



“DIGITAL TWIN-BASED PREDICTIVE MAINTENANCE OF SMART MANUFACTURING EQUIPMENT”

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Abstract: The increasing use of automation, connected machines, intelligent sensors, and data analytics has changed the way manufacturing equipment is operated and maintained. Conventional corrective and scheduled maintenance strategies often result in unexpected machine failures, unnecessary component replacement, production interruption, and increased maintenance expenditure. Digital Twin technology provides an alternative approach by creating a continuously updated virtual representation of physical manufacturing equipment. This study investigates the application of a Digital Twin-based predictive maintenance framework for monitoring the health of smart manufacturing equipment and identifying developing faults before functional failure occurs. The study further identifies data quality, model accuracy, computational requirements, cybersecurity, and integration with existing manufacturing systems as important considerations for industrial implementation. The proposed framework demonstrates how Digital Twin technology can support reliable and intelligent maintenance decision-making in modern smart manufacturing environments.

Keywords: Digital Twin, Predictive Maintenance, Smart Manufacturing, Condition Monitoring, Machine Learning, Industry 4.0

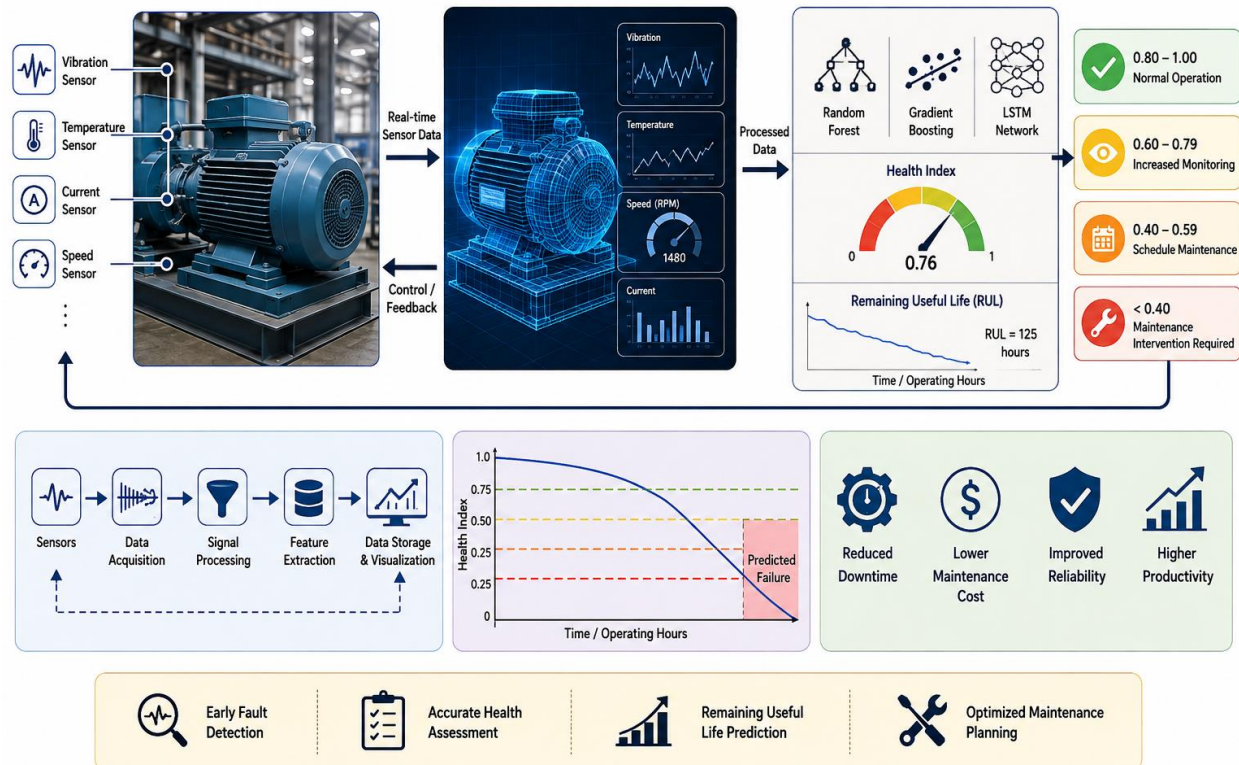
Introduction:

Modern manufacturing industries are undergoing a major transformation through the adoption of Industry 4.0 technologies. Production machines are increasingly connected through sensors, industrial communication systems, cloud platforms, artificial intelligence, and cyber-physical systems. These developments allow manufacturers to collect large quantities of information



regarding equipment operating conditions, production performance, energy consumption, quality, and machine health.

