Journal of Computers Vol. 36 No. 6, December 2025, pp. 223-239
https://doi.org/10.63367/199115992025123606015

# Predictive Maintenance of Industrial Robots Based on Digital Twin: A Case Study of an Automated Production Line

Zhi-Jia Wang, Yue-Hong Zhao, Dong-Hua Lu, Jia-Xuan Zhang, and Hao-Sheng Lu*

Qinhuangdao Vocational and Technical College,
Qinhuangdao City 066100, Hebei Province, China

wangzhijia198505@126.com, zhaoyuehong1113@163.com, 396726949@qq.com,
119607585@qq.com, 328137417@qq.com

*Received 2 November 2025; Revised 4 December 2025; Accepted 12 December 2025*

**Abstract.** Unplanned downtime and unexpected failures of industrial robots pose significant challenges to automated production lines. To improve system reliability and maintenance efficiency, this study proposes a predictive maintenance framework based on digital twins, integrating real-time monitoring, data-driven analysis, and intelligent fault prediction. This framework combines multi-sensor data acquisition, virtual-physical synchronization, and machine learning models for robot health assessment and degradation trend analysis. By constructing a digital twin model, the kinematics and operational behavior of the physical robot can be dynamically reflected, enabling continuous status tracking and early fault identification. The proposed method has been implemented and validated on an automated production line, demonstrating its ability to improve maintenance planning, reduce unplanned downtime, and support the transition to intelligent and sustainable manufacturing.

**Keywords:** digital twin, predictive maintenance, industrial robots, fault diagnosis, smart manufacturing, automated production line

## 1 Introduction

Industrial robots play a crucial role in smart manufacturing by enabling high-precision operations, consistent product quality, and continuous production efficiency [1]. However, as production systems become increasingly complex and automated, the reliability and stability of industrial robots have become critical factors affecting productivity. Unexpected failures or unplanned downtime can lead to serious production interruptions, economic losses, and maintenance inefficiencies [2]. Traditional preventive maintenance strategies, which rely on fixed schedules or threshold-based monitoring, often fail to capture the dynamic and nonlinear degradation patterns of robotic components, resulting in either premature maintenance or undetected faults [3]. To address these challenges, predictive maintenance (PdM) supported by digital twin (DT) technology has emerged as a promising approach [4]. A digital twin establishes a real-time virtual representation of a physical system, integrating sensor data, simulation models, and analytic to predict equipment health and optimize maintenance decisions [5]. Despite significant progress, most existing studies focus on individual component monitoring or simulation-based validation, lacking real-time data synchronization and generalization across different robot types or working conditions. In this study, a digital-twin-based predictive maintenance framework is developed and validated for industrial robots operating within automated production lines. The proposed approach aims to achieve real-time health monitoring, early fault prediction, and intelligent maintenance scheduling. The main contributions of this work are as follows: (1) a hybrid digital twin framework integrating physical–virtual synchronization with AI-based prediction models; (2) implementation and validation in an actual automated production environment; and (3) comparative analysis of prediction performance and system efficiency against conventional maintenance strategies. Section I proposes a predictive maintenance framework for industrial robots based on digital twins, integrating machine learning models to enhance real-time monitoring, early fault detection, and maintenance planning. section II leverages digital twin technology to overcome the limitations of traditional maintenance methods, improving fault diagnosis, operational efficiency, and system reliability of industrial robots. Section III employs a four-layer architecture combining sensor data, digital twin models, and machine learning techniques

* Corresponding Author

to monitor robot health and predict faults, thereby enabling proactive maintenance decisions. Section IV describes an automated production line system applied to a production line containing six ABB IRB 1600 robots, demonstrating its ability to reduce unplanned downtime, optimize maintenance planning, and extend robot life. Section V shows that an LSTM-GA model optimized using a genetic algorithm outperforms traditional models, providing more accurate degradation predictions and adapting to dynamic operating conditions, thus improving maintenance planning. Section VI demonstrates that the predictive maintenance framework based on digital twins can effectively improve the efficiency and reliability of industrial robots, providing a comprehensive solution for reducing downtime and costs, and has the potential for future research in multi-robot systems and enhanced predictive capabilities.

## 2 Related Work

Since digital twin technology has the potential to improve the efficiency and reliability of automated production lines, its integration into predictive maintenance of industrial robots has become a recent research hotspot. Digital twin technology provides a virtual copy of the physical system, enabling real-time monitoring, performance analysis and predictive decision-making, which is crucial for maintaining robot systems in dynamic manufacturing environments. Xu et al. [6] proposed a fault diagnosis method combining digital twin and deep transfer learning to improve predictive maintenance. They used an automotive body side panel production line as an example to demonstrate how this integrated method can detect faults early in the development and maintenance phases. Deep transfer learning models are particularly important because they can facilitate knowledge transfer in different operating environments, thereby more accurately and efficiently detecting faults in robot systems. This method emphasizes the role of digital twins in predictive maintenance, enabling early detection of potential faults, thereby significantly reducing downtime and improving system reliability. Based on architectural innovation, Touhid et al. [7] proposed a predictive maintenance method based on digital twins, which can more effectively utilize digital twin technology to achieve early detection of robot system faults. This paper proposes a cloud-based industrial robot digital twin framework that integrates virtual robot models into a comprehensive health monitoring and control system. By connecting the virtual model of the robot to a cloud platform, the framework enables real-time monitoring and maintenance management. The solution was validated in a case study involving SCARA robots in a production workshop. The use of a distributed cloud platform is crucial for enabling real-time monitoring, which is a core component of predictive maintenance in modern automated systems. This cloud-based approach also emphasizes the scalability and flexibility of digital twin models, enabling them to operate across different machines and industries. Kousi et al. [8] further extended digital twin technology by developing a modular digital twin framework that can manage and control various types of manufacturing systems, including robots, regardless of machine type or brand. The framework is designed for online connectivity and features self-learning capabilities, enabling continuous performance evaluation and predictive maintenance. The self-learning capability is particularly important because it allows the system to adapt to new data and continuously improve its predictive capabilities over time. This modularity and adaptability ensure that digital twin technology can be applied to a variety of robots, making it a versatile tool for predictive maintenance in different industrial environments. Kuts et al. [9] took a pragmatic approach by experimentally comparing digital twin-based virtual reality (VR) interface operation with traditional control methods. Their research highlights the practical advantages of digital twin technology in robot operation and maintenance, especially in virtual operation. By integrating VR technology, operators can interact with virtual models of the robot, making it easier to identify faults and simulate maintenance scenarios without directly affecting the physical system. This integration improves the overall efficiency and effectiveness of predictive maintenance because it allows operators to visualize potential problems and plan interventions in advance. Werner et al. [10] further improved the performance of digital twin technology in predictive maintenance by introducing other methods to enhance digital twin technology and proposed an enhanced process monitoring approach. By integrating more advanced modeling techniques, their approach aims to gain a more comprehensive and accurate understanding of the robot's health status. Enhancing process monitoring with digital twin technology not only helps in fault detection but also optimizes performance, thereby supporting proactive maintenance decisions. This approach aligns with the overall goal of reducing downtime and extending the lifespan of robot systems. In addition to improving fault detection, combining physics-based models with degradation curves provides a promising approach for predictive maintenance. Gupta et al. [11] proposed a framework that combines these models to predict potential faults over the next 18 months. By leveraging physics-based digital twins, their framework can predict robot degradation and proactively schedule maintenance to ensure the robot system is addressed before catastrophic failures occur. This framework highlights the value of integrating physics-based models to better predict the long-term behavior of industrial robots, thereby making predictive maintenance more reliable and efficient. Mojumder [12] studied cognitive digital twin technology using steel pipe manufacturing as an example, exploring its broader impact on the sustainability and performance of the manufacturing industry.

