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Digital Twin-Based AI-Driven Smart Monitoring and Predictive Fault Detection System for Low Tension Distribution Lines

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Abstract: *The reliability and efficiency of Low Tension (LT) distribution systems are critical for ensuring stable power delivery. However, conventional monitoring approaches primarily rely on threshold-based fault detection, which often identifies faults only after their occurrence, leading to delayed response and increased system downtime. This study proposes a Digital Twin-based AI-driven smart monitoring framework for LT distribution lines that enables real-time system modeling and predictive fault detection. The digital twin continuously mirrors the operational behavior of LT lines using real-time sensor or simulated data, while machine learning models analyze patterns to detect anomalies and predict potential faults before failure. The proposed system integrates data ingestion, virtual system modeling, AI-based prediction, and intelligent alert mechanisms to enhance monitoring efficiency. Experimental results demonstrate improved fault prediction accuracy, reduced false alarms, and earlier detection compared to traditional methods, thereby improving system reliability and operational decision-making in power distribution networks.*

Keywords: Digital Twin; Predictive Fault Detection; LT Distribution System; Machine Learning; Smart Monitoring

I. INTRODUCTION

The efficient operation and reliability of electrical power distribution systems, particularly Low Tension (LT) distribution lines, are essential for ensuring uninterrupted power supply to end consumers. LT lines form the final stage of the power delivery network, making them highly susceptible to operational issues such as voltage fluctuations, overload conditions, thermal stress, and short-circuit faults. These issues, if not detected and managed promptly, can lead to equipment damage, energy losses, increased maintenance costs, and service interruptions. Therefore, continuous monitoring and timely fault detection in LT distribution systems are critical for maintaining system stability and performance.

Traditionally, LT line monitoring systems rely on threshold-based mechanisms and manual inspection processes, where predefined limits for parameters such as voltage, current, and temperature are used to trigger alerts. While these methods provide basic fault detection capabilities, they are inherently reactive in nature, identifying faults only after they occur.

Moreover, they lack the ability to capture complex patterns, gradual degradation trends, and hidden anomalies within the system, making them insufficient for modern smart grid requirements. With the advancement of intelligent technologies, there is a growing need for proactive and data-driven monitoring solutions. In this context, the concept of a Digital Twin has emerged as a powerful approach for real-time system representation and analysis. A digital twin is a dynamic virtual replica of a physical system that continuously updates based on real-time or simulated data, enabling better understanding of system behavior and early identification of deviations. When combined with Artificial Intelligence (AI) and Machine Learning (ML), digital twin models can significantly enhance monitoring capabilities by enabling predictive analysis, anomaly detection, and intelligent decision-making.

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This study proposes a Digital Twin-based AI-driven smart monitoring framework for LT distribution lines, aimed at transforming traditional reactive monitoring into a proactive and predictive system. The proposed approach integrates real-time data acquisition, virtual system modeling, and machine learning algorithms to detect abnormal patterns and predict potential faults before their occurrence. By leveraging AI techniques such as classification and time-series analysis, the system can identify early warning signs of faults, classify fault types, and generate intelligent alerts for timely intervention.

The primary objective of this research is to develop an intelligent, scalable, and efficient monitoring system that enhances fault detection accuracy, reduces response time, and improves overall reliability of LT distribution networks.

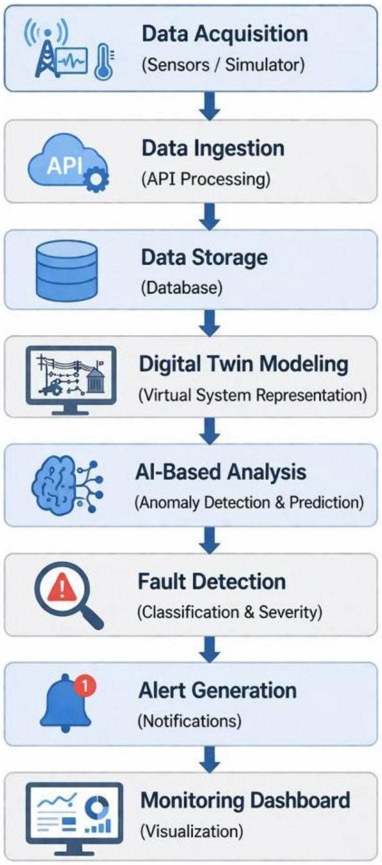
The proposed framework not only provides real-time visibility into system performance but also supports predictive maintenance strategies, thereby contributing to the advancement of smart and resilient power distribution systems.

