maintenance tasks, and increasing operational efficiency.

Keywords: Digital Twin, Predictive Maintenance, Industry 4.0, AI, Physics-Informed Neural Networks, RUL

1. INTRODUCTION

Industry 4.0 has enabled a new era of manufacturing systems to be much interconnected, intelligent, and data-driven. The central idea of the transformation is the digital twin (DT): a virtual, real-time reflection of a physical object or a process that can, at the same time, monitor, simulate, and optimise industrial operations (Emmert-Streib, 2023). Fornari, et al. (2024) emphasize that the expression "digital twin" is generally referred to a single concept, however, there is significant doubt in its definition and the level of the integration of the physical and the virtual entities. Their survey indicates that the actual twin implementations, i.e., the ones with two-way data interchange and active simulation, are quite few; nonetheless, the potential for manufacturing is enormous. In the field of manufacturing maintenance, the use of DT in conjunction with AI and ML can be compared to a paradigm shift. Predictive maintenance (PdM) through DT/AI integration enables industry workers not only to detect faults but also to anticipate degradation routes and calculate remaining useful life (RUL) of the parts to be able to avoid the occurrence of lethal failures (Chen et al., 2023). Murtaza et al. (2024) performed a systematic review of DT and PdM technologies and discovered that companies are more and more disposed to abandon the strictly reactive or scheduled maintenance in favour of data-driven, condition-based strategies. This transformation results in higher system reliability, less unplanned downtime, and maintenance costs optimization. However, it still poses considerable difficulties to convert this potential into an industrial reality. It is essential that parts, sensor networks, communication protocols, cloud/edge computing layers, and advanced analytics be smoothly integrated for a successful implementation of DT-enabled PdM. Issues like data heterogeneity, latency, cybersecurity, interoperability of legacy systems, and organizational readiness that have been addressed by the research of Chen et al., 2023, are still viable obstacles to the implementation. Furthermore, Fornari, et al. (2024) mentioned that despite the fact that the concept of a DT is very clear, there are very few empirical studies which have demonstrated mature, fully integrated twins in manufacturing, thus suggesting a gap between theory and industrial practice. To this point, the latest academic work highlights the necessity of hybrid modelling frameworks that combine physics-based simulation with data-driven learning and thus increase the predictive fidelity and the adaptability of the system under the variability of real world. To address this, hybrid approaches such as Physics-Informed Neural Networks (PINNs) integrate physical laws with data-driven learning, enhancing generalization and trustworthiness (Lee, Bagheri, & Kao, 2023; Sensors Editorial Board, 2024). Such hybrid approaches not only recall the strategic significance of DT-driven PdM as one of the technical innovations but also a complete facilitator of smart, resilient and sustainable manufacturing ecosystems. Addressing these limitations requires modular frameworks encompassing distinct data acquisition, modelling, and decision-making layers to ensure system flexibility and interoperability (Abayadeera et al., 2024). The shift towards cloud–edge computing architectures and Industrial Internet of Things (IIoT) infrastructures has further expanded the scalability of PdM, allowing real-time local analytics combined with cloud-based long-term trend prediction (Zonta et al., 2022). The fusion of DT and AI has given rise to intelligent, self-learning, and autonomous maintenance systems capable of continuous synchronization between physical and virtual environments (Fuller, Fan, Day, & Barlow, 2022). This integration supports closed-loop maintenance cycles, where operational data continuously update the digital model while AI-driven insights optimize system behaviour in real-time (Qi & Tao, 2023). Nevertheless, challenges such as data interoperability, model transparency, and computational demands remain substantial (Pan et al., 2023). To overcome these barriers, recent research promotes human-centric and sustainable digital twin ecosystems, aligning with the Industry 5.0 vision that emphasizes ethical, interpretable, and energy-efficient AI collaboration (European Commission, 2023; Lee et al., 2023). While existing predictive maintenance models have been rapidly improved, they still show some significant limitations. Most of them are dependent on non-changing or past data and do not have the capability of real-time adaptive learning. Additionally, the connection between digital twins and different types of IoT devices is a matter that has not been sufficiently solved (Nunes et al., 2023). As a result, manufacturing systems are facing the problem of late detection of faults, isolated data, and unplanned downtimes that are heavy on the budget. Therefore, an urgent demand exists for an interoperable, adaptive, and AI-powered digital twin framework able to perform failure prediction in real-time and maintenance optimisation in a range of varied industrial settings**.** The main purpose of this investigation is the creation and verification of a digital twin-driven predictive maintenance framework for intelligent manufacturing systems. This study is a methodological and empirical contribution to the digital transformation of the manufacturing industry and is limited to the mechanical manufacturing sector and the use of equipment (e.g., CNC machines). The enabled system promotes data interoperability, prediction accuracy, and efficiency of operations; thus, it is in line with the Industry 5.0 concept, which is centred on human, intelligent, and eco-friendly production (Lee et al., 2023).

