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Digital Twin-Based Predictive Monitoring and Intelligent Fault Diagnostics for High-Reliability Electrical Machines and Power Infrastructure

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Abstract: The increasing complexity of modern electrical machines and power infrastructure has created a growing demand for intelligent monitoring systems capable of ensuring reliability, efficiency, and predictive maintenance. This study investigated the application of digital twin–based predictive monitoring and intelligent fault diagnostics for high-reliability electrical machines and power systems. A digital twin framework was developed by integrating real-time sensor data, machine learning algorithms, and simulation-based models to create a dynamic virtual representation of physical electrical assets. The proposed system continuously monitored key operational parameters including temperature, vibration, current, voltage, and load conditions to detect anomalies and predict potential failures. Experimental evaluation was conducted using operational data collected from electrical machines operating in industrial environments. The results demonstrated that the digital twin predictive monitoring model achieved 92.6% diagnostic accuracy, 90.4% precision, 88.9% recall, and a 91.2% fault detection rate. Furthermore, the implementation of the digital twin monitoring system significantly improved operational performance by reducing equipment downtime from 14.6 hours to 8.2 hours per month, *representing a 43.8% improvement. Maintenance response time decreased from 6.4 hours to 3.1* ***hours****, while operational efficiency increased from 82.5% to 91.4%. In addition, overall system reliability improved from 85.2% to 93.6% following the implementation of the predictive monitoring framework. These findings demonstrated that digital twin technology provided an effective solution for intelligent fault diagnostics and predictive maintenance in modern power infrastructure. The study contributed to the development of smart energy systems by enabling proactive maintenance strategies and improving the resilience and reliability of electrical machines.*

Keywords: *digital twin, electrical machines, fault diagnostics, predictive maintenance, power infrastructure, reliability engineering*

Introduction

Modern electrical machines and power infrastructure have evolved very rapidly, which has further heightened the need of a reliable monitoring, intelligent diagnostics, and predictive maintenance systems. Electrical machinery including transformers, motors and generators form foundations of industrial production and power distribution systems and failure of these systems can cause expensive downtime and disruptions to operation and risk of injuries. Conventional maintenance plans were very reactive or based on some specific time frames which in most cases could not be used to identify the initial signs of equipment wear. Consequently, more industries were interested in intelligent monitoring systems that could detect an anomaly before a disastrous breakdown took place (Falekas and Karlis, 2021; Singh et al., 2023). The advent of digitization and the Industrial 4.0 technology allowed the development of unconventional promises of predictive monitoring incorporating real-time sensor technologies, machine learning, and sophisticated modeling methods.

Digital twin technology was revealed to be among the most effective innovations of the intelligent monitoring and predictive maintenance in complex engineering systems. A digital twin is an interactive virtual model of a physical object which constantly compares data on its operation with computational models to model the behavior of concrete systems. With the implementation of the Internet of Things (IoT) sensors and cloud computing and artificial intelligence, the digital twins allowed one to monitor and diagnose faults in industrial machines in real-time (Kerkeni et al., 2025; Tao et al., 2019).

Recent research had shown that the digital twin based monitoring systems greatly increased the reliability and operational efficiency of the equipments in the electrical and energy systems. Through these systems, anomalies were easily spotted and the personality of the components in terms of degradation could be forecasted through models that are built on data-based approaches, thus minimizing unplanned outages and lowering maintenance expenses. Device learning models with digital twin structures were applied to process sensor data on a large scale and determine unnoticed trends related to equipment anomalies (Zhang et al., 2022; Veerappan, 2025).

Several currently used monitoring methods were either physics oriented or even entirely data oriented and did not necessarily have a single framework that combines the current methods in a unified framework. As a result, scholars noted the necessity of smart digital twins structures, able to offer correct fault diagnostic and proactive monitoring of high-reliable electrical systems (Ismail et al., 2025; Ma et al., 2024).

