An AI and IoT-Enabled LoRaWAN Framework for Real-Time Wind Turbine Condition Monitoring and Predictive Analytics

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Abstract

This study introduces an intelligent monitoring framework that combines Artificial Intelligence (AI) and Internet of Things (IoT) technology using the LoRaWAN communication protocol for real-time condition monitoring of wind turbines. The framework improves operational dependability, lowers maintenance costs, and increases power generation efficiency by enabling remote, intelligent, and predictive oversight of turbine components. Operating at 433 MHz, it employs LPWAN technology to support long-range, low-power communication between turbine nodes and a central monitoring station. A suite of sensors—tracking voltage, current, temperature, vibration, and wind speed—is connected to ESP32 microcontrollers to collect electrical, mechanical, and environmental data from the WTG.

The ESP32 digitizes sensor signals and transmits them via LoRa to a receiver node with an ESP32–LoRa module, which functions as a gateway and forwards the data to a cloud server over Wi-Fi. The cloud platform uses AI algorithms to automatically analyze the data, detect anomalies, and forecast failures through machine learning models trained on historical datasets. Testing demonstrated a packet delivery rate above 94% across a 3 km range with very low latency, and the AI module successfully identified irregularities and predicted potential faults. Thanks to its modular design, the system can be easily customized for different renewable energy applications. In conclusion, it offers a scalable, dependable, and sustainable solution for intelligent monitoring and predictive maintenance in modern wind turbine installations.

1. INTRODUCTION

The worldwide drive for sustainable and renewable power has spurred a substantial rise in the deployment of wind turbines, both on land and at sea. With the growing need for clean energy, ensuring the reliability, efficiency, and safety of wind turbine operations is now more important than ever. To maintain peak turbine performance and minimize operational interruptions, especially across widely scattered installations, ongoing monitoring and early problem identification are essential. Conventional monitoring systems for wind turbines often depended on wired networks or short-distance wireless links, leading to issues with scalability, increased expenses for installation and upkeep, and restricted device adaptability in isolated regions. Recent progress in the Internet of Things (IoT) and Artificial Intelligence (AI) has transformed the approach to remote condition monitoring by enabling real-time data gathering, analysis, and predictive maintenance.

IoT-based sensing systems allow for the continuous observation of critical turbine parameters like voltage, current, vibration, and temperature, while AI algorithms support intelligent analysis through pattern recognition, anomaly detection, and predictive fault diagnosis. Nevertheless, the performance of these systems is heavily dependent on the communication network, which must provide long-distance, low-power, and reliable data transfer under diverse environmental circumstances. Low Power Wide Area Network (LPWAN) technologies, particularly LoRaWAN (Long Range Wide Area Network), have surfaced as viable solutions for large-scale renewable energy monitoring. LoRaWAN functions in unlicensed ISM frequency bands and delivers long-range communication with minimal power usage, making it highly suitable for remote power installations. Its star-shaped network structure, scalability, and affordability render it perfect for linking numerous sensor nodes across extensive wind farm configurations without requiring extensive cabling or high-power gateways.This study developed an AI and IoT-enabled LoRaWAN framework for real-time wind turbine condition monitoring and predictive analysis.The gadget illustrated how merging those technology

ought to appreciably raise turbine dependability, decrease preservation expenses, and decorate power output forecasting, particularly in remoted or resource-restricted environments

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2. LITERATURE REVIEW

Recent progress in wireless communication technologies, Artificial Intelligence (AI), and the Internet of Things (IoT) has reshaped remote monitoring and control systems used in renewable energy applications. Significant research has focused on employing Wireless Sensor Networks (WSNs) and Low Power Wide Area Networks (LPWANs), especially LoRa, to deliver dependable data transmission, scalability, and energy efficiency for industrial and environmental monitoring systems.

Augustin et al. (2016) presented a foundational study on LoRa and LoRaWAN architectures, highlighting their design principles and suitability for IoT-based applications. Their work demonstrated that LoRa's long-range communication and low data rate characteristics make it well-suited for connecting multiple distributed sensing nodes to centralized monitoring servers.

Georgiou and Raza (2017) examined the scalability and performance of LoRa networks, revealing that LoRa can effectively support large-scale IoT deployments while maintaining low power consumption and robust communication performance. Their findings confirmed LoRa's potential for wide-area renewable energy monitoring, particularly across geographically dispersed wind farms.