## 3 Methodology

This paper proposes a predictive maintenance framework for industrial robots based on digital twins and machine learning models. The framework employs a four-layer architecture, including a physical layer, a data layer, a model layer, and an application layer. The system integrates real-time data from various sensors to continuously monitor and evaluate the robot's status. The data undergoes preprocessing such as denoising, normalization, and feature extraction to prepare for building a digital twin model. This model, based on a combination of kinematic and dynamic models, reflects the robot's behavior and is synchronized in real-time with the physical robot via OPC UA or MQTT protocols. The system utilizes machine learning techniques such as LSTM and genetic algorithms to predict the robot's health indicators and potential faults, thereby enabling early fault detection and optimized maintenance decisions. The system's continuous feedback loop helps maintain synchronization between the physical and virtual models, providing adaptive learning and predictive capabilities, thus improving reliability and reducing downtime. This framework provides a comprehensive solution for real-time predictive maintenance of automated manufacturing systems, ensuring the stability and efficiency of system operation.

### 3.1 Overall Architecture

As shown in Fig. 1, the proposed predictive maintenance system based on digital twins adopts a four-layer framework design, including a physical layer, a data layer, a model layer, and an application layer. The system aims to establish a bidirectional mapping between the physical robot and its virtual counterpart, thereby enabling real-time monitoring, state estimation, and predictive maintenance decisions [13].

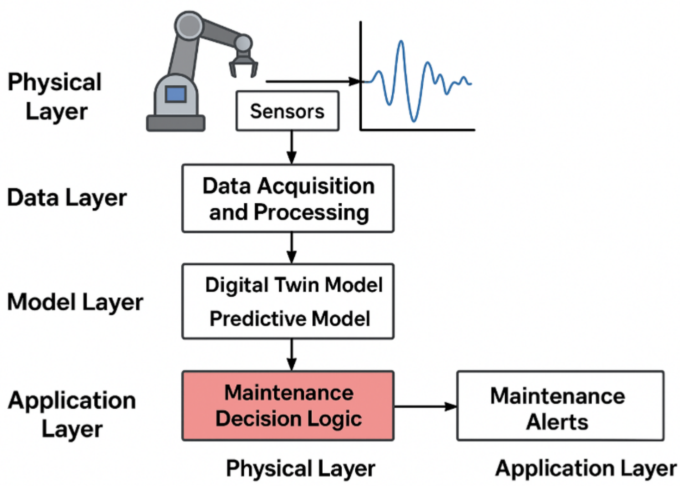


**Fig. 1.** A predictive maintenance framework for industrial robots based on digital twin and machine learning models

At the physical layer, multiple sensors are deployed on the industrial robot to collect vibration, current, and temperature data [14]. These raw signals represent the robot's dynamics and operating state, specifically as follows:

$$S(t) = [v(t), i(t), T(t)] \tag{1}$$

Where $v(t)$, $i(t)$, $T(t)$ denote the vibration velocity, motor current, and joint temperature at time $t$, respectively. The acquired data are sampled at frequency $f$ and digitized into discrete sequences:

$$S_k = S(\frac{k}{f_s}), k = 1, 2, \ldots, N \tag{2}$$

The Data Layer performs preprocessing, noise filtering, and feature extraction [15]. The filtered signal $\tilde{S}_k$ is obtained through a Butter-worth low-pass filter:

$$\tilde{S}_k = \frac{1}{1 + (j\omega / \omega_c)^{2n}} S_k \tag{3}$$

Where $\omega_c$ is the cutoff frequency. Feature extraction converts time-domain signals into health indicators $F_j$:

$$F_j = \{\mu, \sigma, RMS, \kappa, \gamma\} \tag{4}$$

Where $\mu$ is the mean, $\sigma$ the standard deviation, $RMS$ the root-mean-square, $\kappa$ the kurtosis, and $\gamma$ the skewness of the signal. The Model Layer represents the digital twin's core, which reconstructs the robot's dynamic behavior using kinematic and dynamic models [16]. The robot's kinematic equation is formulated as:

$$\dot{X} = J(q)\dot{q} \tag{5}$$

Where $\dot{X}$ denotes the end-effector position, $J(q)$ is the Jacobian matrix, and $\dot{q}$ is the vector of joint velocities. The corresponding dynamic model is expressed by:

$$\tau = M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) \tag{6}$$

Where $\tau$ represents joint torque, $M(q)$ the inertia matrix, $C(q, \dot{q})$ the Coriolis and centrifugal term, and $G(q)$ the gravity vector. The Digital Twin Synchronization Module continuously updates the virtual model based on real-time sensory feedback [17]. The state update equation is given by:

$$\hat{x}_{t-1} = Ax_t + Bu_t + K(y_t - Cx_t) \tag{7}$$

Where $\hat{x}_{t-1}$ is the estimated state, $u_t$ the control input, $y_t$ the measured output, and $K$ the Kalman gain matrix. The synchronization accuracy is evaluated by the residual error:

$$e_t = \| y_t - C\hat{x}_t \|_2 \tag{8}$$

A small $e_t$ indicates high fidelity between physical and virtual models. Communication between the physical and virtual environments is achieved via an OPC UA or MQTT protocol, ensuring low-latency data exchange. The communication delay is modeled as: Communication between the physical and virtual environments is achieved via an OPC UA or MQTT protocol, ensuring low-latency data exchange. The communication delay is modeled as:

$$T_d = T_s + T_q + T_p \tag{9}$$

Where $T_s$ is sensing delay, $T_q$ queue delay, and $T_p$ packet transmission delay. To maintain synchronization stability, a compensation control is applied:

$$u_t' = u_t + K_c(x_t - \hat{x}_t) \tag{10}$$

Where $K_c$ is the compensation gain matrix. The Health Evaluation Module quantifies the robot's degradation using a health index $H_t$:

$$H_t = 1 \frac{D_t - D_{min}}{D_{max} - D_{min}} \tag{11}$$

Where $D_t$ is the instantaneous degradation feature, and $D_{min}$, $D_{max}$ are reference limits. The degradation trend can be approximated by an exponential model:

$$D_t = D_0 e^{\lambda t} \tag{12}$$

Where $D_0$ is the initial degradation and $\lambda$ the degradation rate constant. The Remaining Useful Life (RUL) is estimated when $H_t$ falls below a failure threshold:

$$RUL = \frac{1}{\lambda} ln(\frac{D_{cr}}{D_t}) \tag{13}$$

Where $D_{cr}$ denotes the critical degradation level. For predictive analytics, the model layer applies a temporal state-space prediction:

$$\hat{H}_{t+1} = f(H_t, F_t, \theta) \tag{14}$$

Where $f$ denotes the learned mapping function parameterized by $\theta$. The training objective minimizes prediction error:

$$L = \frac{1}{N} \sum_{t=1}^{N} (\hat{H}_t - H_t)^2 \tag{15}$$

To ensure model robustness, a regularization term is added:

$$L_{total} = L + \lambda_r \|\theta\|_2^2 \tag{16}$$

The Application Layer translates predictive results into maintenance decisions [18]. A decision rule for triggering maintenance alerts is defined as:

$$\delta_t = \begin{cases} 1 & H_t < H_{th} \\ 0 & H_t \geq H_{th} \end{cases} \tag{17}$$