Mechanical equipment used in manufacturing is subjected to continuous loading, friction, vibration, thermal cycling, lubrication degradation, tool wear, and other operating stresses. Components such as bearings, gears, motors, spindles, cutting tools, pumps, conveyor systems, and drive mechanisms gradually deteriorate during operation. Failure of any critical component may result in production interruption, poor product quality, equipment damage, safety risks, and significant economic losses.



Traditional maintenance practices can generally be divided into corrective, preventive, and condition-based maintenance. Corrective maintenance is carried out after equipment has already failed. Although this approach avoids unnecessary maintenance during healthy operation, unexpected failures may result in long periods of production downtime. Preventive maintenance is performed according to predetermined intervals, such as operating hours or calendar time. This strategy reduces certain unexpected failures but can result in the replacement of components that still possess significant useful life.

Predictive maintenance provides a more intelligent approach. Instead of depending only on fixed maintenance schedules, the actual condition and degradation behaviour of the machine are continuously evaluated. Maintenance can therefore be planned when evidence suggests that the equipment is approaching an unacceptable operating state.

Digital Twin technology has emerged as an important tool for implementing such strategies. A Digital Twin can be considered a digital representation of a physical system that is continuously



connected with information obtained from the physical asset. Kritzinger et al. distinguished between digital models, digital shadows, and fully integrated Digital Twins according to the level of information exchange between the physical and virtual systems.

Tao et al. demonstrated the broader potential of Digital Twin concepts for integrating physical and virtual information across product design, manufacturing, and service activities. Their work highlighted the importance of combining lifecycle information with virtual models rather than analysing physical-system information separately.

For maintenance applications, the Digital Twin can continuously receive sensor measurements from manufacturing equipment and update its internal representation of the machine. The virtual model can then be used to identify abnormal operating conditions, estimate degradation, simulate possible future behaviour, and provide information for maintenance planning.

The combination of Digital Twin technology with machine learning further strengthens this capability. Machine-learning models can learn patterns associated with normal operation and various fault conditions. Variables such as vibration amplitude, bearing temperature, motor current, acoustic signals, rotational speed, lubricant condition, and operating load can therefore be analysed together rather than independently.

The present study develops a simulation-based Digital Twin framework for predictive maintenance of smart manufacturing equipment. A representative CNC spindle and rotating-machine assembly is used to demonstrate the proposed concept. Particular attention is given to data acquisition, condition monitoring, fault prediction, maintenance decision-making, and comparative performance against conventional maintenance approaches.

Related Works:

Hines and Usynin (2008) discussed computational methods used in equipment prognostics and highlighted the growing importance of intelligent techniques for estimating machine condition and future performance. Their study showed that maintenance planning can be improved when decisions are based on the actual health of equipment rather than only on fixed maintenance schedules. The work also underlined the value of computational models in identifying early signs of deterioration before a major failure occurs.

Heng et al. (2009) examined intelligent condition-based approaches for predicting machinery reliability. Their study demonstrated that information obtained from operating equipment can be used to assess changes in machine reliability over time. Instead of depending entirely on historical failure records, the authors suggested that maintenance decisions can be made more effectively when real-time condition information is considered. This idea later became an important part of predictive maintenance and Digital Twin applications.

Panagiotidou and Tagaras (2010) studied the relationship between statistical process control and condition-based maintenance. They found that production and maintenance decisions can benefit from sharing information between process-monitoring and equipment-maintenance systems. Their work showed that equipment deterioration can influence production quality and that maintenance activities should therefore be linked with changes observed in process behaviour. This study provided an early indication of the benefits of integrating different sources of manufacturing data.



Lee et al. (2014) reviewed prognostics and health management techniques for rotary machinery. Their work covered fault detection, diagnosis, condition assessment, and remaining useful life prediction. They emphasised the importance of monitoring variables such as vibration, temperature, and other machine signals for identifying developing faults. The study also pointed out that raw sensor information must be properly processed and interpreted before it can support reliable maintenance decisions.