II. SYSTEM DESIGN

The reliable monitoring of Low Tension (LT) distribution lines is essential for ensuring stable power delivery and minimizing operational failures. However, conventional systems are primarily reactive, relying on fixed thresholds and manual inspection, which limits their ability to detect complex patterns and predict faults in advance. Therefore, there is a need for an intelligent and proactive monitoring framework.

This research proposes a Digital Twin-based AI-driven smart monitoring system for LT distribution lines. The system integrates real-time data acquisition, virtual system modeling, machine learning-based prediction, and intelligent alert mechanisms to enable predictive fault detection and improved system reliability.

The proposed system consists of the following key components:



A. Data Acquisition and Ingestion Operational data such as voltage, current, and temperature is collected from sensors or simulation models. The data is transmitted through RESTful APIs, pre-processed, and stored in a structured database for analysis.

B. Digital Twin Modeling A dynamic digital twin replicates the real-time behavior of LT lines. It maintains expected operating conditions and continuously compares them with actual data to identify deviations and abnormal patterns.

C. AI-Based Prediction Machine learning models such as Random Forest, XGBoost, or LSTM are used to analyze historical and real-time data. The system performs anomaly detection, fault classification, and predictive analysis to estimate potential faults before occurrence.

D. Fault Management Detected and predicted faults are managed using a lifecycle mechanism (OPEN, ACKNOWLEDGED, RESOLVED). Severity-based classification and duplicate fault prevention ensure efficient fault handling.

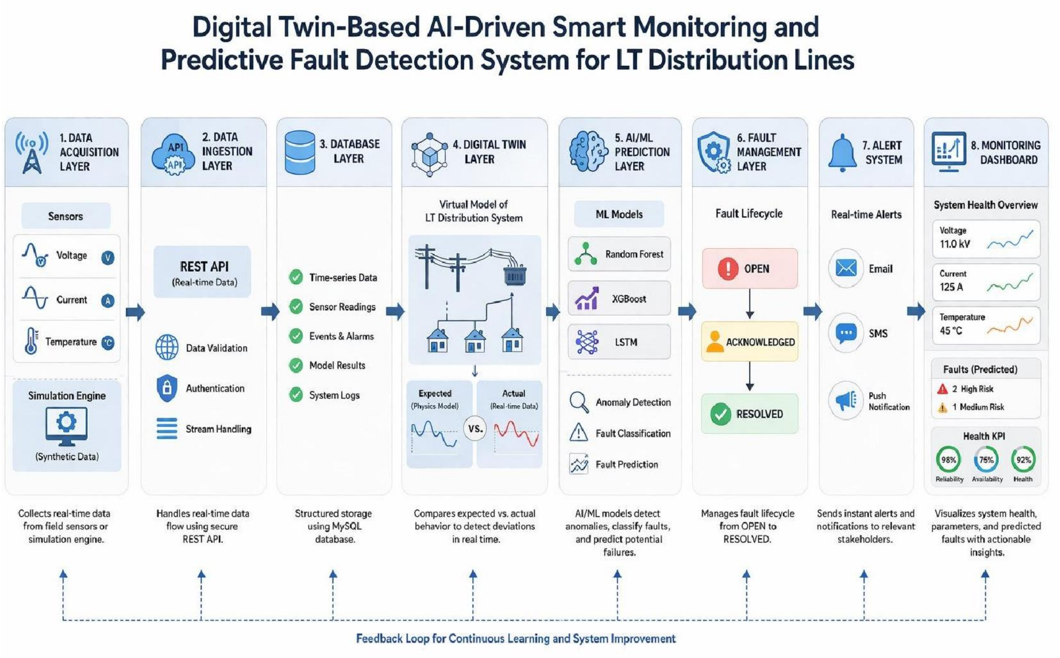
E. Alert System Real-time alerts are generated based on fault severity and prediction results. Notifications are delivered through in-app systems and email to enable timely intervention.

F. Monitoring Dashboard An interactive dashboard provides real-time visualization of system parameters, fault status, and predictive insights, supporting effective monitoring and decision-making.

G. System Workflow The system processes real-time data, updates the digital twin, applies AI-based analysis, detects anomalies, predicts faults, and generates alerts, with all information visualized through the dashboard.