Finally, maintenance priority is determined by a risk index combining degradation rate and production impact:

$$R_t = \alpha\lambda + \beta P_t \tag{18}$$

Where $P_t$ denotes production loss probability, and $\alpha$ $\beta$ are weighting factors determined by operational priorities.

### 3.2 Data Acquisition and Processing

Accurate and reliable data acquisition is fundamental to the predictive maintenance of digital twin systems. The framework proposed in this paper deploys a multi-sensor network on an industrial robot to acquire key operating parameters such as vibration, motor current, acoustic emission, and joint temperature. Each sensor node is connected via an industrial communication bus to ensure synchronous sampling and minimal latency. The acquired signals are transmitted to an edge gateway, which performs initial preprocessing before forwarding the data to the digital twin server [19]. The data preprocessing flow comprises four main stages: denoising, normalization, segmentation, and feature extraction. Denoising employs a Butter worth filter combined with wavelet thresholding to eliminate high-frequency interference [20]. Normalization is used to re-scale the signal to a fixed range [0,1] to ensure a consistent input distribution for the predictive model. Segmentation divides the continuous signal stream into partially overlapping sliding windows to maintain temporal continuity. Within each window, multiple time-domain and frequency-domain features are extracted, including root mean square (RMS) [21], kurtosis, skewness, and spectral energy. To better characterize the degradation process, the extracted features are further transformed using Principal Component Analysis (PCA) or t-distributed random neighborhood embedding (t-SNE) [22] to reduce noise and redundancy while retaining key information related to mechanical wear and joint vibration modes. The generated feature vectors are stored in a time-series database at the data layer, serving as synchronous input for digital twin model updates and predictive analytics. All data exchanges adhere to the OPC UA standard to ensure interoperability and security between heterogeneous industrial systems. To formalize the feature extraction process, the time-domain RMS feature is computed as:

$$RMS = \frac{1}{\mathrm{N}}\sum_{i=1}^{N} x_i^2 \tag{19}$$

Kurtosis, reflecting impulsive degradation characteristics, is defined as:

$$Kurtosis = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{x_i - \mu}{\sigma}\right)^4 \tag{20}$$

### 3.3 Digital Twin Model Construction

The digital twin model is the core of the predictive maintenance framework, creating a high-fidelity virtual representation of the industrial robot in Table 1 [23].

**Table 1.** Digital twin model for predictive maintenance phases and components

| Phase | Key components | Description |
|---|---|---|
| Model Initialization | Geometric and Kinematic Model | Based on robot's CAD structure and manufacturer specifications. |
| | Dynamic Parameters | Determined through experimental calibration and manufacturer data sheets. |
| | Physics-Based Simulation Environment | Establishes a virtual environment for robot motion visualization and simulation. |
| State Synchronization | Real-time Sensor Data Mapping | Connects physical robot to digital twin using protocols like OPC UA or MQTT. |
| | State Observer | Corrects model drift to ensure high accuracy between virtual and physical robot states. |
| Behavior Evolution | Machine Learning Models | Captures nonlinear degradation patterns and updates robot health metrics based on historical sensor data and real-time state variables. |
| | Hybrid Model | Combines physics-based modeling with machine learning to predict potential failures and simulate future degradation scenarios. |
| Outcome | Continuous Synchronization and Autonomous Fault Prediction | Digital twin model dynamically updates and predicts robot's health, enabling real-time predictive maintenance and autonomous fault detection. |

This model integrates mechanical, electrical, and control subsystems to reproduce the robot's behavior in a real-world environment. The construction process comprises three key phases: model initialization, state synchronization, and behavior evolution. In the initialization phase, a geometric and kinematic model is constructed based on the robot's CAD structure and manufacturer specifications. Dynamic parameters such as link mass, inertia, and friction coefficient are determined through a combination of experimental calibration and manufacturer data sheets. A physics-based simulation environment is established for visualizing and simulating robot motion. The state synchronization phase connects the physical robot to its digital twin in real time. Sensor data acquired from the physical layer is continuously mapped to the virtual environment using OPC UA or MQTT protocols. A state observer based on Kalman filters or adaptive estimation algorithms corrects model drift, ensuring a high degree of match between the virtual robot's state and the physical robot's state. This bidirectional communication enables the digital twin to reflect the current physical state and provide predictive feedback to the control system. The behavior evolution phase introduces data-driven intelligence into the digital twin model. Machine learning models are embedded in the digital twin model to capture complex nonlinear degradation patterns that cannot be described purely by physical equations. These hybrid models combine historical sensor data and real-time state variables to dynamically update the robot's health metrics and predict potential failures. Through continuous synchronization, the digital twin model not only reflects the current operating state but also simulates potential future degradation scenarios under different loads and environmental conditions. The resulting digital twin model acts like a living replica of the industrial robot, capable of self-updating, adaptive learning, and autonomous fault prediction. This fusion of physical modeling and data-driven analysis lays the technological foundation for real-time predictive maintenance in automated production environments.

### 3.4 Predictive Model

The predictive model is the core of the predictive maintenance framework based on digital twins [24]. Its main purpose is to identify potential faults and predict the remaining service life of industrial robot components in real time. Based on dynamic operational data collected from the physical layer, a hybrid approach combining Long Short-Term Memory (LSTM) [25] neural networks and Genetic Algorithm (GA) optimization strategies is employed to capture time dependencies and adaptively adjust model parameters. LSTM networks were chosen because they can effectively model sequential sensor data such as vibration, temperature, and motor current, thereby effectively capturing long-term dependencies and nonlinear degradation patterns. GA [26] is used to optimize hyper parameters such as learning rate, number of hidden units, and dropout probability to ensure high prediction accuracy and computational efficiency. During operation, the predictive model continuously receives real-time data streams from the digital twin environment. The model outputs a predicted degradation index or health score, which reflects the robot's current state and evolution trend. When abnormal deviations or accelerated degradation are detected, the system automatically updates the digital twin model and generates maintenance recommendations. This dynamic predictive process can detect faults early and support maintenance planning decisions, thereby significantly reducing unplanned downtime and ensuring the stable and efficient operation of automated production lines. This predictive model functions as an intelligent decision-making engine, closely linked to the real-time information flow of the digital twin. The Long Short-Term Memory network possesses a strong ability for time learning, capable of identifying slow-evolving wear patterns while filtering out random operational noise; while the genetic algorithm enhances its adaptability by automatically identifying the optimal hyperparameter configurations under different robot states and working conditions. This hybrid structure ensures that the model remains robust even when facing workload fluctuations, environmental disturbances, or unexpected anomalies. As the digital twin continuously synchronizes the physical behaviors of the robots with their virtual representations, the predictive model receives constantly changing and rich data streams, enabling it to update the health assessment in real time and adjust the predictions according to changing circumstances. Once early deterioration trends or potential fault characteristics are detected, the system will issue an active warning and recommend the best intervention window, ensuring that maintenance actions are scheduled before a failure occurs. This highly integrated mechanism significantly enhances the responsiveness and intelligence of predictive maintenance, helping to more accurately estimate the remaining useful life, timely prevent faults, and achieve smoother production scheduling in automated manufacturing environments.