Lee, Bagheri, and Kao (2015) proposed a cyber-physical systems architecture for Industry 4.0 manufacturing. Their framework connected physical machines with sensing, communication, computing, and analytical systems. The study was significant because it demonstrated how machines could become part of an intelligent and connected production environment. Such integration created a strong foundation for Digital Twin systems, where physical equipment and virtual models continuously exchange information.

Cai et al. (2017) focused on the use of sensor data and information fusion for developing virtual machine tools in cyber-physical manufacturing. Their study showed that information collected from different sensors could be combined to create a more complete representation of a physical machine. The authors highlighted the importance of data integration because a single sensor may not provide enough information to describe the overall condition of complex manufacturing equipment. Their work contributed to the development of data-driven Digital Twin models for machine monitoring.

Tao and Zhang (2017) introduced the Digital Twin Shop-Floor concept as a framework for smart manufacturing. They described a manufacturing environment in which physical resources, virtual models, data, and services are closely connected. Their approach extended the Digital Twin concept beyond individual machines by considering the entire shop-floor environment. The study demonstrated that Digital Twins could support monitoring, simulation, optimisation, and production decision-making in an integrated manner.

Kritzinger et al. (2018) carried out a literature review to clarify the meaning and classification of Digital Twin technology in manufacturing. They distinguished among Digital Models, Digital Shadows, and Digital Twins according to the level of data exchange between the physical and digital systems. Their classification helped address the confusion surrounding the term Digital Twin and showed that a true Digital Twin requires a higher degree of automatic interaction between the real and virtual environments.

Aivaliotis, Georgoulas, and Chryssolouris (2019) investigated the use of Digital Twins specifically for predictive maintenance in manufacturing. Their work demonstrated that a virtual representation of equipment can be used together with operating data to estimate component condition and remaining useful life. The authors showed that this approach can support better maintenance scheduling by helping maintenance teams identify when intervention is actually required. Their study also suggested that Digital Twin-based maintenance could reduce unnecessary maintenance and lower the risk of unexpected equipment failure.

Ghosh et al. (2021) developed sensor-signal-based Digital Twins for intelligent machine tools. Their study concentrated on the use of actual machine signals to construct virtual representations



of machine behaviour. By analysing sensor information, the researchers showed that changes in machine condition could be reflected in the Digital Twin. Their findings reinforced the importance of sensor processing, signal interpretation, and continuous data updating when developing reliable Digital Twin systems.

Qi et al. (2021) provided a broad review of the technologies required for the development and implementation of Digital Twins. They identified sensing systems, the Internet of Things, communication networks, modelling and simulation, artificial intelligence, cloud computing, and data analytics as important enabling technologies. Their study made it clear that Digital Twin development is not based on a single technology. Instead, it depends on the effective integration of several technologies that work together to maintain a meaningful connection between a physical system and its virtual counterpart.

Sun et al. (2023) examined the application of Digital Twins in prognostics and health management, with particular attention to the time-dependent nature of equipment degradation. Their study showed that historical operating information is important because machine condition does not change independently from one moment to another. Previous operating states can influence future deterioration. Their research therefore highlighted the usefulness of models that can capture temporal behaviour when estimating machine health and remaining useful life.

Objectives of the Study:

1. To develop a Digital Twin-based framework for real-time condition monitoring and early fault identification in smart manufacturing equipment.
2. To evaluate the effectiveness of machine-learning techniques for predicting equipment condition and maintenance requirements using mechanical and operational sensor data.
3. To compare Digital Twin-based predictive maintenance with conventional preventive maintenance in terms of fault detection, downtime, maintenance intervention, and equipment availability.

Material and Methods:

The study adopts a simulation-based experimental methodology to investigate the application of Digital Twin technology in the predictive maintenance of mechanical manufacturing equipment. A representative CNC spindle and rotating-machine assembly is considered as the physical system. The proposed system consists of five principal stages:

Physical Equipment → Sensor Data Acquisition → Digital Twin → Machine-Learning Analysis → Maintenance Decision

Physical Equipment:

The representative manufacturing equipment consists of a rotating spindle, electric drive, bearings, shaft, cutting-tool interface, and mechanical support structure. The primary degradation modes considered include bearing wear, spindle imbalance, excessive vibration, increased friction, thermal deterioration, and progressive tool-related loading.