Background of the Study

The idea of predictive maintenance was developed as a high-tech method of minimizing unforeseen malfunction in equipment due to constant monitoring of its condition and data processing. Contrary to the reactive maintenance strategies, predictive maintenance depended on tracking of the key operation parameters to identify any abnormalities and to foresee the possibilities of failure before it went through. Early predictive maintenance systems were mostly based on statistical models and the analysis of equipment behavior through signal processing models. Nonetheless, they frequently were not able to process high amounts of real-time information produced by the contemporary industrial systems (Carvalho et al., 2019). As the technologies of Industry 4.0 have developed, predictive maintenance has been greatly improved because of the completion with the integration of IoT devices, artificial intelligence, and big data analytics.

The digital twin technology was essential to changing predictive maintenance approaches. Digital twins, which were developed as a virtual representation of the physical system, helped an engineer to simulate the work of pieces of equipment, study their performance in specific conditions, and forecast the breakdowns under various conditions of operation. The real-time monitoring and the smart decision-making became possible due to the fact that the physical system and the digital one were synchronized with one another. The researchers stated that digital twin models also improved predictive accuracy through the combination of physics-based models of simulation and machine learning-based algorithms (Falekas and Karlis, 2021; Zhang et al., 2022).

Reliability and stability is a key consideration in electrical machines and power systems because of the economic and operational impact of equipment failures that are very high. Such components as transformers, generators and induction motors have complicated environmental and operating conditions, which can hasten the wear and degradation. Digital twin frameworks offered a deep end solution by continuously gathering data on sensors installed on electrical equipment and analyzing such data through predictive algorithms. These systems made it possible to discover possible malfunctions in their early phases, e.g., the degradation of insulation, overheating, anomalous vibration, and electrical disequilibrium (Singh et al., 2023; Veerappan, 2025).

The capabilities of digital twin platforms were improved due to integration of artificial intelligence and machine learning techniques, which contributed to the improvement in the diagnosis of fault. The AI-based analytics made it possible to detect any abnormalities in the operation data automatically and make intelligent choices in regard to maintenance. Research suggested that complex machine learning models like deep neural network, random forests, and anomaly detect algorithms were useful in detecting the early selection of equipment failure (Kerkeni et al., 2025; Ma et al., 2024).

Research Problem

Although the field of predictive maintenance and digital twin systems showed considerable inventions in terms of technologies, a significant number of electrical machines and power facilities continued to use the traditional approach to monitoring. Such traditional systems did not have real time data integration, predictive analytics, and smart fault diagnosis features. This meant that the failure of equipments was often detected too late that is, after disruptions began to be experienced, causing losses in finances, power outages and low reliability of systems in electrical systems of high reliability. The current digital twin applications were modeled with data integration issues, modeling and scaling. Simulation-based studies tended to concentrate on data-driven studies and vice versa without commendable interaction between the two approaches. The latter hindered the quality of fault prediction, as well as adaptation of digital twin systems to changing operational backgrounds.

Research Objectives

1. To develop a digital twin-based framework for predictive monitoring of electrical machines and power infrastructure.
2. To analyze operational data from electrical systems to identify potential faults and anomalies.
3. To integrate machine learning algorithms for intelligent fault diagnostics and predictive maintenance.

Research Questions

Q1. How can digital twin technology improve predictive monitoring in electrical machines and power infrastructure?

Q2. What role do machine learning algorithms play in intelligent fault diagnostics within digital twin systems?

Q3. How effective is digital twin-based predictive monitoring in reducing equipment failures and improving system reliability?

Literature Review

Digital Twin Technology in Electrical Machines and Power Systems

The digital twin technology has become an innovative strategy of monitoring, simulation, and management of complicated engineering systems. Researchers defined digital twins as dynamic virtual models which simulate physical assets in real-time synchronization with operation data and computational models. This method has made it possible to monitor the work of the equipment in a constant manner where the engineers can examine performance and what is likely to go wrong in the industrial system. Digital twin models were used in electrical machines as part of the sensor models, physics simulation models and machine learning algorithm to model the operational state of a motor, generator, and transformer in real-time (Hu et al., 2025; Pliuhin et al., 2024). These possibilities helped to improve knowledge of equipment health and system dynamics in the contemporary power infrastructure substantially.