## 4 Case Study: Automated Production Line

This case study outlines the implementation of a predictive maintenance framework for industrial robots based on a digital twin system in Table 2. The system employs a hierarchical approach to create a virtual copy of the robot and continuously collects real-time operational data via sensors such as vibration, temperature, current, and position. This data is preprocessed, including noise filtering and feature extraction, to generate key health indicators such as RMSE vibration values, peak current, and temperature gradients. These indicators are fed into a predictive model that combines a LSTM network and a GA for hyper parameter tuning, enabling accurate fault prediction and real-time health monitoring. This model is embedded in a digital twin environment that calculates parameters such as RUL and performance degradation to support early fault detection and maintenance planning. The system is monitored through an interactive dashboard, allowing engineers to gain insights into the robot's condition and make informed maintenance decisions [27]. To validate the system, two evaluation strategies were employed: controlled fault simulation and historical data analysis. These strategies evaluated the model's predictive accuracy and robustness. System performance metrics included prediction accuracy, root mean square error, reduction in downtime, and cost savings. The results show that the predictive maintenance framework can effectively reduce unplanned downtime, extend robot life, and minimize maintenance costs, providing a reliable solution for maintaining operational efficiency in automated production environments.

**Table 2.** Overview of predictive maintenance framework using digital twin for industrial robots

| Section | Details |
|---|---|
| System Description | Six ABB IRB 1600 robots equipped with sensors for vibration, temperature, current, and position monitoring. Data helps in predictive maintenance, reducing downtime and extending lifespan. |
| Digital Twin Implementation | The digital twin system collects and preprocesses sensor data, uses LSTM with GA optimization for failure prediction, and provides real-time health metrics via an interactive dashboard. |
| Experimental Setup | Validated using controlled fault simulation and historical data analysis for accuracy and robustness. |
| Evaluation Metrics | Prediction Accuracy: Measures failure prediction. |
| | RMSE: Quantifies prediction error. |
| | Downtime Reduction: Measures unplanned downtime reduction. |
| | Cost Savings: Includes reduced maintenance frequency and extended component lifespan. |

### 4.1 System Description

This case study focuses on an automated production line in a medium-sized factory, which uses six six-axis articulated robots (ABB IRB 1600) to perform various tasks, including assembly, welding, and material handling. These robots are critical to the manufacturing process, and their efficient and uninterrupted operation directly impacts the overall performance of the production line. These robots are equipped with a range of sensors that continuously monitor their operating status, providing crucial information about their health and performance. Each robot on the production line is equipped with multiple types of sensors to monitor key operating parameters. Vibration sensors are mounted at the robot's joints to detect mechanical wear, misalignment, or other kinematic problems. These sensors can identify deviations from normal operating conditions, such as abnormal vibrations, which may indicate potential faults in the robot's motors, gears, or structural components. In addition to vibration sensors, temperature sensors are mounted on the robot's motors and gearboxes to monitor temperature conditions. Overheating is a common failure in industrial robots, especially during high-load operation. Excessive temperatures can lead to component performance degradation, reduced efficiency, and ultimately, failure. Continuous temperature monitoring allows for early detection of overheating signs, enabling preventative measures to be taken before serious damage occurs. Current sensors are used to monitor the robot's power consumption and detect load fluctuations. These sensors track current variations, indicating potential electrical problems such as motor overload or electrical imbalance. Load fluctuations significantly impact robot operational stability, so monitoring current patterns helps detect anomalies that may affect performance early. Furthermore, the robot is equipped with position and velocity encoders for precise motion tracking. These encoders provide real-time data on the position and velocity of the robot's joints and end effectors, ensuring the accuracy and reliability of motion patterns. Any deviation from the expected motion trajectory is identified, preventing potential errors during assembly, welding, or material handling. All these sensors work together to provide comprehensive real-time data on the robot's operational status, enabling the identification of mechanical wear, overheating, abnormal loads, and irregular motion patterns. The ability to continuously collect and analyze this data is crucial for effective predictive maintenance. Predictive maintenance allows factories to proactively identify potential failures and schedule maintenance, minimizing unplanned downtime and extending robot lifespan. Given the high-frequency nature of production cycles, even brief downtime can result in significant economic losses, making predictive maintenance essential. The ability to predict when a robot will require maintenance allows production lines to maintain optimal performance levels, reducing the risk of unexpected failures and improving the overall efficiency and reliability of automated systems. The functions and descriptions of each sensor are shown in Table 3.

**Table 3.** Functions and descriptions of each sensor

| Sensor type | Installation location | Core functions |
|---|---|---|
| Vibration Sensors | At the robot's joints | Detect mechanical wear, misalignment, or other kinematic issues; identify abnormal vibrations to warn of potential faults in the robot's motors, gears, or structural components. |
| Temperature Sensors | On the robot's motors and gearboxes | Continuously monitor temperature conditions; detect early signs of overheating to prevent component performance degradation, efficiency reduction, and failures caused by high temperatures. |
| Current Sensors | In the robot's power system | Monitor power consumption and load fluctuations; track current variations to warn of electrical problems such as motor overload or electrical imbalance, ensuring operational stability. |
| Position and Velocity Encoders | At the robot's joints and end effectors | Precisely track motion status; provide real-time data on position and velocity to identify deviations from expected motion trajectories, ensuring the accuracy of tasks like assembly, welding, and material handling. |

