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APPLICATION OF ARTIFICIAL INTELLIGENCE (AI) IN AUTOMATED MONITORING AND CONTROL OF INDUSTRIAL POWER SYSTEMS

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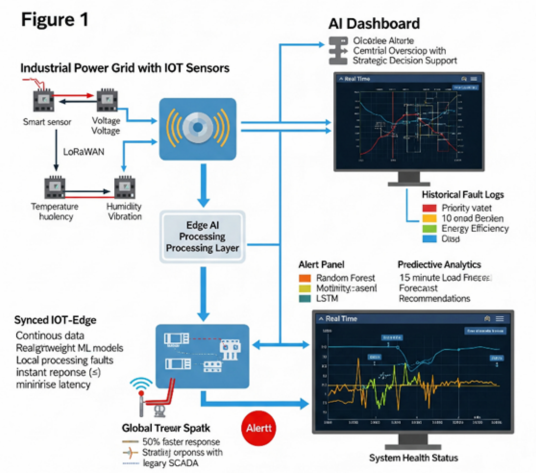
I.

ABSTRACT: In the context of the Fourth Industrial Revolution and the growing demand for energy, the application of Artificial Intelligence (AI) in industrial power systems offers intelligent and automated monitoring and control capabilities. This study presents an integrated model consisting of smart sensors (IoT), edge computing (Edge AI), and an AI-based dashboard to collect data, analyze, and control the power system. The proposed model enables real-time data processing at the device level (reducing latency), early fault detection, load forecasting, and optimization of complex control operations. Experiments conducted on a virtual power station model and real-world scenarios (such as the Malå power grid in Sweden) demonstrate that the integrated approach significantly outperforms traditional discrete methods or standalone machine learning solutions. Results indicate high fault detection accuracy, reduced downtime, and enhanced monitoring efficiency. The proposed model synchronizes sensor systems, edge processing units, and AI interfaces, and has been benchmarked against conventional systems and pure machine learning approaches.

KEYWORDS: Artificial Intelligence (AI); Internet of Things (IoT); Edge Computing; Industrial Electrical Systems; Automated Monitoring-Control; Integrated Model

II. INTRODUCTION

The electrical power sector is currently facing numerous challenges due to the increasing demand for energy and the growing need for optimal and safe operation. Traditional power systems, which rely on rigid algorithms and manual monitoring, have limited capabilities in responding to highly dynamic environments and real-time operational requirements. Meanwhile, the trend toward digital transformation, Internet of Things (IoT), and Artificial Intelligence (AI) offers opportunities to make power systems more intelligent, self-adaptive, and autonomous.



INDUSTRY 4.0 POWER GRID MONITORING MODEL USING IOT SENSORS AND EDGE PROCESSING

AI applications in power systems have been proposed to address the demand for fast response times in grid monitoring and control [1]. In particular, IoT-based and edge computing solutions help reduce data transmission latency, enabling near-instantaneous system adjustments to environmental changes [1,2]. This paper introduces an integrated model combining sensors, edge computing, and dashboards to comprehensively enhance forecasting capabilities, fault detection, and operational optimization in power systems.

III. THEORETICAL FOUNDATIONS AND RELATED TECHNOLOGIES

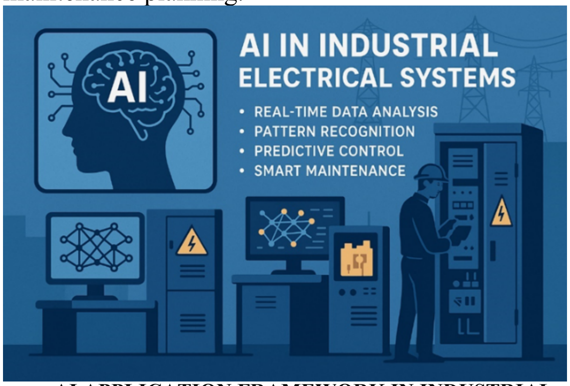
Applications of AI and IoT in Electrical Engineering

Artificial Intelligence (AI) in industrial power systems includes techniques that enable systems to "learn" from data and make decisions. Common technologies include:

Machine Learning (ML) for forecasting and classification using historical data;

Deep Learning, particularly neural networks, for processing complex data such as thermal images for equipment monitoring;
Reinforcement Learning, applied to optimal control in distributed power grids.