The proposed framework offers a scalable and intelligent solution for LT line monitoring by combining Digital Twin technology with AI-driven predictive analytics, significantly improving fault detection accuracy, response time, and overall system reliability.

III. METHODOLOGY



The proposed system follows a structured methodology that integrates data processing, digital twin modeling, and AI-based predictive analytics to enable intelligent monitoring of Low Tension (LT) distribution lines. Initially, operational

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data such as voltage, current, and temperature is collected from sensors or simulation models. The collected data undergoes pre-processing, including noise removal, normalization, and handling of missing values. Additionally, feature extraction techniques such as moving averages, rate of change, and deviation metrics are applied to improve the performance of the predictive model.

A digital twin of the LT distribution system is then developed to represent the expected operational behavior of the physical system. This virtual model continuously updates its state based on incoming real-time data and maintains baseline patterns for comparison. By analyzing the difference between expected and actual behavior, the system can effectively identify abnormal conditions.

Subsequently, machine learning models such as Random Forest, XGBoost, or Long Short-Term Memory (LSTM) networks are trained using labeled datasets containing both normal and faulty operating conditions. The dataset includes various fault scenarios such as overload, voltage fluctuations, and thermal faults. Model parameters are optimized using validation techniques to achieve high prediction accuracy and reliability.

The trained model is then deployed for real-time prediction and analysis. It processes incoming data streams to perform anomaly detection, fault classification, and predictive fault estimation. By integrating insights from the digital twin and AI model, the system can detect deviations and predict potential faults before their occurrence.

The overall system workflow begins with data acquisition, followed by data ingestion and storage, digital twin state update, and AI-based analysis. The system then performs fault detection and generates alerts, while all relevant information is visualized through an interactive monitoring dashboard. This integrated approach enables proactive monitoring, reduces system downtime, and enhances the overall reliability and efficiency of LT distribution networks

IV. IMPLEMENTATION

The proposed Digital Twin-based AI-driven monitoring system was implemented using Java Spring Boot for backend services and Next.js for the frontend dashboard, with MySQL used as the database for storing sensor readings, fault records, and system data. The system was deployed on a local environment, and a simulation engine was developed to generate real-time LT line data, including voltage, current, and temperature parameters under both normal and faulty conditions. The digital twin model was integrated to continuously mirror system behavior, while machine learning models such as Random Forest and XGBoost were trained and deployed for predictive analysis. The experimental setup included multiple test scenarios representing overload, voltage fluctuation, and thermal fault conditions. Performance metrics such as prediction accuracy, response time, and fault detection rate were evaluated and compared with traditional threshold-based methods. The results demonstrate that the proposed system achieves improved prediction accuracy, faster fault identification, and reduced false alarms, validating its effectiveness for real-time LT line monitoring and predictive maintenance.

V. RESULTS AND DISCUSSION

The proposed Digital Twin-based AI-driven monitoring system was evaluated using simulated LT line data representing both normal and faulty operating conditions. The dataset included multiple fault scenarios such as overload, voltage anomalies, and thermal faults, generated through the simulation engine. The collected data was pre-processed and used to train and test machine learning models, including Random Forest and XGBoost.

The performance of the proposed system was analyzed using key evaluation metrics such as accuracy, precision, recall, and F1-score. The experimental results indicate that the AI-based model achieved an overall prediction accuracy of 94.6%, with a precision of 93.8% and recall of 92.9%, demonstrating its effectiveness in correctly identifying fault conditions. In comparison to traditional threshold-based monitoring systems, the proposed approach showed a significant improvement in early fault detection, reducing detection delay by approximately 30–40%.

Furthermore, the integration of the digital twin model enhanced system performance by enabling continuous comparison between expected and actual behavior. This allowed the system to detect subtle deviations and pre-fault