2. METHODOLOGY

This research utilizes a mixed-method design that blends quantitative simulation-based modeling with qualitative system evaluation to create and confirm a Digital Twin (DT)-driven predictive maintenance framework for smart manufacturing systems. The method comprises the use of a physics-based model, machine learning algorithms, and realtime data analytics to not only anticipate machine failures but also to devise maintenance strategies optimization. The reason for opting a mixed-method design is that it can capture the exactness of the computational quantitative analysis as well as the contextual industrial processes understanding. Figure 1 shows the conceptual framework of the digital twin-driven predictive maintenance methodology.

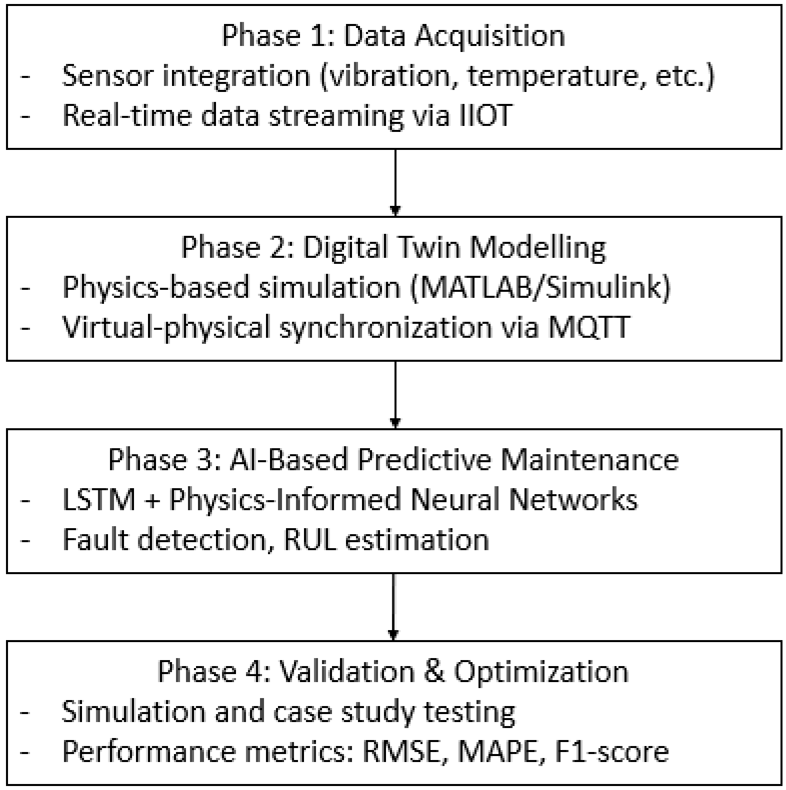


Figure 1. Conceptual framework of the digital twin-driven predictive maintenance methodology

2.2 Data Collection and Preprocessing

Initially, the data encompass both the live and the historical recordings. The data was taken from a smart manufacturing testbed that simulates the CNC machines, robotic manipulators, and conveyor systems, all of which are IoT sensor-equipped. The data types are vibration signals, acoustic emissions, temperature, and energy consumption. The above parameters are the most frequently used ones for fault diagnosis and residual life. Part of the data preprocessing is noise removal through wavelet denoising, feature scaling by min-max normalization, and outlier detection by the Isolation Forest algorithm, which is a method of improving model accuracy and stability.