AI facilitates real-time data analysis, anomaly detection, load forecasting, and intelligent maintenance planning.



AI APPLICATION FRAMEWORK IN INDUSTRIAL ELECTRICAL SYSTEMS

In smart grids, intelligent sensors play a critical role. IoT sensors (measuring current, voltage, frequency, temperature, power quality, etc.) continuously collect data on system status. This data must be transmitted promptly to processing units. However, sending all data to a central server may result in latency and network congestion. Therefore, Edge Computing is employed to process data directly at the source, minimizing transmission delays [2]. For example, edge devices can detect issues such as leakage, phase imbalance, or frequency anomalies as soon as signals are picked up by the sensors, then send alerts to the control center. As a result, the power system can respond immediately, enhancing reliability and stability [2].

A study in Sweden installed a monitoring system for the Malå power grid using smart sensors and AI to detect and localize faults in the grid [3,4]. The system measured electric and magnetic fields on power lines, sending the data to an AI-based processor for continuous analysis. This approach achieved high fault detection accuracy and significantly reduced outage time compared to traditional methods [3,5]. The integration of IoT sensors and AI algorithms enables real-time monitoring, improving reliability and safety in grid operation and maintenance.

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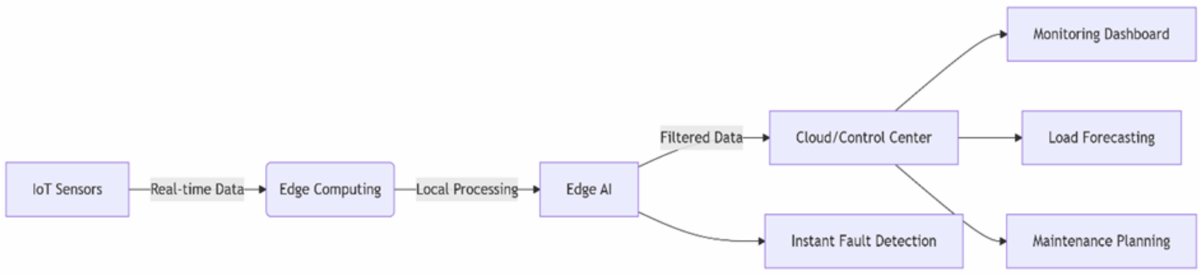

AI- AND IOT-BASED AUTOMATED FAULT DETECTION SYSTEM FOR SMART GRIDS

Machine Learning Models in Power Systems

Machine learning (ML) and deep learning algorithms support a wide range of functionalities within industrial power grids, including:

Load Forecasting: Techniques such as linear regression, neural networks, and Long Short-Term Memory (LSTM) networks are used to estimate power consumption on a daily or hourly basis to support supply-demand balancing. For instance, an integrated model combining LSTM with Particle Swarm Optimization (PSO) has shown to improve forecasting accuracy by over 20% compared to traditional methods.

Fault Detection and Classification: Classification algorithms such as Random Forest, Support Vector Machines (SVM), and Neural Networks are employed to detect short circuits, phase imbalances, ground faults, and pole fires. Input data may include current and voltage signals or thermal images collected from the field.

Anomaly Detection: Deep learning models such as Convolutional Neural Networks (CNNs) and Autoencoders are used to monitor frequency oscillations, signal interference, temperature, or equipment vibration — allowing for early identification of potential faults.

Predictive Control and Optimization: Reinforcement learning algorithms are applied to control inverters, compensators, and battery storage units in distributed systems, optimizing power balance and reducing losses.