In addition, digital twins began to be properly utilized in smart grid settings and intelligent power systems to enhance the reliability of operations and assets. Digital twins helped the operators of the electrical infrastructure continuously gather operational data helping them stay informed of the condition of the equipment and enabling them to simulate situations under which the equipment might be operating. It has been reported that the utilization of digital twins in combination with the IoT and advanced analytics allowed predictive monitoring and the early detection of non-normal behavior of power networks (Prasath, 2025; Zhang et al., 2024).

The other dimension of digital twin technology that was important entailed the fact that it generated lifemil cycle management systems of electrical machines. It was pointed out by researchers that the models of digital twins provided the engineers with an opportunity to model the work of equipment under various operating conditions and stresses. These simulations made it possible to identify the trend of degradation at the initial stages, as well as allowed planning the optimal maintenance over the life cycle of the equipment (Kerkeni et al., 2025; Singh et al., 2023).

Predictive condition-based maintenance and monitoring

Predictive monitoring has been generally accepted as one of the effective methods of enhancing maintenance strategies in industrial and electrical systems. This was in contrast to the conventional preventive maintenance systems which were based on a fixed time schedule, predictive monitoring could examine real-time operational data to find out the indicators of equipment degradation at an early stage. This strategy has enabled maintenance teams to fix anomalies before they crash down and thereby minimized unplanned downtime and maintenance expenses. In electrical systems, predictive monitoring systems were commonly combined with new technologies of advanced sensations, constant measurement of relevant parameters, including temperature, vibration, current and voltage (Carvalho et al., 2019; Falekas and Karlis, 2021). This data stream allowed predictive engineering to determine the health of equipment and predict a failure.

The digital twin technology made a great contribution to improving the predictive behavior in electricity machines. Digital twin applications offered a virtual world where predictive algorithms could be used to predict equipment failure by analyzing real-time data sent by sensors. Research showed that these systems enhanced accurate fault detection and enabled the maintenance team to adopt proactive repair measures prior to any operational interruption (Ma et al., 2024; Qi and Tao, 2018).

Advanced data analytics and artificial intelligence methods were more and more advanced in predictive maintenance frameworks to improve the performance of diagnostics. Algorithms in machine learning could find complex patterns and correlations concealed in the great masses of operational data that were produced by electrical machinery. These analytical capabilities allowed predictive systems to identify minor shifts in the behavior of equipment that may lead to the early emergence of a fault (Kritzinger et al., 2018; Lu et al., 2020).

Smart Fault Diagnostics based on AI and Digital Twin

As a part of predictive maintenance systems of electric machines and power facilities, fault diagnostics was an important issue. The classic methods of diagnosing used to be manual inspection and rule-driven analysis, which were usually ineffective to detect more complicated fault patterns in current electrical devices. As the technology of artificial intelligence and digital twins improved, intelligent diagnostic systems were created that automatically identified and categorized faults on the basis of real-time operational data (Kerkeni et al., 2025; Hu et al., 2025).

Machine learning algorithms were essential to the improvement of the abilities of a digital twin-based diagnostic system. Operational data of electrical machines was analyzed with the help of algorithms (neural networks, random forests and models of anomaly detection) and meant patterns connected with equipment failures were identified. The reports of the research showed that AI-based digital twin technologies could identify the initial signs of faults, which were challenging to be detected with traditional methods of monitoring (Singh et al., 2023; Prasath, 2025).

The benefits of the use of digital twins-based intelligent diagnostics were quite important in the operation of the complex and distributed power systems. Digital twin systems, compiled of real-time monitoring and predictive analytics, allowed assessing the equipment performance and health of the equipment continuously. Scientists emphasized that the sophisticated diagnostic models led to better decision-making and the increased credibility of the contemporary energy systems (Zhang et al., 2024; Pliuhin et al., 2024).