### 4.2 Implementation of the Digital Twin

The digital twin system implemented in this case study employs a hierarchical approach to create a virtual copy of a physical robot for real-time monitoring of its health and performance. At the heart of the system is a continuous data acquisition process, where sensors on the robot constantly collect operational data such as vibration, temperature, current, and position. This raw sensor data is then preprocessed to remove noise and normalize values, ensuring data consistency and reliability for analysis. In the preprocessing step, key features are extracted, such as the RMS value of vibration, peak current readings, and temperature gradients of various robot components. These features are crucial for assessing the robot's health, as they provide information about factors such as mechanical wear, electrical stress, and thermal stress, all of which indicate the robot's current state. After data cleaning and feature extraction, the data is fed into a predictive model that combines a LSTM neural network with hyper parameter optimization based on a GA. LSTM is particularly well-suited for time-series data, such as data generated by industrial robot sensors, as it can capture long-term dependencies and trends in data over time. A GA is used to optimize the hyper parameters of the LSTM network, enabling it to better predict robot behavior under different conditions and accurately predict potential failures. This predictive model is embedded in a digital twin environment that continuously calculates real-time health metrics for each robot component. These health metrics include parameters such as RUL and performance degradation, which are crucial for early failure detection and maintenance planning. To make the system easier to use and operate, an interactive dashboard was created. This dashboard displays key information about the robot's status, such as current health metrics, predicted remaining useful life, and maintenance alerts. Engineers can use this dashboard to monitor performance trends, enabling them to make informed decisions about when to perform maintenance. This dashboard serves as a central hub for operations, allowing the maintenance team to understand the robot's condition and helping them prioritize maintenance work to avoid unplanned downtime. The implementation of the digital twin adopts a modular architecture that separates data acquisition, model computation, and visualization layers, ensuring scalability and flexible deployment across different robot platforms. The process framework is shown in Fig. 2.

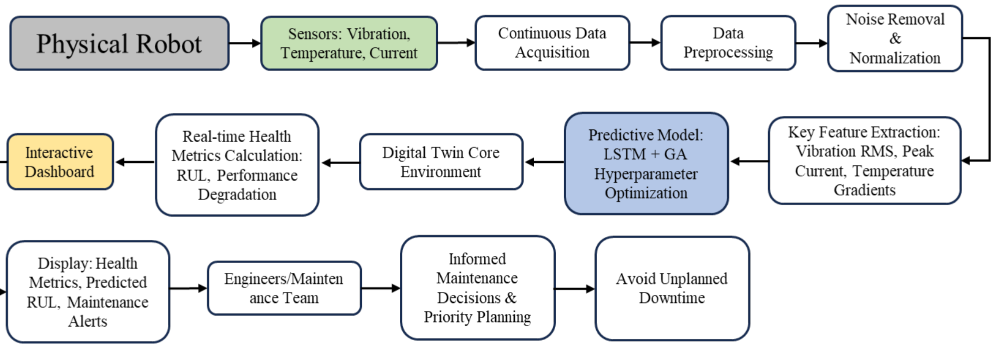


**Fig. 2.** Process structure diagram

### 4.3 Experimental Setup

To validate the effectiveness and accuracy of the predictive maintenance framework, the research team employed two key strategies: controlled fault simulation and historical data analysis. These methods aim to evaluate the system's ability to predict faults under simulated and real-world conditions. The controlled fault simulation method was used to create artificial degradation scenarios that simulate common fault modes in industrial robots. Its goal is to stress-test the predictive maintenance system by introducing real-world operating conditions. In this method, specific fault modes such as robot joint wear and motor overload are simulated over time. The wear model simulates the gradual degradation of mechanical components, a common challenge in high-cycle operation. Additionally, occasional motor overloads are simulated to mimic the stresses the robot might encounter under heavy or abnormal loads. By introducing these fault modes, the system's ability to detect early signs of faults and predict future degradation can be evaluated. This strategy tests the system's robustness in identifying faults during real-world operation. In addition to simulated faults, the research team also utilized historical operational data from the robot to validate the predictive maintenance system. This data-set covers three years of real-world operational history, including detailed sensor readings, historical fault records, and maintenance event logs. These operational data enabled the research team to assess the accuracy of system failure predictions based on past performance, rather than solely relying on controlled simulations. By comparing system predictions with actual failures and maintenance logs, the team was able to evaluate the model's predictive accuracy under real-world conditions.

### 4.4 Evaluation Metrics

The performance evaluation of predictive maintenance systems based on digital twins is based on the following key metrics: Prediction Accuracy: This metric measures the model's ability to accurately predict impending failures and performance degradation. High prediction accuracy ensures proactive maintenance, preventing unintended failures. In quantitative terms, prediction accuracy can be evaluated using the standard classification accuracy formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{21}$$

Root Mean Square Error: RMSE quantifies the difference between predicted and actual performance degradation. A lower RMSE value indicates that the model's predictions more closely match the robot's actual behavior, which is crucial for providing reliable robot health information. This metric is typically computed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{22}$$

Downtime Reduction: This metric compares the reduction in unplanned production downtime before and after implementing the predictive maintenance system. Its purpose is to demonstrate that the system can schedule maintenance based on real-time health data, rather than relying on reactive repairs, thus effectively reducing unplanned downtime. The reduction rate can be expressed as:

$$Downtime\ Reduction = \frac{D_{before} - D_{after}}{D_{before}} \times 100\% \tag{23}$$

Cost Savings: Predictive maintenance systems aim to reduce overall maintenance costs by extending component lifespan and minimizing production losses. By accurately predicting failures and scheduling maintenance before catastrophic events occur, the system can reduce the frequency of emergency repairs and unplanned downtime. Metrics for cost savings include reduced maintenance frequency, extended component lifespan, and minimized production disruptions caused by robot downtime. In addition to these core indicators, a comprehensive assessment will also take into account the system's response capability, the model's stability under different operating loads, and the interpretability of health predictions. The system's response capability reflects the speed at which the predictive model updates the deteriorated estimates upon receiving new sensor data, which is crucial for real-time maintenance decisions. Model stability ensures that even if the robot suddenly encounters workload changes, environmental disturbances, or temporary anomalies, the predictive results remain consistent. A common measurement is the variance of predicted health indicators:

$$Stability = Var(\hat{y}) \tag{24}$$

Moreover, interpretability plays an increasingly important role in industrial applications because maintenance engineers must understand why the system predicts a certain failure trend in order to trust and act upon its recommendations. By examining these supplementary aspects through the lens of evaluating accuracy, root mean square error, reduction in downtime, and cost savings, the assessment framework can comprehensively evaluate the reliability, practicality, and long-term impact on production efficiency of the predictive maintenance system. This multi-indicator approach ensures that the predictive system based on digital twins not only performs well in controlled experiments but also continues to create value during its continuous deployment in the actual manufacturing environment.