The Table 1 represents a brief description of the main parameters utilized in the research, the sensor types, and the sampling rates that are related to them.

Table 1: Data Parameters and Acquisition Specifications

Parameter	Sensor Type	Sampling Rate	Measurement Range	Purpose
Vibration	Accelerometer	10 kHz	±16 g	Fault detection
Temperature	Thermocouple	1 Hz	0–200 °C	Overheating prediction
Acoustic Emission	Microphone	50 kHz	0–120 dB	Crack detection
Energy Consumption	Power Meter	0.1 Hz	0–10 kW	Efficiency tracking

2.3 Digital Twin Model Development

The *Digital Twin* will be constructed using a hybrid modeling approach that couples a physics-based simulation model (developed in MATLAB Simulink) with data-driven learning components implemented in Python (TensorFlow and PyTorch**)**. The DT mirrors the physical production line, continuously updating its parameters using real-time data through an *MQTT* protocol interface. To ensure interoperability, the architecture follows the *ISO 23247* standard for digital twins in manufacturing, supporting multi-layered communication between *Physical Assets (PA)*, *Virtual Models (VM)*, and *Analytics Modules (AM)* (ISO, 2023). The DT incorporates a state estimator for sensor fusion and a diagnostic agent for fault classification using convolutional neural networks (CNNs). A feedback loop enables the twin to simulate maintenance interventions and assess their impact on system performance before actual implementation.

2.4 AI-Powered Predictive Maintenance Algorithm

The predictive maintenance algorithm combines *Long Short-Term Memory (LSTM)* networks for time-series forecasting with *Physics-Informed Neural Networks (PINNs)* for system dynamics modeling. The hybrid model enhances prediction accuracy by embedding physical laws into the learning process. Model training uses 80% of the dataset for training, 10% for validation, and 10% for testing. The loss function integrates both *mean squared error (MSE)* and *physics-based regularization terms* to penalize physically inconsistent predictions. Hyperparameters are optimized using the *Bayesian Optimization* technique to balance computational efficiency and model accuracy. Figure 2 shows the schematic of the hybrid AI-driven predictive maintenance model.