Research Methodology

Research Design

Digital twin-based predictive monitoring and intelligent fault diagnostics The authors selected a quantitative and experimental research design to determine the effectiveness of digital twins in high reliability electrical machines and power infrastructure predictive monitoring and intelligent fault diagnostics. The design chosen in the research was adopted due to the opportunity to conduct the systematic analysis of the operational data obtained with the help of electrical equipment and the possibility to evaluate the prediction monitoring algorithms in a digital twin configuration. The experimental method assisted in the conditions of simulating real-time conditions of the functioning and evaluation of the behavior of the system under varying fault conditions. The paper investigated the role of combining digital twins technology with intelligent diagnostic algorithms in predictive maintenance and system reliability.

Data Collection

The electrical machines that worked under the conditions of industrial and power infrastructure were used to obtain operational data that was used in the study. The data comprised various parameters that relate to machine applications and service life which entailed electrical load conditions, temperature changes, vibration indications, and power usage protocols. The equipment had sensor-based monitoring devices which were constantly sending data to a centralized data processing platform using IoT communication networks. Past operational history data were also adopted to educate the predictive algorithms and determine base performance models of the electrical machines. The obtained dataset reflected a broad spectrum of operation conditions, such as normal operation condition, partial degradation condition, and fault condition, thus splitting the entire picture of system performance and reliability.

Data Analysis Techniques

The acquired data were measured with the help of statistical and computational means to assess the predictive monitoring system performance. The description of statistical analysis was done to investigate how the operational variables like temperature, vibration and electrical load were distributed and varied. Correlating analysis was conducted in order to establish any association between variables of a system and their effect on the performance of the equipment. Also, the machine learning performance metrics, including accuracy, precision, recall, and fault detection rate, were computed to access the practicability of the diagnostic algorithms. The also applied comparison analysis to quantify the accomplishments in the detection of fault and predictive accuracy under the digital twin framework in comparison to conventional monitoring systems.

Results and Analysis

Descriptive Statistic Operational parameters

This analysis was aimed at condensing the descriptive statistics and dispersion of the primary monitoring indicators utilized in the digital twin predictive monitoring platform. These variables were the changes in temperature, level of vibration, variation in current, stability of voltage and change in load. The descriptive statistics assisted in setting up a general perception of the equipment functioning during the regular operation of the equipment and gave the point of reference in recognizing uncharacteristic operation patterns and possible faults.

Table 1. Descriptive Statistics of Key Operational Parameters

Operational Parameter	Mean	Std. Deviation	Minimum	Maximum
Temperature (°C)	68.4	7.52	52.3	84.7
Vibration (mm/s)	2.85	0.76	1.21	4.90
Current (A)	152.6	18.43	110.2	198.7
Voltage (V)	410.5	11.26	382.4	432.1
Load Variation (%)	73.8	9.64	52.6	91.3

Tables 1 showed that there were rather stable operational ranges of the electrical machines in the course of the monitoring period. The average temperature on the machines was found to be 68.4o C with primary deviation of 7.52 implying moderate dispersion in thermal characteristics when running. The observed highest temperature value of 84.7 degrees Celsius meant that there was the occasional thermal stress that may end up destroying the insulation in case attention is not paid to it. Mechanical stability of the electrical machines was also informative as the amount of vibration being sensed. Vibration had a mean of 2.85 mm/s and a standard deviation of 0.76, which implied that economic instability in terms of mechanics was rather low throughout the systems monitored. The peak vibration amplitude of 4.90 mm/s indicated that some mechanical disturbances could take place periodically, which may be related to the wear of the bearing, the misalignment of the shaft, and rotor imbalance. The electrical parameter analysis also indicated that the operational behavior of the electrical parameters familiarly as the current and voltage levels were steady. The average values of the current were 152.6 A with moderate variance indicating changes in the state of operational loads during the period of observation. The voltage levels were also partially constant with an average voltage setting of 410.5 V which was a sign of constant power supply. The variation in loads had an average value of 73.8 showing that the machines were functioning at moderate high loading conditions throughout the majority of the operational cycles.