## 5 Results and Analysis

Fig. 3 shows three curves representing the robot degradation index over time. The solid black line represents the actual degradation index. The dashed blue line represents the degradation index predicted by the proposed LSTM-GA model, which combines an LSTM network and a GA for optimization; the dashed red line represents the prediction result of the baseline LSTM model. It can be seen that the prediction result of the LSTM-GA [24] model matches the actual degradation index well, effectively capturing the overall trend and local fluctuations in the degradation process, indicating that the model can effectively simulate the dynamic and nonlinear characteristics of robot degradation. In contrast, the prediction result of the baseline LSTM model shows significant deviation in the later stages of degradation, especially in the accelerated degradation phase, exhibiting a certain lag and failing to respond promptly to abrupt changes in the degradation process. The baseline LSTM model cannot accurately capture rapid changes in the degradation process, thus exhibiting certain prediction errors. This indicates that the baseline LSTM model has certain shortcomings in capturing rapidly changing degradation patterns. By introducing the LSTM-GA model optimized by a genetic algorithm, the prediction accuracy can be significantly improved, providing a more reliable basis for maintenance decisions and reducing the risk of unplanned downtime. The LSTM-GA model better adapts to the nonlinear changes in robot degradation and responds promptly, ensuring early maintenance when the robot reaches a critical degradation state. This result validates the advantages of combining genetic algorithm optimization with LSTM, improving the accuracy and reliability of predictive maintenance systems and providing strong support for robot maintenance in smart manufacturing. Furthermore, considering the various operating environments and loads faced by industrial robots in production, the superiority of the LSTM-GA model is also reflected in its adaptability to different working conditions. In practical applications, robot degradation is typically affected by multiple factors such as ambient temperature and load fluctuations, which can lead to changes in degradation patterns. Compared to traditional threshold-based monitoring methods, the LSTM-GA model can dynamically adjust its prediction strategy to adapt to these external changes, thus providing more accurate predictions in complex industrial environments. Moreover, through continuous real-time monitoring and model updates, digital twin technology ensures the long-term stability and reliability of the LSTM-GA model, supporting the efficient operation of the robot system throughout its entire life cycle. The model's dynamic learning and adjustment capabilities enable predictive maintenance systems not only to cope with the current degradation state but also to predict future degradation trends. This enables proactive maintenance planning, effectively reducing production downtime, lowering maintenance costs, and extending robot lifespan. Therefore, the successful application of the LSTM model combined with genetic algorithms in robot degradation prediction demonstrates the enormous potential of digital twin technology in intelligent manufacturing and industrial robot maintenance. This combination provides a new approach, driving the transformation of industrial robot maintenance from traditional time- and experience-based methods to more intelligent, data-driven, and precise predictive maintenance methods, providing strong technical support for the sustainable development of intelligent manufacturing.

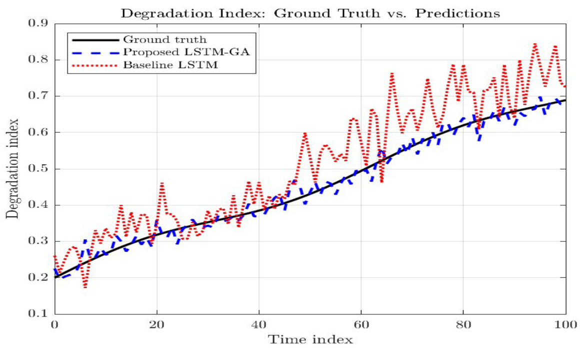


**Fig. 3.** Degradation index prediction-ground truth vs. proposed LSTM-GA vs. baseline LSTM

Fig. 4 shows the RMSE values of different models in predicting the degradation index to compare their prediction accuracy. The horizontal axis represents the proposed LSTM-GA model, the baseline LSTM model, Random Forest, and Support Vector Regression, respectively, while the vertical axis represents the RMSE value of each model. As can be seen from the figure, the proposed LSTM-GA model exhibits the lowest RMSE value, indicating that it has the best accuracy in predicting the degradation index. In contrast, the baseline LSTM model has an RMSE of 0.075. Although it still shows good accuracy compared to other traditional models, its error is larger than that of the LSTM-GA model. The Random Forest model has an RMSE of 0.085, which is relatively poor. Although it is a tree-based prediction method, it fails to effectively capture the dynamic characteristics of the degradation process when processing time series data. Finally, the Support Vector Regression model has an RMSE of 0.072, which is slightly better than Random Forest, but still inferior to LSTM-GA and the baseline LSTM model. This result demonstrates that the LSTM model optimized using a genetic algorithm offers higher prediction accuracy compared to other common machine learning models, especially when dealing with complex time-series data. By optimizing its hyper parameters, the LSTM-GA model can better adapt to nonlinear changes in the degradation process, thus exhibiting higher accuracy and reliability in predictive maintenance of industrial robots. Furthermore, while other traditional machine learning models such as random forests and SVR can provide reasonable predictions in some cases, they fail to achieve the same accuracy as the LSTM-GA model when dealing with the dynamic changes in robot degradation predictions, highlighting the superiority of the LSTM-GA model in such tasks. In addition, the bar chart clearly highlights the performance gap between deep learning–based models and conventional machine learning approaches. The substantial reduction in RMSE achieved by LSTM-GA suggests that evolutionary optimization successfully alleviates key issues such as suboptimal weight initialization, vanishing gradients, and unstable learning rates—factors that often limit the predictive capacity of standard LSTM architectures. The relatively high RMSE of Random Forest further confirms that models without temporal memory struggle to model long-term degradation dependencies. Meanwhile, the modest improvement of SVR over Random Forest implies that kernel-based regression can partially capture nonlinear patterns but still lacks the sequential modeling capability required for accurate prognostics.

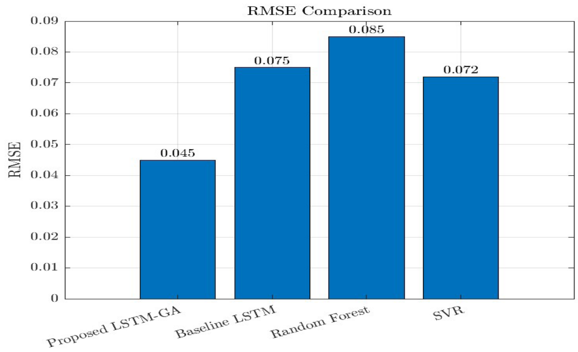


**Fig. 4.** RMSE comparison of different prediction models

This Fig. 5 shows the predicted changes in the robot's RUL over time. The horizontal axis represents time, and the vertical axis represents the remaining useful life. The three curves in the figure represent: the actual degradation curve, the LSTM-GA model proposed in this paper, and the baseline LSTM model, respectively. As shown in the figure, the prediction results of the LSTM-GA model proposed in this paper agree well with the actual degradation curve, especially in the rapid degradation phase, accurately reflecting the changing trend of RUL, indicating that the model can accurately capture the robot's degradation process. In contrast, although the baseline LSTM model can reflect the overall degradation trend, it has a significant lag in certain time periods, especially when the degradation rate is high, causing its predicted values to deviate from the actual degradation curve. This shows that the LSTM-GA model, through optimization by a genetic algorithm, can effectively improve the model's accuracy, especially when facing complex nonlinear degradation processes. In contrast, the prediction capability of the baseline LSTM model is relatively limited and cannot fully capture the detailed changes in the degradation process. The difference in prediction accuracy is crucial for practical applications. In industrial production, robot degradation often exhibits complex nonlinear patterns. Traditional prediction methods based on fixed rules or simple models are difficult to accurately capture degradation details, leading to delays or over-predictions in maintenance decisions. Therefore, LSTM models optimized using genetic algorithms offer a more flexible and accurate prediction method. They can not only identify early signs of failure in a timely manner but also adjust according to actual degradation, thereby improving the accuracy and reliability of predictions. This data-driven intelligent prediction method provides a more scientific basis for robot maintenance in intelligent manufacturing, helping to optimize maintenance plans, reduce unexpected downtime, improve production efficiency, and extend robot lifespan.