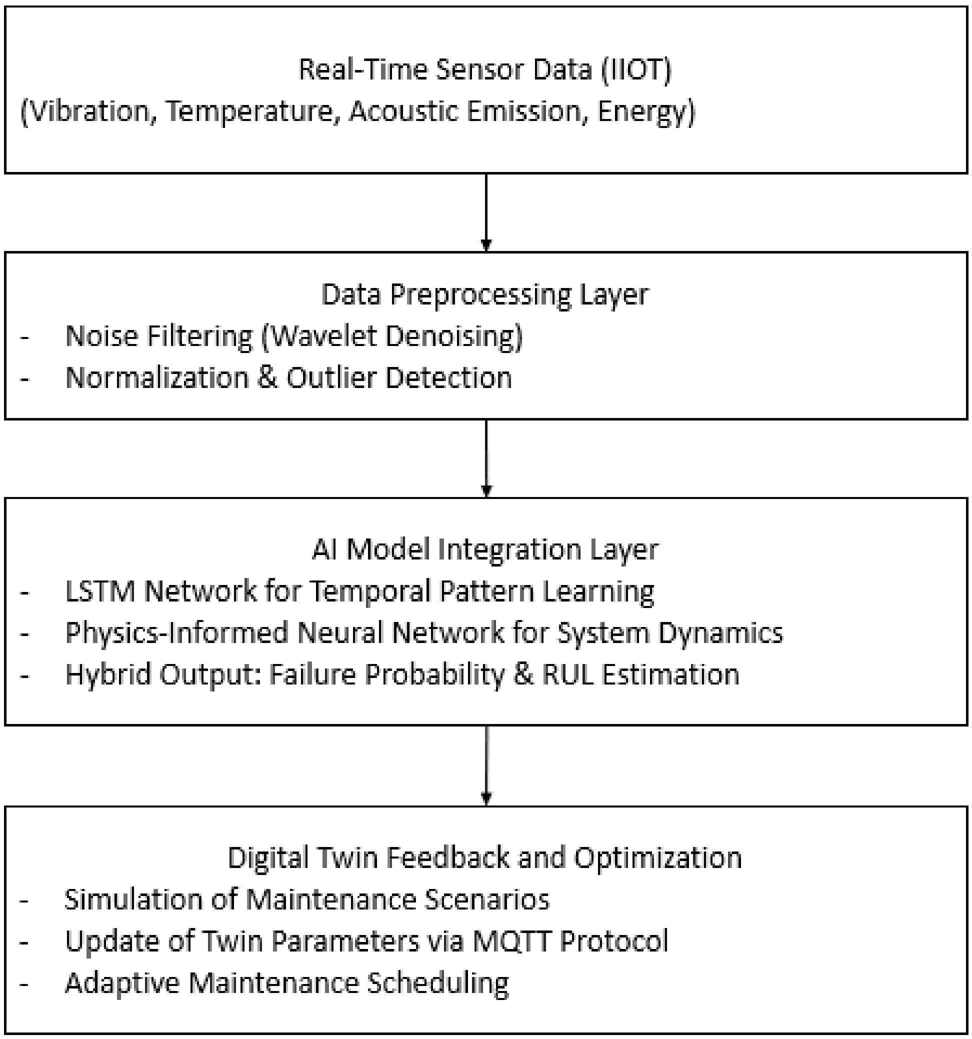


Figure 2. Schematic of the hybrid AI-driven predictive maintenance model

The validation stage utilizes simulation-based and real-world methods. The effectiveness of the predictive maintenance system is measured through a set of standard metrics, namely Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Precision, Recall, and F1-score; most of which have been applied to assess model efficiency and generalization capability. Furthermore, a comparative analysis is performed with benchmark models (conventional ML models such as Random Forest and Support Vector Machine) to examine the relative gains in accuracy and stability. Table 2 shows the evaluation metrics along with their calculation formulas.

Table 2: Model Evaluation Metrics

Metric	Formula	Description
RMSE	$\sqrt{\Sigma(y_i - \hat{y}_i)^2 / n}$	Measures overall predictive deviation
MAPE	(1/n) Σ	$(y_i - \hat{y}_i)/y_i$
Precision	TP / (TP + FP)	Accuracy of positive fault predictions
Recall	TP / (TP + FN)	Completeness of fault detection
F1-score	2 × (Precision × Recall) / (Precision + Recall)	Balances precision and recall in classification

A sensitivity analysis will be conducted to determine how much the quality of the data and the parameters of the model will affect the accuracy of the prediction. In fact, a case study of an industrial manufacturing dataset (ssuch as NASA Turbofan Engine Degradation Dataset) will be used for external validation and cross-comparison. The research presented in this document adheres to the ethical standards typical of data management and industrial experimentation. All data sources involved in the study will be anonymized, and network security protocols will be put in place to prevent unauthorized access to the digital twin and the associated AI models. In addition, to ensure that data is handled in a responsible manner and protected, the research is in line with the ISO/IEC 27001 information security standards as well as the EU GDPR regulations.