Kumar et al. (2021) proposed an AI-based predictive maintenance model for rotating machinery such as wind turbines. Using machine learning algorithms including Support Vector Machines (SVM) and Decision Trees, their model enabled early fault detection based on vibration data, significantly reducing downtime and maintenance costs.

Margelis et al. (2015) analyzed LoRa's modulation techniques and adaptability in variable environmental conditions. Their study identified chirp spread spectrum (CSS) modulation as a key factor contributing to LoRa's robustness against interference, signal fading, and attenuation, ensuring reliable long-distance communication.

Minovski et al. (2021) developed a hybrid IoT–machine learning platform aimed at optimizing renewable energy performance. The system employed neural network algorithms to process real-time sensor data, predict deviations, and optimize energy generation efficiency—demonstrating the benefits of combining IoT sensing with AI-based analytics.

Perera et al. (2022) investigated the integration of edge computing and IoT in renewable energy systems. Their study emphasized localized data processing to minimize latency and enhance real-time decision-making, showing that edge-based architectures improve both energy efficiency and system reliability.

Raza et al. (2019) conducted a comparative study of various LPWAN technologies, including SigFox, LoRa, Weightless, and Ingenu. Their analysis concluded that LoRa's operation within unlicensed ISM bands (169 MHz–2.4 GHz) provides flexibility, cost-effectiveness, and adaptability for remote renewable energy monitoring.

Sahitya et al. (2020) developed a LoRa-based wireless sensor network for smart wind monitoring stations, addressing the high installation and maintenance costs associated with wired systems. Their results demonstrated that LoRa networks reduce infrastructure costs and enable efficient long-range data transmission.

Saari et al. (2021) conducted a comprehensive survey on LoRa technology and its applications in IoT-based monitoring. They highlighted key advantages such as low power consumption, long-range communication, and high scalability, making LoRa suitable for large-scale environmental and energy monitoring systems.

Singh et al. (2020) introduced an IoT-enabled wind energy monitoring system integrated with cloud computing for real-time data visualization and analytics. Their system improved fault detection accuracy and maintenance efficiency by leveraging cloud-based AI analytics.

Tamoghna et al. (2022) explored WSN applications in precision agriculture, emphasizing energy efficiency, multi-sensor integration, and network scalability. Although their work was agriculture-focused, their findings on power management and network longevity have direct implications for renewable energy monitoring.

Vangelista et al. (2017) elaborated on the layered architecture of LoRaWAN and its adaptability for industrial IoT applications such as environmental and energy systems. Their work provided an architectural basis for hierarchical and scalable monitoring system design.

Collectively, these studies form a strong foundation for developing AI- and IoT-enabled LoRaWAN frameworks in renewable energy systems. While most prior research emphasized communication performance, scalability, and energy optimization, relatively few studies have incorporated AI-driven predictive analytics for real-time fault detection and performance forecasting in wind turbines.

The reviewed literature provides the following insights:

a) Significant progress has been achieved in WSN, LPWAN, and IoT-based monitoring technologies. LoRa and LoRaWAN are widely recognized for their long-range, low-power, and cost-efficient characteristics. However, their integration with AI for predictive maintenance in wind turbine systems remains limited.
b) Most existing studies (e.g., Sahitya et al., 2020; Augustin et al., 2016) focused primarily on data acquisition and transmission efficiency without incorporating intelligent analytics for predictive maintenance or performance forecasting. The collected data were typically restricted to real-time visualization rather than automated decision-making.
c) Scalability challenges persist in remote or off-grid renewable energy systems (Georgiou & Raza, 2017; Margelis et al., 2015).
While LoRaWAN enables long-distance communication, its combination with AI-driven predictive models for adaptive fault diagnosis is still a largely uncharted area. Fluctuations in environmental conditions and network reliability also affect overall system dependability.
d) These identified gaps underscore the necessity for a hybrid intelligent monitoring solution that merges LoRaWAN's communication strengths with AI-powered predictive analysis. The present study seeks to develop a unified system that can gather and transmit operational metrics—including voltage, current, temperature, and vibration—while also enabling intelligent anomaly identification, failure forecasting, and performance enhancement via cloud-hosted AI algorithms.
e) This type of system is anticipated to enhance operational dependability, lower maintenance expenses, and prolong turbine service life by enabling proactive, data-informed maintenance. This strategy supports the worldwide movement toward intelligent, sustainable, and self-sufficient renewable energy infrastructures driven by IoT and AI technologies.