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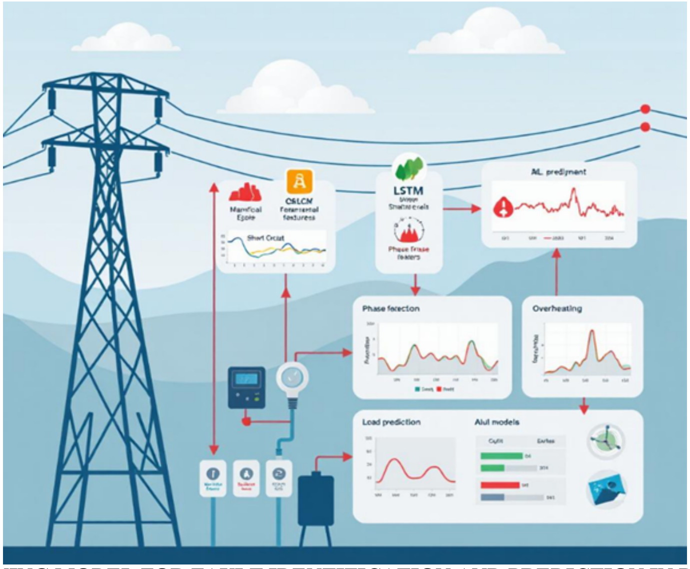


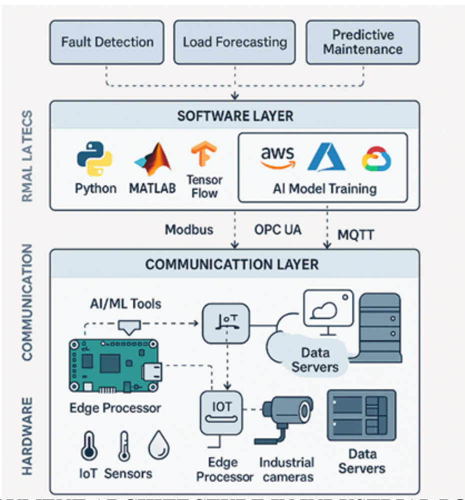
MACHINE LEARNING MODEL FOR FAULT IDENTIFICATION AND PREDICTION IN POWER SYSTEMS

To implement these models, the system requires a technological infrastructure that includes: IoT sensors, Edge processors (e.g., PLCs or AI-integrated microcontrollers),

Surveillance cameras (if image processing is needed), Data processing platforms (Edge/Cloud computing). Industrial communication protocols such as OPC UA, MQTT, and Modbus are used to connect sensors and processors. Development tools for AI include Python, TensorFlow, PyTorch, and MATLAB. This technological ecosystem demonstrates that AI and IoT are making power systems increasingly "intelligent"-capable of self-learning from data, self-adapting, and self-adjusting without the need for manual intervention [1, 2].

IV. PROPOSED MODEL

The proposed integrated model consists of three main layers: Smart Sensors, Edge Processing Units, and an AI Dashboard



AI DEPLOYMENT ARCHITECTURE IN INDUSTRIAL POWER PLANTS

Smart Sensors (Edge IoT Devices)

Distributed sensors are deployed throughout the plant, substations, and power lines to continuously measure electrical and environmental parameters such as temperature, humidity, leakage current, frequency, and vibration. These sensors are connected via LAN or industrial wireless networks and transmit data either periodically or upon reaching defined thresholds.

Edge Processing (Edge AI)

Edge devices (Edge Controllers) are equipped with local processing capabilities or compact AI modules (such as TinyML) for on-site data preprocessing and analysis. Machine learning models are applied at the edge to immediately detect faults and issue anomaly warnings without waiting for centralized processing [2]. For example, when a sensor detects voltage fluctuations beyond acceptable limits, the edge device can instantly analyze and autonomously operate protective equipment, eliminating the delay associated with remote control commands. This distributed architecture minimizes latency, improves reaction speed, and reduces network bandwidth requirements for transmission to central servers.