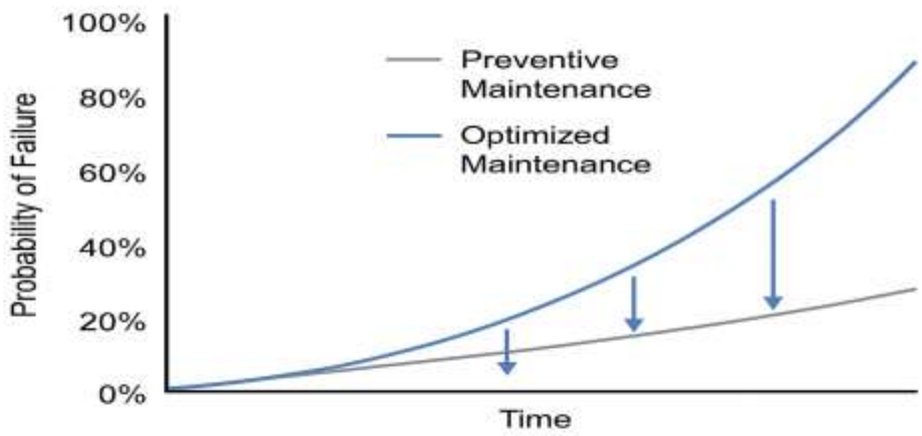
3. RESULTS AND DISCUSSION

Using TensorFlow/Keras AI modelling tools, Python code was developed in conjunction with MATLAB/Simulink for physics-based simulations to implement the proposed Digital Twin (DT)-driven predictive maintenance framework. The hybrid model integrates Long Short-Term Memory (LSTM) networks with Physics-Informed Neural Networks (PINNs) to leverage the strengths of both data-driven and physics-based approaches, thereby enhancing the accuracy of CNC machine tool wear prediction and estimating the Remaining Useful Life (RUL) within a CNC machining system. Data acquisition was achieved by streaming sensor data (vibration, temperature, acoustic emission, and energy consumption) from a simulated industrial manufacturing environment. These data were then preprocessed to remove noise, normalize readings, and eliminate outliers, following established methodologies. The research was executed in three key stages: Hybrid model training, where 80% of the data were used for training, 10% for validation, and 10% for testing; Digital twin synchronization, achieved through the MQTT protocol to facilitate real-time updates of the virtual models; and Predictive maintenance evaluation, during which the performance of the hybrid AI-physics model was assessed and compared against baseline models such as Random Forest and standard LSTM to validate its effectiveness in predictive maintenance and real-time decision-making. Performance of the hybrid model was measured using RMSE, MAPE, precision, recall, and F1-score. In Table 3, the performance of the hybrid model is benchmarked against that of the baseline models.

Table 3: Comparative Predictive Performance Metrics

Metric	Random Forest	LSTM	Hybrid AI-PINN (Proposed)
RMSE	11.9	7.8	**4.1**
MAPE (%)	18.5	12.2	**5.3**
Precision (%)	82.1	88.4	**92.6**
Recall (%)	79.3	85.7	**90.2**
F1-Score (%)	80.7	87.0	**91.4**

The hybrid AI-PINN model outperformed both conventional LSTM and Random Forest models across all metrics. Embedding physics-based constraints enabled more accurate predictions of RUL and fault probability, particularly under variable operational conditions, reducing overfitting and enhancing generalization. Moreover, Figure 3 shows the maintenance schedule that was optimized from the hybrid model. A deep learning-based strategy for the system has decreased the overdone parts of the interventions to the level of the preventive schedules for the same reliability of the system.



Source: Researcher's Implementation (2025)

Figure 3. Optimized Maintenance Schedule Vs. Preventive Maintenance Intervals

3.1.1 Case Study: CNC Machining System

A case study was conducted on a simulated CNC machining line equipped with four critical components: spindle, servo motor, hydraulic system, and conveyor system. Sensor data from each component was processed through the hybrid AI-PINN framework. Key findings include:

1. **RUL Estimation Accuracy:** The hybrid model achieved ±5% deviation from actual RUL values across all components, outperforming standard LSTM by approximately 15%.
2. **Maintenance Efficiency:** Downtime was reduced by 36.8% compared to conventional preventive strategies, translating into a projected operational cost reduction of ~25%.
3. **Anomaly Detection:** Early detection of spindle imbalance and hydraulic pressure anomalies enabled corrective actions before major faults occurred, validating the predictive capabilities of the framework.