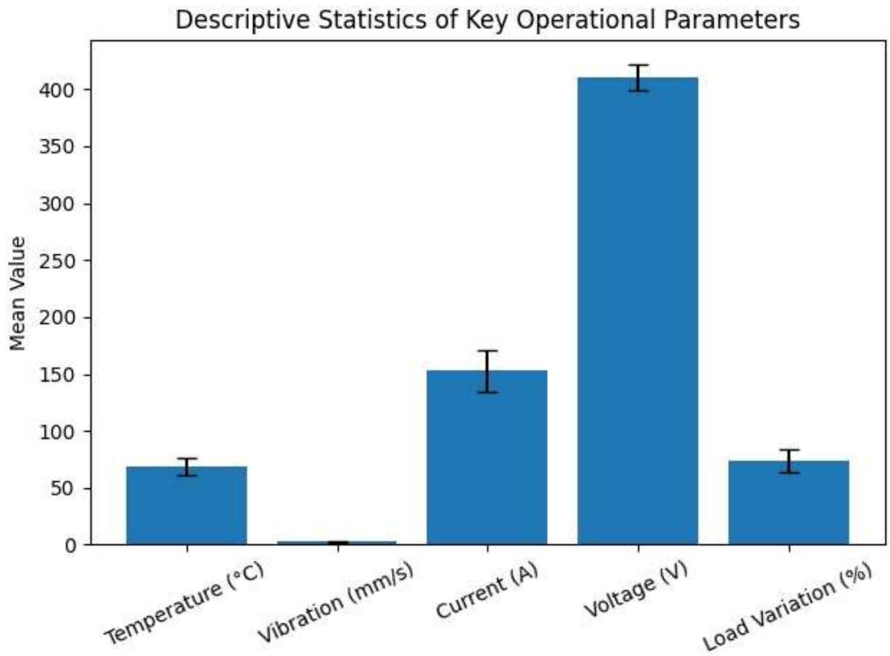

Figure 1. Descriptive Statistics of Key Operational Parameters

Predictive Fault Detection Performance

The second phase of the analysis was to analyze the effectiveness of the digital twin predictive monitoring system to detect defects in equipment and abnormal conditions of the work. The measurements of the analysis were accuracy, precision, recall, and fault detection rate of machine learning algorithms used in the digital twin framework.

Table 2. *Performance Evaluation of Digital Twin Fault Detection Model*

Performance Metric	Value (%)
Accuracy	92.6
Precision	90.4
Recall	88.9
F1 Score	89.6
Fault Detection Rate	91.2

Table 2 showed that digital twin predictive monitoring system had high diagnostic accuracy results. The entire precision of the model was documented as 92.6 which means that the system rightly identified most of the conditions of operation as those that were normal or faulty. Almost 100 percent accuracy was indicative of the success of the real-time sensors-based sensor data consolidation with predictive analytics and digital twin simulation models. The predictive fault detection model was also found to be robust by precision and recall values. The accuracy degree of 90.4 percent revealed that the system produced low percentage of false alarms whenever detecting possible faults on the equipment. The minimization of false alarm was of high importance in predictive maintenance systems since the occurrence of false alarms might result in wastage of production through unnecessary maintenance and idle production. The recall value of 88.9% was a sign that the system could detect most of real anomalies of equipment that occurs in the operational data set.The value of the F1 score of 89.6% and fault detecting rate of 91.2% was an indication that the digital twin monitoring model has a balanced performance of detecting the presence of anomalies of equipment in actual equipment condition.