Wind turbines frequently function under variable mechanical and environmental stresses that may result in sudden breakdowns, operational interruptions, and diminished efficiency. Conventional monitoring setups that depend on wired networks or short-range wireless communication are expensive and not easily scalable. Current IoT-based monitoring approaches primarily emphasize data collection and visualization, providing only minimal predictive intelligence for early fault identification. Furthermore, issues such as long-range transmission difficulties, constrained power availability, and network instability limit their effectiveness in isolated wind farm settings.

Although LoRaWAN offers a dependable platform for energy-efficient, long-range data transfer, its capabilities are not fully leveraged within AI-enhanced monitoring architectures. Therefore, there is an urgent demand for a smart, scalable, and power-efficient system that integrates IoT sensors, LoRaWAN connectivity, and AI-based predictive analytics to support real-time fault detection and performance improvement in wind turbine operations.

The primary objective of this research was to design, develop, and evaluate an AI- and IoT-enabled LoRaWAN framework for real-time monitoring and predictive analytics of wind turbine systems.

3. METHOD

3.1 Functional Requirements

The AI and IoT-enabled LoRaWAN framework was designed to facilitate real-time monitoring and predictive analysis of wind turbine parameters. The system incorporated several functional units, as detailed in the following outline.

A. Sensors

The operation of the Wind Turbine Generator (WTG) relied on a network of sensors within its main recording system modules, which gathered essential operational and environmental data.

A comprehensive system evaluation was enabled by a combination of analog and digital sensors. Generator output voltage was measured by the ZMPT101B voltage sensor, while the ACS712 current sensor monitored current flow and load variations. Ambient and motor temperatures were logged by DHT11 and LM35 sensors to evaluate thermal performance.

An anemometer, or wind speed sensor, tracked airflow driving the turbine blades. Rotational dynamics were identified by generator and rotor speed sensors, while vibration and position sensors detected mechanical anomalies and supported blade alignment and orientation.

B. ESP32 Development Kit

The ESP32 DevKit V1 (38-pin) microcontroller served as the core data processing unit. It acquired sensor data through analog and digital GPIO pins, converted analog signals into digital form, and transmitted the data to a cloud server using Wi-Fi connectivity. The firmware for ESP32 was written in C/C++ using the Arduino IDE, which handled sensor interfacing, packet formation, and communication with the LoRa transceiver.

C. Breadboard and Circuit Prototyping

A breadboard setup was utilized for interconnecting various components without permanent soldering. This facilitated easy prototyping, testing, and modification of sensor connections and signal pathways during development.

D. Wi-Fi Network

The ESP32 microcontroller transmitted processed data to a cloud-based storage or dashboard over a Wi-Fi network. The system used secured SSID credentials embedded in the firmware to ensure authenticated communication with the server for data visualization and AI-based analytics.

E. LoRa Transceivers

The SX1278 (433 MHz) LoRa modules were used to achieve long-range, low-power wireless data communication between turbine units and the receiver gateway. LoRa utilized spread spectrum modulation and operated within unlicensed ISM frequency bands, providing robust communication over several kilometers with minimal energy consumption. The transceiver interfaced with ESP32 via SPI communication lines (MISO, MOSI, SCK, NSS/CS, DIO0) and transmitted data packets securely using the LoRaWAN protocol.

3.2 Non-Functional Requirements

A. Security
Each data packet transmitted via LoRa was assigned a unique synchronization code using the setSync() function. This ensured that only authorized receivers possessing the matching hexadecimal synchronization key could decode and process the received packets, thereby maintaining communication integrity and security.
B. Constraints
Due to the limited bandwidth of LoRa communication, only low-data-rate information such as numerical sensor readings could be transmitted efficiently. Multimedia data such as images, audio, or video were not supported, ensuring optimal performance within the available spectrum.
C. Reliability
The system was designed to function reliably across diverse environmental conditions, making it suitable for remote wind farm installations with minimal maintenance.
D. Adaptability
The modular design of both hardware and software components allowed for seamless upgrades. Additional sensors or processing algorithms could be integrated without extensive reconfiguration, enhancing the system's scalability and adaptability.