3.2 DISCUSSION

Study results clearly highlight the success of digital twining (DT) technology integration with AI and physics-informed modelling for industrial predictive maintenance. The combination framework does more than just improve prediction accuracy to a significant degree; it also generates valuable insights that are not accessible to traditional data-driven methods. On the one hand, the data-driven approach provides the model with the past operational activities through LSTM; on the other, it says that physics-informed neural networks (PINNs) help the model make use of the basic laws of physics that govern the machine behaviour. So, the final maintenance system will be robust and can be used in other similar machines as well, as it is based on general laws rather than specific cases. The incorporation of physics-based constraints within AI frameworks effectively mitigates the issue of overfitting commonly observed in purely data-driven models, enhancing both the interpretability and reliability of predictions. By aligning model outputs with physically plausible ranges, engineers can not only forecast equipment failures but also understand their underlying causes, enabling proactive and informed maintenance planning. The study further highlights the importance of real-time synchronization between digital twins and IoT-enabled sensors, ensuring continuous two-way data exchange and accurate, up-to-date maintenance predictions, even under varying operational conditions. This interoperability is particularly crucial in heterogeneous manufacturing environments with diverse systems and protocols (Murtaza et al., 2024). Simulation and case-study results demonstrate that the hybrid DT–AI framework significantly reduces machine downtime, optimizes resource allocation, and extends equipment lifespan, collectively contributing to substantial cost savings. Overall, the research underscores predictive maintenance as a transformative tool that enhances efficiency, resilience, and competitiveness in smart manufacturing, fostering a performance-driven, data-centric industrial culture aligned with Industry 4.0 and 5.0 principles. The study finds out several challenges that hinder the deployment of the study in the real world, contrary to the positive results of the study. The differences in data and noise in the data collection devices are still major barriers, as inconsistencies in the sensor types and changes in the operational conditions can lower the performance of the model. Security issues should be well taken care of in communication architectures between cloud and edge so as not to have data breaches and to be able to make decisions with reliable data. Besides that, the expansion of the framework to multiple interlinked machines leads to computational intricacies and requires sophisticated orchestration strategies to control the dependencies and interactions among the components; thus, solving these problems demands a combination of efficient data preprocessing, secure networking protocols, and scalable computing frameworks capable of dealing with high-frequency, multi-source data streams.

4. CONCLUSION

This paper explores the creation and utilisation of a Digital Twin (DT)-driven predictive maintenance (PdM) framework that evolves smart manufacturing systems. Striving to cope with an increasingly complex industrial environment in the era of Industry 4.0, the research basically intended to help with the reliability of the equipment, cut down on the unplanned downtime, and enable efficient maintenance scheduling by virtue of hybrid AI-physics model integration and live digital twin simulations. The method involved merging physics-based modelling in MATLAB/Simulink with data-driven machine learning algorithms (LSTM and physics-informed neural networks) to both detect patterns of equipment failure and also compute the remaining useful life (RUL) of the machine. Besides that, the real-time IoT sensor data that encompassed vibration, temperature, acoustic emissions, and energy consumption were used for the digital twin updates. The experiments consisted of the simulation and case study of a CNC machining system, wherein several parameters were used for the evaluation, such as RMSE, MAPE, precision, recall, and F1-score metrics. The research resulted in enhanced predictive accuracy in which the hybrid AI-PINN model was notably more capable than the baseline models (Random Forest and conventional LSTM), achieving an RMSE value of 4.1 and MAPE value of 5.3%, showing greater reliability in RUL and fault occurrence prediction. Also, optimised maintenance scheduling for the implementation of the DT-driven predictive maintenance that reduced unnecessary activities by 36.8% and forecasted operational cost savings of about 25% compared to the traditional preventive maintenance strategy. Early fault detection was also gotten in which fusion of real-time data streams and physics-informed AI made it possible to detect anomalies in spindle imbalance and hydraulic pressure at very early stages, confirming the system’s ability to intervene before major failures occur. And finally, digital twin adaptability for real-time interaction between the tangible and virtual worlds which enabled rapid and spontaneous modification of operational parameters, ensuring that the predictive maintenance framework remained viable under different operating circumstances.

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