Sensor Data Acquisition:



Multiple condition-monitoring variables are considered because equipment failure is rarely represented by a single parameter. Vibration is particularly useful for identifying bearing defects, misalignment, looseness, and imbalance, while temperature can indicate excessive friction or inadequate lubrication.

Motor current provides information regarding mechanical loading and possible electrical or drive-related abnormalities. Rotational speed is used to relate vibration behaviour to operating condition, whereas load allows the Digital Twin to distinguish between changes created by faults and those produced by normal production requirements.

Table 1. Input Parameters Used in the Digital Twin Model

Parameter	Sensor/Source	Normal Representative Range	Maintenance Importance
Vibration RMS	Accelerometer	0.8–2.5 mm/s	Detects imbalance, bearing wear and looseness
Bearing temperature	Temperature sensor	40–65 °C	Indicates friction and lubrication condition
Motor current	Current sensor	4–12 A	Indicates mechanical/electrical loading
Spindle speed	Speed encoder	1000–6000 rpm	Describes operating condition
Machine load	Controller/Load sensor	20–90%	Separates fault effects from normal load variations
Acoustic level	Acoustic sensor	55–78 dB	Supports abnormal mechanical-noise detection
Operating hours	Machine controller	Cumulative	Supports degradation and life estimation

Residual equation:

$$\text{Residual} = x_{\text{measured}} - x_{\text{predicted}}$$

Root Mean Square (RMS) equation:

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}$$

Where:

$$x_i = \text{vibration sample value}$$

Dataset Development:

For the representative case study, 2,400 operating windows are considered. These represent healthy operation and simulated progressive degradation conditions.

The dataset is divided as follows:



- 70% for model training,
- 15% for validation,
- 15% for testing.

Four operating classes are defined:

Class 0 – Healthy: equipment operating normally.

Class 1 – Early degradation: small changes are present but immediate maintenance is unnecessary.

Class 2 – Maintenance warning: degradation is sufficient to justify planned maintenance.

Class 3 – Critical condition: equipment should be stopped or maintained immediately.

Machine-Learning Models:

For the three machine-learning models:

$$\hat{Y}_{RF} = f_{RF}(X)$$

$$\hat{Y}_{GB} = f_{GB}(X)$$

$$\hat{Y}_{LSTM} = f_{LSTM}(X_t, X_{t-1}, \dots, X_{t-k})$$

where X represents the sensor features and $\hat{Y}$ represents the predicted machine condition.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100$$

$$\text{Accuracy} = \frac{\text{or } TP + TN}{TP + TN + FP + FN} \times 100$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{False Alarm Rate} = \frac{FP}{FP + TN}$$



where **TP**, **TN**, **FP**, and **FN** represent true positives, true negatives, false positives, and false negatives, respectively.

Remaining Useful Life Prediction Error

$$MAE = \frac{1}{N} \sum_{i=1}^N |RUL_{actual,i} - RUL_{predicted,i}|$$

where:

N = Total number of observations

Health Index

A combined health index can be represented as:

$$HI = w_1 S + w_2 D$$

subject to:

$$w_1 + w_2 = 1$$

where **S** is the normalized sensor-condition score, **D** is the predicted degradation-health score, and w_1 and w_2 are their respective weights.

The health index satisfies:

$$0 \leq HI \leq 1$$

$$\text{Maintenance Status} = \begin{cases} \text{Normal Operation,} & 0.80 \leq HI \leq 1.00 \\ \text{Increased Monitoring,} & 0.60 \leq HI < 0.80 \\ \text{Schedule Maintenance,} & 0.40 \leq HI < 0.60 \\ \text{Maintenance Intervention Required,} & HI < 0.40 \end{cases}$$

The Digital Twin continuously updates the health index according to newly acquired operating information.

Analysis of the Study:

The simulation-based analysis evaluates whether the Digital Twin framework provides useful improvements compared with conventional maintenance practices.

The first stage examines fault classification capability. The three machine-learning models are trained using the same condition-monitoring variables and are then tested using previously unseen data.