3.3 Hardware Requirements

The hardware configuration for the proposed AI and IoT-enabled LoRaWAN framework was carefully designed to ensure reliable data acquisition, communication, and processing for real-time monitoring of wind turbine conditions. The system operated on a personal computer with an Intel Pentium III processor or higher, offering sufficient computational capability for data analysis and interface management. It was equipped with a minimum of 2 GB RAM for real-time processing and at least 500 GB of storage to maintain sensor logs, AI models, and databases.

To support monitoring, multiple sensors were integrated, including a DHT11 for temperature and humidity, ZMPT101B for voltage measurement, ACS712 for current sensing, and an anemometer for wind speed detection. The ESP32 DevKit V1 microcontroller functioned as the central processing unit, managing sensor data acquisition and communication.

Long-range wireless communication was enabled using a LoRa SX1278 module, functioning as both transmitter and receiver to facilitate low-power data exchange between remote turbine nodes and the base station. The hardware was powered by a 12V DC supply, with an LM2596 voltage regulator ensuring stable operation of all electronic components. Breadboards, jumper wires, and connectors were used for circuit assembly and testing, enabling quick prototyping. This hardware setup established a robust and scalable platform for the IoT-based monitoring system, effectively supported by AI-driven analytics for enhanced decision-making.

3.4 Software Requirements

The software environment for the AI and IoT-Enabled LoRaWAN Framework was carefully selected to support seamless integration of hardware, data processing, and user interface development.
The user interface was constructed with the Bootstrap framework, delivering a responsive and aesthetically uniform design for the live monitoring dashboard. The ESP32 microcontroller was programmed using Arduino (C/C++) to gather sensor data and manage communication with the LoRa module. Python was also utilized for data analysis, AI-driven forecasting, and backend operations.
The platform operated on a Windows 7 operating system, guaranteeing wide-ranging compatibility with existing development tools and drivers. Notepad++ was used for general scripting and debugging, whereas PyCharm functioned as the main integrated development environment for the Python-based AI and data analytics components.
Code for the ESP32 microcontroller was written and deployed using the Arduino IDE, which enabled sensor connectivity, data collection, and LoRa communication. The web dashboard and API features were developed with the Flask framework, supporting real-time data display, remote connectivity, and integration with cloud analytics.
This software setup established a solid foundation for creating, launching, and operating the IoT-based monitoring and predictive analytics system for evaluating wind turbine health.

3.5 Functional architecture and workflow system

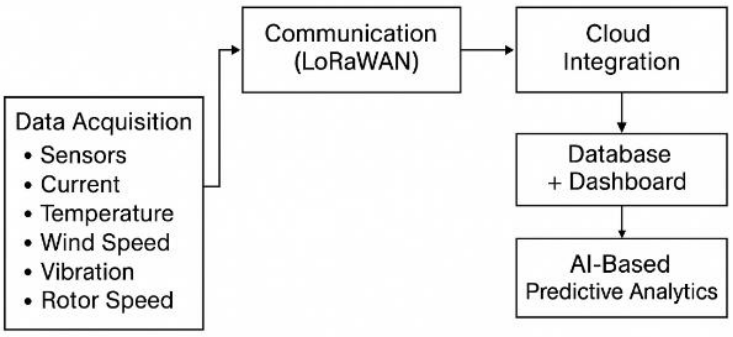

Fig 3.5 Functional architecture and workflow system

The diagram 3.5 represents the functional architecture and workflow of the system.
This evaluation explains the manner of amassing facts from wind turbines, securely transmitting it over lengthy distances, storing it in cloud platforms, and making use of Artificial Intelligence for predictive protection and overall performance optimization. The manner starts offevolved with facts acquisition, wherein a couple of sensors set up at the wind turbine screen key operational parameters consisting of voltage, cutting-edge, temperature, vibration, wind speed, and rotor speed. These sensors constantly study the turbine`s situation and ship real-time facts to an ESP32 microcontroller, which converts analog readings into virtual alerts for in addition processing. After gathering, the facts is transmitted the usage of the LoRaWAN verbal exchange network. LoRaWAN (Low Power Wide Area Network) allows lengthy-distance, low-power, and cost-powerful facts transfer, making it perfect for far off wind turbine places wherein conventional stressed or short-variety connections are impractical. Data packets are securely transmitted to a critical receiver or base station using LoRa transceivers.