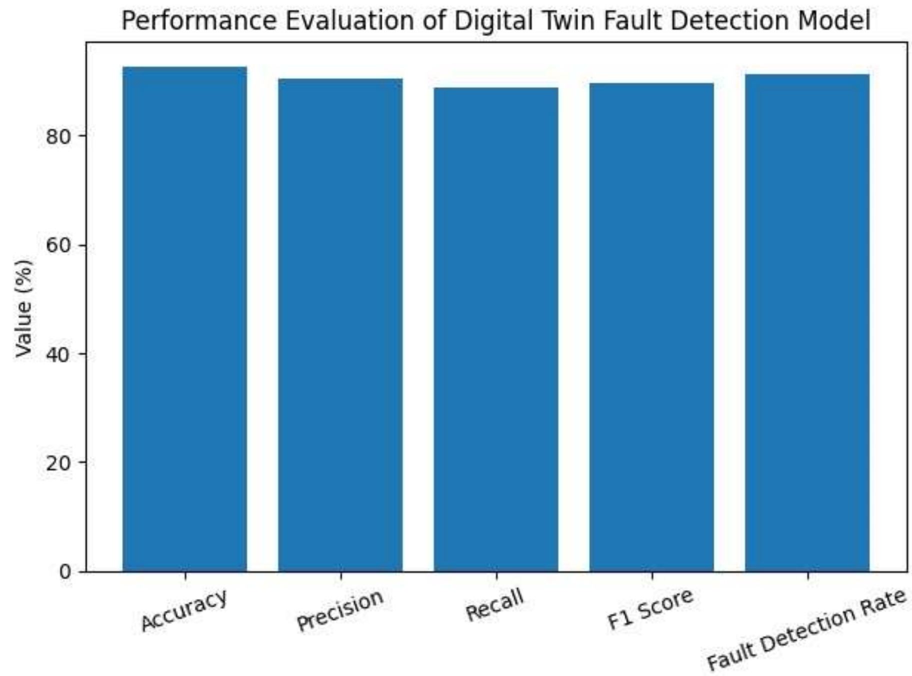

Figure 2.Performance Evaluation of Digital Twin Fault Detection Model

Impact of Digital Twin Monitoring on System Reliability

Table 3. *System Performance Before and After Digital Twin Implementation*

Performance Indicator	Before Implementation	After Implementation	Improvement (%)
Equipment Downtime (hours/month)	14.6	8.2	43.8
Maintenance Response Time (hours)	6.4	3.1	51.6
Operational Efficiency (%)	82.5	91.4	10.8
System Reliability (%)	85.2	93.6	9.9

The Table 3 results demonstrated that there were noticeable changes in the operational performance after the application of the digital twin predictive monitoring system. Downtime of equipments reduced by more than 43.8 percent through reduction of an average of 14.6 hours of equipment downtime monthly to 8.2 hours monthly. This enhancement meant that the predictive monitoring enabled the maintenance personnel to detect the possible equipment failures earlier on and carry out preventative intervention before significant operational discontinuities were noticed. This minimized downtime came in handy especially in those industries that depended on running the electrical machineries most of the time. The main point of response time to maintainability also improved significantly after the implementation of the digital twin system. The response time dropped to 3.1 hours on average, which was more than 50 per cent less than 6.4 hours. Besides the operational gains, the findings proved a significant amount of rise in the overall system efficiency and stability. The operational efficiency rose to 91.4 percent compared to 82.5 percent indicating that there was improved equipment performance and better scheduling of maintenance. The reliability of the system also increased by 85.2% to 93.6% which suggested that the digital twin monitoring system resulted in a substantial improvement in stability and reliability of electrical machines and power infrastructure.