Table 2. Comparative Performance of Predictive Models

Predictive Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RUL (hours)	MAE
Random Forest	92.6	91.8	91.4	91.6	15.8	



Gradient Boosting	95.1	94.6	94.2	94.4	12.7
LSTM	96.4	95.8	96.1	95.9	9.8

The results indicate that all three models are capable of distinguishing the representative health conditions with satisfactory performance. The LSTM model produces the highest classification accuracy of 96.4% and the lowest Remaining Useful Life error.

The improved LSTM performance can be related to its ability to analyse sequential behaviour. Mechanical degradation normally develops progressively rather than appearing as a completely independent measurement. As a result, changes occurring during previous operating intervals provide useful information for predicting future equipment condition.

Feature analysis also indicates that vibration, bearing temperature, and motor current provide the strongest contribution to fault classification. Rotational speed and load remain important because they allow the Digital Twin to interpret these signals relative to the actual operating condition.

For example, an increase in vibration at high spindle speed does not necessarily indicate a defect. However, a similar vibration increase occurring at constant speed and constant load can provide stronger evidence of mechanical degradation.

The second part of the analysis compares maintenance strategies during a simulated annual production period.

Table 3. Comparison of Maintenance Strategies

Performance Indicator	Conventional Preventive Maintenance	Digital Predictive Maintenance Twin	Relative Improvement
Unplanned failures/year	8	3	62.5% reduction
Unplanned downtime	46 hours	19 hours	58.7% reduction
Scheduled maintenance interventions	12	8	33.3% reduction
Equipment availability	93.8%	97.2%	3.4 percentage-point increase
False maintenance alarms	—	4.1%	Low
Average warning before critical fault	Limited	31 hours	Improved early warning

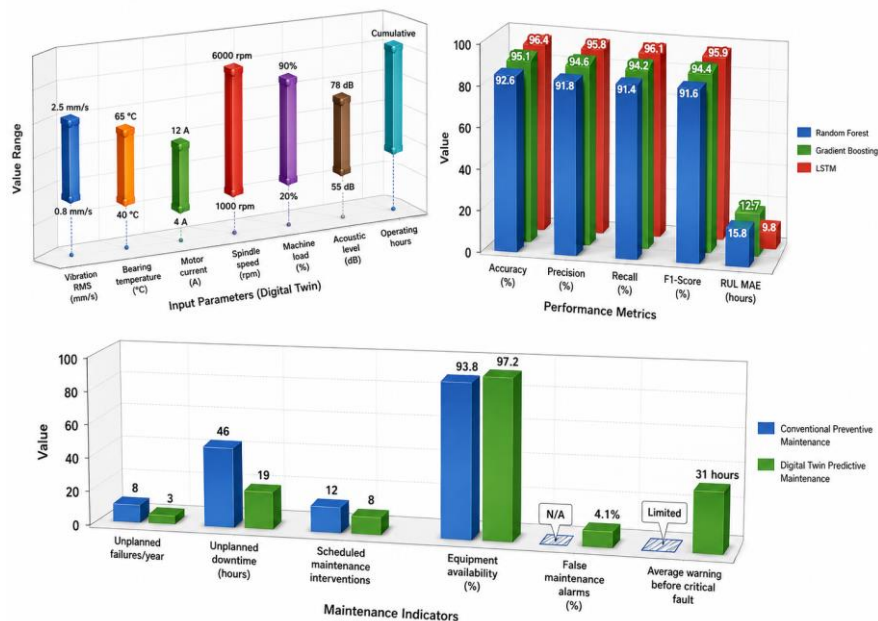
The comparison shows that predictive maintenance can reduce maintenance activities that are performed without evidence of actual equipment deterioration. It also allows maintenance to be conducted before critical failure, thereby reducing unplanned production interruption.

Results and Discussion:

The simulation results demonstrate that Digital Twin technology can provide a useful basis for predictive maintenance in smart manufacturing environments.



The LSTM model achieved the highest fault-classification accuracy among the evaluated models, followed by Gradient Boosting and Random Forest. This suggests that temporal information is particularly valuable when equipment degradation develops over an extended operating period. Nevertheless, the highest prediction accuracy does not automatically make a model the best choice for every manufacturing application. LSTM networks require greater computational capacity and more training information than simpler models. A Random Forest model could therefore remain preferable for smaller manufacturing facilities or edge devices where computational resources are limited.