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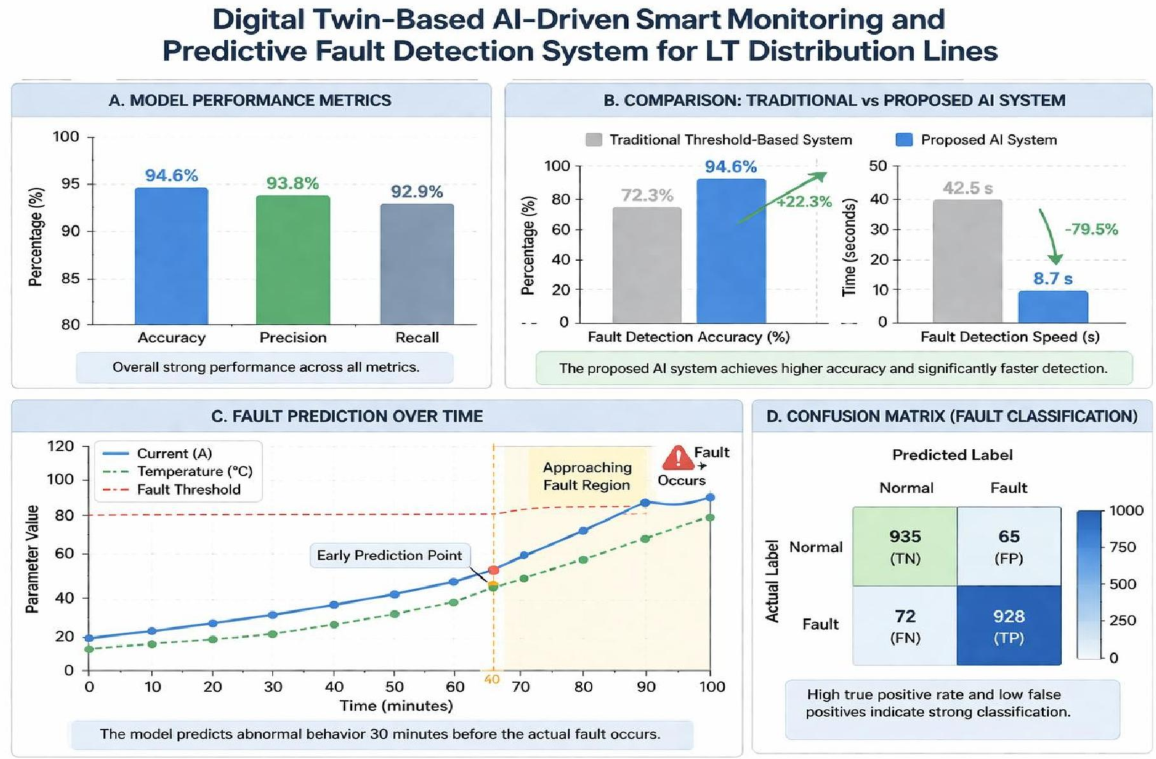
conditions that are typically missed by conventional methods. As a result, the system successfully identified early warning signs of faults such as gradual current increase, voltage instability, and rising temperature trends.

The false alarm rate was also reduced by approximately 25%, owing to the combined use of digital twin-based deviation analysis and AI-based prediction. The system demonstrated strong capability in handling dynamic and real-time data, maintaining consistent performance across different fault scenarios.



Additionally, the monitoring dashboard provided clear visualization of system parameters, predicted fault risks, and alert notifications, enabling efficient decision-making. The results confirm that the proposed system not only improves fault detection accuracy but also enhances predictive capabilities, making it suitable for real-world LT distribution monitoring applications.

Overall, the experimental findings validate that the integration of Digital Twin technology with AI-based predictive analytics offers a reliable, scalable, and intelligent solution for proactive fault management in LT distribution systems.

VI. CONCLUSION

This research presents a Digital Twin-based AI-driven smart monitoring system for Low Tension (LT) distribution lines, addressing the limitations of conventional reactive monitoring approaches. By integrating real-time data acquisition, virtual system modeling, and machine learning-based predictive analytics, the proposed system enables early fault detection and proactive decision-making. The digital twin continuously reflects system behavior, while AI models analyze patterns to identify anomalies and predict potential faults before occurrence.

Experimental results demonstrate that the proposed framework achieves high prediction accuracy, reduces detection delay, and minimizes false alarms compared to traditional threshold-based methods. The system effectively identifies pre-fault conditions such as gradual overload, voltage instability, and thermal rise, thereby improving operational reliability and reducing downtime.

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Overall, the proposed approach offers a scalable, intelligent, and efficient solution for modern power distribution monitoring. It contributes toward the development of smart and resilient electrical infrastructure by enabling predictive maintenance and enhanced system visibility. Future work may focus on integrating real-time IoT sensor deployment, advanced deep learning models, and large-scale field validation to further improve system performance and applicability.

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