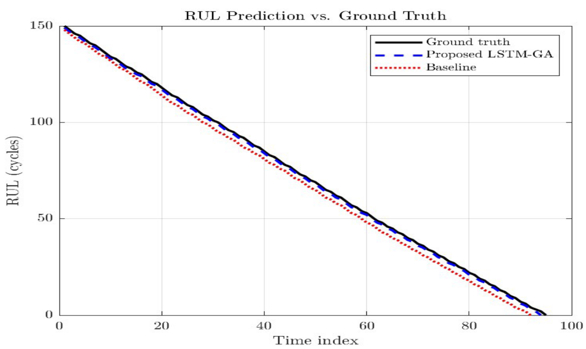


**Fig. 5.** Remaining useful life prediction vs. ground truth

This Fig. 6 displays unplanned downtime for each month, with the horizontal axis representing months and the vertical axis representing unplanned downtime. The bar chart is divided into two groups: before implementation and after implementation. The two bars for each month represent a comparison of robot downtime before and after implementing the predictive maintenance system. The chart shows that unplanned downtime was significantly reduced after implementation, especially in the busiest months of the production cycle. Before implementation, monthly downtime was generally high, mostly exceeding 100 hours, and in some months even exceeding 120 hours. After implementation, unplanned downtime was significantly reduced, with downtime in many months dropping below 50 hours, and even approaching 20 hours. This change indicates that the introduction of the predictive maintenance system significantly improved production line efficiency and reduced unexpected downtime. The high downtime before implementation was likely due to the lack of timely prediction of potential failures in traditional maintenance methods, leading to repairs only when robots experienced sudden malfunctions, frequently resulting in downtime. After implementation, by introducing predictive maintenance, the system can monitor the robot's health status in real time, identify potential problems promptly, and schedule maintenance in advance. This allows maintenance activities to be completed within planned downtime, avoiding production interruptions due to emergency failures. As shown in the figure, predictive maintenance systems, through a data-driven approach, can predict and identify potential robot malfunctions in advance, thereby preventing frequent unplanned downtime. This improvement not only enhances production line stability but also increases equipment availability. Furthermore, reduced downtime translates to increased production efficiency and lower maintenance costs, resulting in greater economic benefits for manufacturing companies. In this way, smart manufacturing maintenance systems are optimized, production lines operate more smoothly, and the long-term stable operation of enterprises is guaranteed. The continuous monthly decline trend shown in the bar chart not only indicates a decrease in extreme failure events, but also demonstrates a significant smoothing of operational fluctuations. Before the implementation of this system, the huge fluctuations in the downtime curve indicated that the production line often faced unpredictable interruptions, which made capacity planning complex and increased the workload of maintenance personnel. After deploying the predictive maintenance system, the range of downtime values became narrower, meaning that machine failures became more predictable, enabling the maintenance team to plan intervention measures more effectively and align them with the production cycle. This stability is particularly valuable during production peaks such as May, July, and August, as even short interruptions during these critical periods could lead to cascading delays and logistical problems. And the downtime remained at a low level during these critical periods, proving the system's strong ability to maintain operational continuity under pressure. In summary, this data indicates that predictive maintenance not only reduces the total duration of failures but also improves the reliability and predictability of the entire production plan, thereby bringing continuous operational and economic benefits.

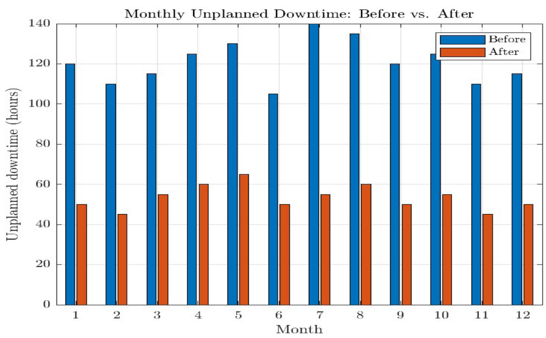


**Fig. 6.** Monthly unplanned downtime before and after implementation

This Fig. 7 compares the changes in annual maintenance-related costs before and after implementing a predictive maintenance system. The horizontal axis represents the time span before and after implementation, and the vertical axis represents annual maintenance costs. The bar chart is divided into three parts: planned maintenance costs, unplanned maintenance costs, and production loss costs. Each group of bars represents the changes in various costs before and after implementing the predictive maintenance system. The chart shows that before the system was implemented, annual maintenance costs were mainly concentrated in unplanned maintenance costs and production loss costs, especially production loss costs, which were significantly higher than planned and unplanned maintenance costs. This indicates that without a predictive maintenance system, frequent failures and downtime during production led to high production losses. Planned maintenance costs were relatively low, indicating that maintenance activities were carried out according to plan, but unplanned downtime caused significant additional costs due to the inability to effectively predict failures. After implementing the predictive maintenance system, unplanned maintenance costs and production loss costs decreased significantly, especially production loss costs, which dropped to nearly 30% of their original level, indicating that the system has a significant effect on reducing unexpected failures and downtime. Conversely, planned maintenance costs increased slightly, but the increase was not large; instead, these costs were optimized and rationally planned. Predictive maintenance allows maintenance activities to be performed during periods of minimal production disruption, thereby reducing production losses and emergency repair needs. This result validates the significant role of predictive maintenance systems in reducing production costs. By predicting potential failures, the system can schedule maintenance in advance, avoiding major production losses and additional repair costs caused by sudden downtime, thus significantly improving production efficiency and reducing overall maintenance expenditures. This provides a more precise and effective solution for maintenance management in smart manufacturing, optimizing the allocation of production resources and saving enterprises substantial costs.

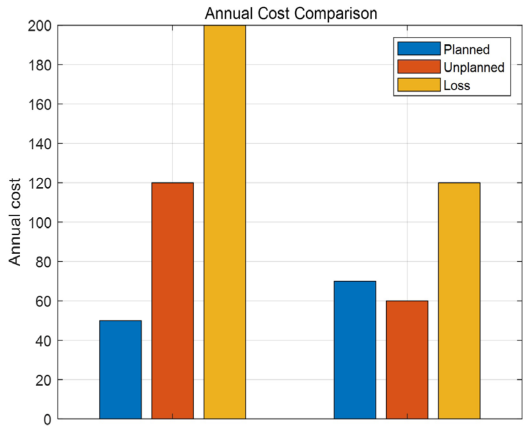


**Fig. 7.** Annual maintenance-related cost comparison before and after implementation

## 6 Conclusion

This study proposes and validates a predictive maintenance framework based on digital twins and LSTM-GA models, aiming to improve the maintenance efficiency and reliability of industrial robots in automated production lines. Predictive experiments based on actual degradation data demonstrate that, compared to traditional LSTM models and other machine learning methods, the LSTM model optimized by a genetic algorithm can more accurately predict robot degradation processes, significantly reducing unplanned downtime and effectively mitigating production losses. Furthermore, implementing the predictive maintenance system optimizes annual maintenance costs by reducing unplanned maintenance and production losses, while also lowering planned maintenance costs, providing a strong guarantee for the stable operation of the production line. The LSTM-GA model, through real-time monitoring and data-driven prediction, can accurately capture subtle changes in robot degradation, identify potential failure risks in advance, and schedule maintenance activities during periods of minimal production interruption, thereby reducing unexpected downtime caused by equipment failures. These results validate the broad application potential of predictive maintenance systems in smart manufacturing, providing a scientific and intelligent solution for robot maintenance management.