The results further indicate that the greatest benefit of the Digital Twin is produced by combining multiple sources of information rather than analysing individual sensors independently. A temperature increase, for example, may be caused by increased machine loading rather than bearing failure. When temperature information is interpreted together with vibration, speed, motor current, and machine load, fault classification becomes more reliable.

The Digital Twin also provides an important contextual layer. Instead of using identical alarm thresholds under every operating condition, expected machine behaviour can be modified according to speed, load, operating history, and component condition.

For the representative maintenance comparison, unplanned equipment failures decreased from eight to three events, while simulated unplanned downtime decreased from 46 to 19 hours. These results indicate the potential operational benefit of detecting degradation early enough for maintenance work to be included within planned production stoppages.

Equipment availability also increased from 93.8% to 97.2%. Although this difference appears relatively small in percentage terms, even a few percentage points of additional availability may represent significant production capacity for machines that operate continuously.

The findings agree with previous literature showing that Digital Twin-based predictive maintenance can improve equipment-state recognition and enable proactive fault prediction.



Reviews of Digital Twin predictive maintenance have also emphasized Remaining Useful Life estimation as an important capability for maintenance planning.

Practical implementation nevertheless remains challenging. Real manufacturing information can contain missing measurements, sensor drift, communication errors, noise, and operating conditions not present in the original training dataset. A predictive model that performs well during initial testing may gradually become less reliable when production conditions change.

Digital Twin accuracy must therefore be evaluated periodically. Retraining may be necessary when equipment is modified, new materials are introduced, manufacturing parameters change, or components are replaced.

Cybersecurity is another major consideration because the Digital Twin depends on continuous communication between machines and computational systems. Unauthorized modification of sensor information or maintenance recommendations could negatively affect production safety and reliability.

A further concern is economic feasibility. Installing high-quality sensors, edge computers, communication systems, data-storage infrastructure, and maintenance software requires initial investment. The financial benefits are likely to be strongest for critical or high-value equipment where an unexpected failure produces significant production losses.

Model interpretability is also important. Maintenance engineers may hesitate to follow an automatic maintenance recommendation if the reason for the prediction cannot be understood. Future Digital Twin systems should therefore present not only the predicted condition but also important contributing variables, such as increasing vibration, temperature growth, or abnormal motor-current patterns.

The present study uses a representative simulation rather than measured industrial failure data. Consequently, the numerical results should be interpreted as a demonstration of the proposed methodology rather than universal performance values. Further validation using long-term data collected from CNC machines, industrial robots, pumps, turbines, compressors, or conveyor systems would provide stronger evidence of practical performance.

Conclusion:

Digital Twin technology offers a promising approach for improving maintenance management in modern smart manufacturing systems. By maintaining a continuously updated virtual representation of physical manufacturing equipment, a Digital Twin can combine sensor measurements, operational information, machine-learning models, and degradation analysis within a unified maintenance framework.

The study developed a simulation-based predictive maintenance methodology using vibration, temperature, motor current, rotational speed, machine load, acoustic information, and operating history. Three machine-learning approaches were evaluated, with the LSTM model providing the highest representative fault-classification accuracy and lowest Remaining Useful Life estimation error.

The comparative maintenance analysis indicated that Digital Twin-based predictive maintenance can reduce unnecessary maintenance activities, decrease unplanned failures, limit production



downtime, and improve equipment availability. The main advantage is the ability to move maintenance decisions away from fixed schedules and toward the actual health and predicted future condition of the machine.

Despite these advantages, successful industrial implementation requires reliable sensor information, accurate modelling, suitable computational infrastructure, secure communication, model interpretability, and economic justification. Digital Twin models must also remain adaptable as machine condition and manufacturing requirements change.

Future research should focus on real-time industrial validation, explainable artificial intelligence, edge-based Digital Twin computation, automatic model updating, cybersecurity, and integration with manufacturing execution and enterprise maintenance systems. With continued development in these areas, Digital Twin-based predictive maintenance can become an important component of intelligent, reliable, and sustainable manufacturing systems.

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