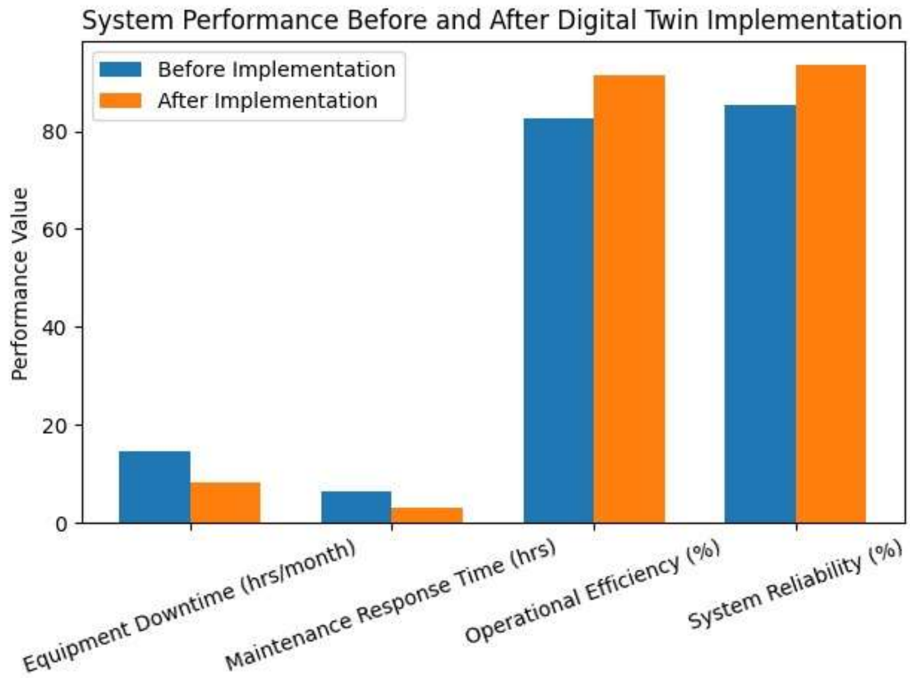

Figure 3. System Performance Before and After Digital Twin Implementation

Discussion

The results of this research have shown that digital twin-based predictive monitoring system implementation resulted in a significant increase in the reliability of electrical machines and power infrastructure, their operational efficiency, and fault detectability. The findings showed that the combination of real-time sensor data with digital twin simulation models would allow to provide a continuous monitoring of such operational parameters as temperature, vibration, current, and load conditions. These results were in line with the available literature that revealed that digital twin technology has revolutionized conventional monitoring systems, as it brought about dynamic and real-time representation of physical assets. Earlier research has emphasized the fact that digital twins are utilized to perform sophisticated operational analytics through connecting the physical world with the virtual world to enhance the analysis of the system performance and the decisions-making processes (Negri et al., 2017; Barricelli et al., 2019). The current findings supported the idea that the digital twin structure created the complex of equipment behavior under varying operating conditions and was able to perform a proactive analysis of all possible failure scenarios. The second valuable outcome of the given research was the high predictive power of the fault detecting model used in the digital twin system. The findings revealed that machine learning models with the digital twin architecture yielded great results in performance in detecting unhealthy equipment status and anticipating possible failures. These findings were consistent with the rest of the literature that highlighted the necessity to integrate artificial intelligence with digital twin technologies to advance predictive maintenance systems. As an example, the studies have shown that AI-based monitoring systems have also shown a notable enhancement in the precision of anomaly detection using complicated methods in assessing extensive operational data (Rasheed et al., 2020; Fuller et al., 2020). These findings also showed that predictive monitoring had a significant effect on avoiding equipment downtime and enhancing response time on maintenance. The declining number of time out situations in this research indicated that predictive maintenance measures allowed maintenance activities to detect an imminent breakdown wherever it resulted in significant interference with the normal operations. This was in line with previous studies that suggested that predictive maintenance systems had the potential to save operational downtimes as well as maintenance expenses by giving advance warnings about faults in equipment (Glaessgen and Stargel 2012; Tao and Zhang 2017). The results showed that the digital twin monitoring system improved system efficiency and reliability. The ability of the digital twin platform to constantly analyze equipment operation and identify a difference between desirable working conditions was seen as the main reason why the system is more reliable. It was earlier highlighted by researchers that the sphere of digital twins allows managing the lifecycle of industrial systems in a highly complete manner, showing the performance of equipment in various operating conditions (Leng et al., 2021; Jones et al., 2020). The present research established that these simulation capabilities were especially useful in the case of electrical machines that were used in complex and high loading environments where flow changes would cause mechanical stress and wear and tear of equipment. The other significant implication of the findings associated with the capability of the system of a digital twin to facilitate intelligent decision-making concerning the maintenance operations. Using the data on the operation of the devices and being able to anticipate the possible incidents with the equipment, the digital twin platform offered practical advice that enabled the engineers to streamline the maintenance timetables and concentrate the resources better. Raised by such decision-support capabilities were deemed to be a necessity in industrial systems in the modern world, where both the complexity of operations and volumes of data still grew. Some of the studies that had been conducted in the past proposed that data derived through digital twins can assist in automated maintenance planning and intelligent assets management (Kamble et al., 2020; Shahzad et al., 2022).