## References


[1] J.Y. Choi, S. Ahn, D. Kim, J. Heo, W.J. Yun, S. Hong, S. Bae, S.H. Ahn, Exploring Challenges and Opportunities in Manufacturing and Intelligence for Future Robotics, International Journal of Precision Engineering and Manufacturing 26(2025) 2203-2222.

[2] A. Vital-Soto, J. Olivares-Aguila, Manufacturing Systems for Unexpected Events: An Exploratory Review for Operational and Disruption Risks, IEEE Access 11(2023) 96297-96316.

[3] A.B. Fazle, R.K. Prodhan, M.M. Islam, AI-Powered Predictive Failure Analysis in Pressure Vessels Using Real-Time Sensor Fusion: Enhancing Industrial Safety and Infrastructure Reliability, American Journal of Scholarly Research and Innovation 2(2)(2023) 102-134.

[4] Y.-C. You, C. Chen, F. Hu, Y. Liu, Z. Ji, Advances of Digital Twins for Predictive Maintenance, Procedia Computer Science 200(2022) 1471-1480.

[5] P. Aivaliotis, K. Georgoulias, G. Chryssolouris, The use of Digital Twin for Predictive Maintenance in Manufacturing, International Journal of Computer Integrated Manufacturing 32(11)(2019) 1067-1080.

[6] Y. Xu, Y.-M. Sun, X.-L. Liu, Y.-H. Zheng, A Digital-Twin-Assisted Fault Diagnosis Using Deep Transfer Learning, IEEE Access 7(2019) 19990-19999.

[7] M.T.B. Touhid, M. Marne, T. Oskroba, S.A. Mirahmadi, E.-S. Zhu, A. Mehrabian, F. Defersha, S. Yang, Building a cloud-based digital twin for remote monitoring and control of a robotic assembly system, The International Journal of Advanced Manufacturing Technology 129(2023) 4045-4057.

[8] N. Kousi, C. Gkournelos, S. Aivaliotis, C. Giannoulis, G. Michalos, S. Makris, Digital twin for adaptation of robots' behavior in flexible robotic assembly lines, Procedia Manufacturing 28(2019) 121-126.

[9] V. Kuts, T. Otto, T. Tähemaa, Y. Bondarenko, Digital Twin Based Synchronised Control and Simulation of the Industrial Robotic Cell Using Virtual Reality, Journal of Machine Engineering 19(2019) 128-144.

[10] A. Werner, N. Zimmermann, J. Lentes, Approach for a Holistic Predictive Maintenance Strategy by Incorporating a Digital Twin, Procedia Manufacturing 39(2019) 1743-1751.

[11] R. Gupta, M.P. Modise, Macroeconomic Variables and South African Stock Return Predictability, Economic Modelling 30(2013) 612-622.

[12] M.U. Mojumder, Impact of Lean Six Sigma on Manufacturing Efficiency Using a Digital Twin-Based Performance Evaluation Framework, ASRC Procedia: Global Perspectives in Science and Scholarship 1(1)(2025) 343-375.

[13] P. Aivaliotis, Z. Arkouli, K. Georgoulias, S. Makris, Methodology for enabling dynamic digital twins and virtual model evolution in industrial robotics - a predictive maintenance application, International Journal of Computer Integrated Manufacturing 36(7)(2023) 947-965.

[14] J. Zhu, Y.-L. Zou, B.-Y. Zheng, Physical-Layer Security and Reliability Challenges for Industrial Wireless Sensor Networks, IEEE Access 5(2017) 5313-5320.

[15] S.-N. Tang, S.-Q. Yuan, Y. Zhu, Data Preprocessing Techniques in Convolutional Neural Network Based on Fault Diagnosis Towards Rotating Machinery, IEEE Access 8(2020) 149487-149496.

[16] W. Chen, Dynamic Modeling of Multi-Link Flexible Robotic Manipulators, Computers & Structures 79(2)(2001) 183-195.

[17] H. Laaki, Y. Miche, K. Tammi, Prototyping a Digital Twin for Real Time Remote Control Over Mobile Networks: Application of Remote Surgery, IEEE Access 7(2019) 20325-20336.

[18] S.J. Wu, N. Gebraeel, M.A. Lawley, Y. Yih, A Neural Network Integrated Decision Support System for Condition-Based Optimal Predictive Maintenance Policy, IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans 37(2)(2007) 226-236.

[19] Y. He, J.-C. Guo, X.-L. Zheng, From Surveillance to Digital Twin: Challenges and Recent Advances of Signal Processing for Industrial Internet of Things, IEEE Signal Processing Magazine 35(5)(2018) 120-129.

[20] X.-G. Liu, Z.-Q. Si, Y. Zhang, X.-C. He, Y.-J. Zhang, Research on Equipment Performance Failure Mode Identification and Early Warning Technology of Steel Rolling Production Line, Metallurgical Equipment and Maintenance 42(6) (2024) 57-59+63.

[21] Z.-F. Xue, L. Yi, G.-Y. Niu, H. Liu, Z.-H. Cheng, X. Fu, F.-J. Duan, Method for measuring average blade tip clearance based on root mean square, Journal of Electronic Measurement and Instrumentation 39(1)(2025) 80-89.

[22] J.-H. Zhong, C. Huang, S.-C. Zhong, S.-G. Xiao, Remaining Useful Life of Rolling Bearing Based on t-SNE, Journal of Mechanical Strength 46(4)(2024) 969-976.

[23] W.-J. Xu, J. Cui, L. Li, B.-T. Yao, S.-S. Tian, Z.-D. Zhou, Digital twin-based industrial cloud robotics: Framework, control approach and implementation, Journal of Manufacturing Systems 58(2021) 196-209.

[24] T. Harries, M. Hartnoll, M. Hafezianrazavi, H. Meek, A. Nassehi, Digital twins for predictive maintenance, Procedia CIRP 118(2023) 306-311.

[25] X.-B. Liu, Q.-X. Yan, B. Yi, T.-Q. Yao, W.-J. Gu, Optimization of Process Parameters in Process Manufacturing Based on Ensemble Learning and Improved Particle Swarm Optimization Algorithm, China Mechanical Engineering 34(23) (2023) 2842-2853.

[26] C. Wang, H.-F. Tian, Y.-F. Wu, Time Optimal Trajectory Planning of Water Treatment Tank Handling Robot Using DBN -GA Algorithm, Digital Manufacture Science 22(4)(2024) 290-295.
[27] S.-W. Wang, M.-J. Xue, Application of GA-LSTM Model in Fault Prediction of CNC Machine Tools, Machine Tool & Hydraulics 51(24)(2023) 197-201.