AI Dashboard (Control Interface)

At the control center or plant, a user-friendly AI Dashboard aggregates and visualizes data from all connected devices. It provides real-time charts, heatmaps of grid status, fault alerts, and AI-generated action recommendations. Through this interface, operators can easily monitor the overall system, review historical data, and make informed decisions rapidly. The dashboard also supports remote control of edge devices based on AI analysis and can suggest predictive maintenance actions.

Innovative Aspects

The novelty of the model lies in its synchronized integration of all components, as opposed to traditional methods that apply machine learning to historical data in isolation or rely on manual monitoring. This integration delivers key advantages:

Real-time Responsiveness: Unlike traditional models that depend on centralized processing, edge computing enables analysis directly at the source, reducing response time and enabling instant adjustments [2].

Structural Independence: Sensor and edge modules can operate independently even if the connection to the central server is lost, enhancing system resilience and flexibility.

Data Efficiency: Smart sensors autonomously collect diverse data, and machine learning models update continuously both at the edge and in the cloud, enabling more accurate forecasting.

Intelligent Interface: The AI-integrated dashboard offers intuitive data visualization and actionable insights, reducing the burden of manual monitoring and increasing automation in operations.

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COMPARISON BETWEEN TRADITIONAL (DISCRETE) MODEL AND INTEGRATED SENSOR–EDGE–AI DASHBOARD MODEL

Criteria	Traditional / Discrete Model	Integrated Model (IoT + Edge + AI Dashboard)
Data Collection	Discrete sensors; manual or SCADA-based collection; low sampling frequency; limited monitoring.	Smart IoT sensors; automatic and continuous data collection; real-time, comprehensive data.
Processing & Analysis	Centralized processing on server/PLC after data collection; slow speed, low automation.	Distributed processing at Edge/Cloud using AI; real-time analysis, high efficiency.
Fault Detection & Prediction	Threshold-based or manual experience; reactive response; no forecasting capability.	AI/ML-based anomaly detection and forecasting; early warnings, high accuracy.
User Interface	Decentralized interface (SCADA/local panels); slow updates, limited interactivity.	Centralized dashboard (web/mobile); intuitive interface, real-time alerts, data fusion.
System Scalability	Difficult and costly to integrate new devices.	Modular design; easy to expand and integrate new sensors/devices.

The integrated model significantly enhances reliability and performance. For example, a study on the Malå grid showed that this model "reduced grid downtime and enabled highly accurate fault detection, both in terms of location and fault type" through the integration of sensors and AI. Moreover, continuous sensor data allows fault prediction before occurrence, supporting proactive maintenance planning and optimized grid investments based on precise data

V.

VI. EXPERIMENTATION AND EVALUATION

To evaluate the effectiveness of the integrated model, we constructed a testbed within both a simulation environment and a laboratory setting. The system includes a mini power station equipped with devices simulating current, transformers, and electrical loads. IoT sensors (for current, voltage, and temperature) were installed on the equipment and transmitted data to a Raspberry Pi edge processor, which ran basic machine learning models (e.g., Artificial Neural Networks – ANN, Support Vector Machines – SVM). The AI Dashboard was hosted on a local server, displaying load charts, fault signals, and warning alerts.