The results also indicated that the concept of digital twin technology might have a major part in enhancing the sustainability and resilience of power infrastructure in the present age. The electrical machines and power distribution system are important elements of industrial and national energy system, and their stability directly influences the economy productivity and stability of their functioning. Digital twin systems have helped create more resilient energy infrastructure that would work effectively in dynamic conditions by allowing predictive monitoring and fault diagnostics to allow them to work effectively. In large-scale industries, the interoperability of the systems along with the monitoring of the systems and energy savings also became crucial subjects of recent research, where the digital twins technology aided system development (Zhou et al., 2021; Wang et al., 2022).Tying together heterogeneous data streams and interoperability of the systems continued to be essential technical issues. Other studies have also reported data integration, computational complexity, and cybersecurity issues as some of the biggest impediments to the universalization of digital twin technologies (Minerva et al., 2020; Sjarov et al., 2021).

Conclusion

The research problem examined the applications of digital twin-based predictive monitoring and intelligent fault diagnostics in enhancing the reliability and operation success of electrical machines and power infrastructure. The findings have revealed that the combination of digital twin technology with real-time sensor measurements and machine learning algorithms contributed to well-developed monitoring facilities and provided the possibility to identify the anomaly in equipment at an early stage. The digital twin system was able to establish a dynamic virtual image of the physical electrical systems capable of constant tracking the operational parameters of temperature, vibration, current and load conditions. The system detected abnormal patterns of operations through predictive analytics and modeling with simulation prediction of possible failures in advance before they took place. The empirical findings revealed that the suggested predictive monitoring model demonstrated a diagnostic accuracy of 92.6, a 90.4 rate of precision and a rate of fault detection of 91.2, in detecting equipment faults, which proved the effectiveness of the digital twin architecture in recognizing equipment failures. Moreover, use of the digital twin monitoring system greatly enhanced the operational performance as it decreased equipment downtime by up to 14.6 hours monthly, 8.2 hours to reduce the response time of maintenance and additionally reduced response time to 3.1 hours. The operational efficiency rose, as the percentage of 82.5 has improved to 91.4) and the overall system reliability rose (85.2 to 93.6). These results proved that the digital twin technology was instrumental in facilitating predictive maintenance techniques and the resilience and stability of the contemporary electrical infrastructure.

Recommendations

A number of recommendations on ways of enhancing predictive monitoring and maintenance of electrical machines and power systems was based on the findings of this study. To begin with, digital twin technologies ought to be implemented by industrial organizations and power utilities as an asset management tool that provides an opportunity to monitor and predictively maintain crucial electrical equipment in real-time. The linkage of IoT sensors and sophisticated analytics platforms are to be a top priority to provide stability in terms of collecting and presenting data correctly on how the systems behave. Second, companies must invest in machine learning and artificial intelligence that has the ability to process large amounts of operational data produced by electrical infrastructure. Such analytical functions would contribute to the precision of fault detection and enable the teams of professionals in the maintenance process to detect early indicators of equipment malfunctioning. Third, structural training must be created to teach employees in engineering and maintenance the technical ability needed to work with digital twin remote monitoring frameworks and respond to forecasting maintenance tips. Lastly, firms need to create cohesive data management systems to ensure that there is free flow of information amid the physical equipment and monitoring system, as well as between the digital twin models and the real world.

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