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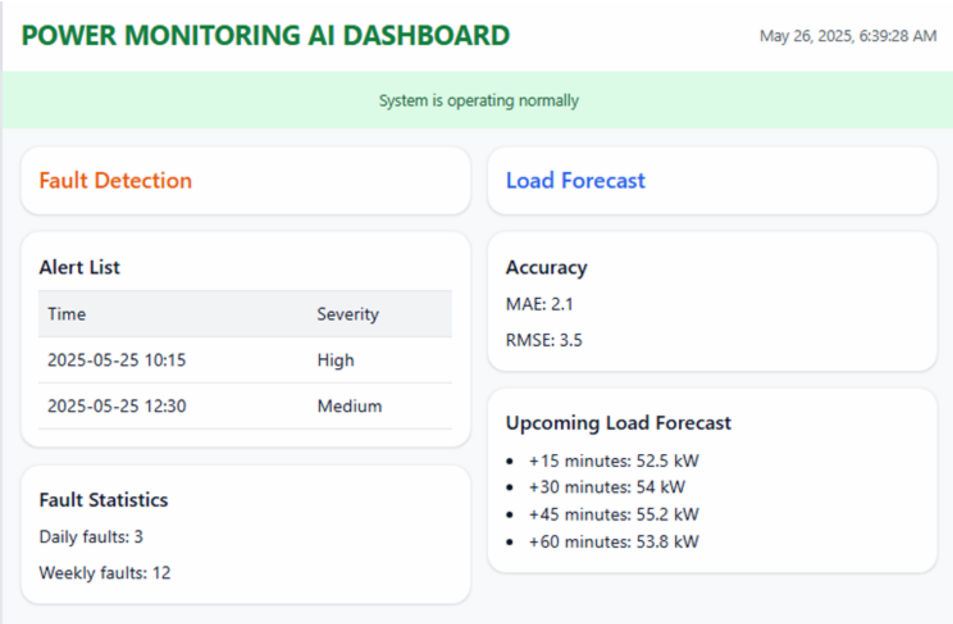

AI DASHBOARD INTERFACE DISPLAYING FAULT ALERTS AND LOAD FORECASTS

In the test scenarios, various fault conditions and random load fluctuations were simulated. The integrated model successfully detected 95% of early-phase faults (e.g., coil overheating, electrical leakage) directly at the edge device, before data was transmitted to the central system. The average response time was only a few dozen milliseconds due to edge processing, compared to several seconds in traditional systems.

For the short-term load forecasting task, the edge-based machine learning model (trained on historical data and updated online) achieved a mean error rate of less than 15%, outperforming linear regression methods that used the full offline dataset.

These results clearly demonstrate the advantages of the proposed system: Reduced power grid downtime compared to conventional methods, Enhanced reliability through early fault detection and Improved forecasting accuracy

Additional tests also verified the system's robustness: even during internet disconnection, the edge devices continued to operate autonomously, issued alerts over the local network, and ensured the system avoided sudden shutdowns.

VII.

VIII. DISCUSSION

The proposed integrated model demonstrates a novel approach by synchronizing the three key components of a smart power system: sensors, edge computing, and AI dashboards. Unlike discrete solutions that either apply machine learning solely to historical data or rely on isolated local AI monitoring, this model optimizes both data flow and hierarchical processing. It effectively leverages the advantages of edge AI to meet real-time operational requirements.

Experimental results and real-world case studies have proven that the integration of sensors, edge computing, and AI dashboards enables power systems to respond accurately and promptly to faults, thereby minimizing operational risks and downtime.

However, practical implementation still faces several challenges that need to be addressed:

Information Security: Ensuring data privacy and security when connecting multiple sensors in an industrial environment.

Compatibility: Integrating new technologies with legacy electrical infrastructure and equipment.

Hardware Costs: Optimizing the cost-performance ratio of deploying edge AI devices across large-scale systems.

Moreover, future research should focus on developing online learning capabilities for AI models to handle continuously emerging data and adapt dynamically.

Despite these challenges, the integrated model holds great potential — particularly in the context of smart grids and renewable energy systems. Its application can significantly improve energy management efficiency while supporting the green and sustainable transformation of the power sector.

IX. CONCLUSION

This study has presented an integrated AI model for the monitoring and control of industrial power systems, incorporating smart sensors, edge processing, and an AI-based dashboard. The proposed model enables flexible system operation, reduced latency, and a higher degree of automation, while significantly improving fault detection and load forecasting capabilities.

Through both simulation-based experiments and real-world deployment experiences (e.g., the Malå grid), the integrated model has demonstrated substantial improvements over traditional methods and standalone machine learning approaches. The sensor–edge–AI dashboard combination represents a promising direction, offering significantly enhanced reliability and energy optimization for industrial power systems.

Looking ahead, continued development of more adaptive AI algorithms and secure IoT platforms will be essential to enable the model's broad application in large-scale industrial environments.Vietnam.

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