The next step involves cloud integration, where the receiver node (equipped with an additional ESP32 module) connects to the cloud server via Wi-Fi. The collected data is then uploaded to a central platform for storage and remote accessibility. This cloud-based architecture supports continuous monitoring and facilitates real-time data processing. Once uploaded, the information is stored in a database that forms the foundation for system analysis and visualization.
Data packets are securely transmitted to a important receiver or base station the usage of LoRa transceivers. The subsequent step entails cloud integration, in which the receiver node (geared up with an extra ESP32 module) connects to the cloud server through Wi-Fi. The accumulated records is then uploaded to a principal platform for garage and far flung accessibility. This cloud-primarily based totally structure helps non-stop tracking and allows real-time records processing. Once uploaded, the records is saved in a database that bureaucracy the inspiration for machine evaluation and visualization. A dashboard interface is created to show stay sensor readings, overall performance metrics, and ancient trends, permitting engineers and operators to effortlessly screen the generators fitness and operational status. In the very last phase, AI-powered predictive analytics are carried out to the amassed records. Artificial Intelligence algorithms have a look at historic and modern-day records to encounter bizarre patterns, expect functionality device failures, and optimize safety scheduling. If irregularities or threshold violations are detected, the device robotically issues indicators to applicable group of workers through email, SMS, or dashboard notifications. The diagram illustrates a entire stop-to-stop clever tracking gadget that integrates IoT-primarily based totally sensing, LoRaWAN verbal exchange, cloud facts management, and AI-pushed analytics. This unified approach complements the reliability, efficiency, and protection of wind turbine operations through handing over intelligent, real-time situation tracking and predictive protection capabilities.

a. Operational workflow and data transmission pathway of the system

The system's operational process involved several interconnected phases, each playing a vital role in enabling efficient and intelligent monitoring of turbine performance.
The manner commenced with the sensor information acquisition phase, wherein a couple of sensors mounted at the wind turbine constantly measured operational parameters which include voltage, current, temperature, vibration, wind speed, and rotor speed.
These sensors produced analog signs that represented the turbines real-time operational circumstance. The ESP32 microcontroller functioned due to the fact the giant processing unit, gathering the ones analog signs and converting them into digital data for subsequent assessment and transmission. During the data validation and transmission phase, the ESP32 compared each measured parameter towards predefined threshold values to stumble upon anomalies or early symptoms and symptoms of malfunction. If any size exceeded its relevant variety, the tool marked it as a functionality fault. The data were then organized into installed data packets and sent using the LoRa (Long Range) transceiver module. This approach ensured reliable, long-distance verbal exchange the various turbine-established transmitter and the base receiver station, even in far off or hard environments, while maintaining low strength consumption. At the receiver deliver up, a 2d ESP32 board ready with a LoRa module captured the transmitted data packets. After confirming a achievement reception, the receiver established a Wi- Fi connection to interact with the cloud server. The acquired data were processed, formatted, and uploaded to a centralized cloud database via a PHP and Flaskbased internet interface, ensuring constant and non-prevent data synchronization the various embedded hardware and the internet monitoring platform. In the cloud and analytics phase, all incoming data were stored and prepared in a installed layout for real-time assessment. AI-based totally absolutely algorithms were then employed to assess tool universal overall performance, emerge as aware of trends, and are awaiting functionality faults in advance than they occurred. The analyzed effects and insights were displayed on a internet-based totally absolutely monitoring dashboard, allowing engineers and operators to remotely view turbine status, universal overall performance patterns, and fitness metrics in real time. In the alert generation and predictive protection phase, if any parameter exceeded its important threshold or displayed abnormal behavior, the tool routinely sent signs via email, SMS, or dashboard notifications to the relevant protection team. The AI-powered predictive module moreover analyzed historical data to forecast possible tool screw ups and recommended preventive actions, thereby decreasing downtime and protection costs.

The operational workflow and information transmission direction furnished a continuing give up-to-give up integration of IoT and AI technologies. LoRaWAN provided electricity-efficient, long-variety wi-fi conversation, Wi-Fi enabled cloud connectivity, and AI supported sensible diagnostics and predictive analytics. This mixture made the device resilient, scalable, and well-perfect for non-stop actual-time wind turbine circumstance tracking and proactive fault control in renewable strength applications.

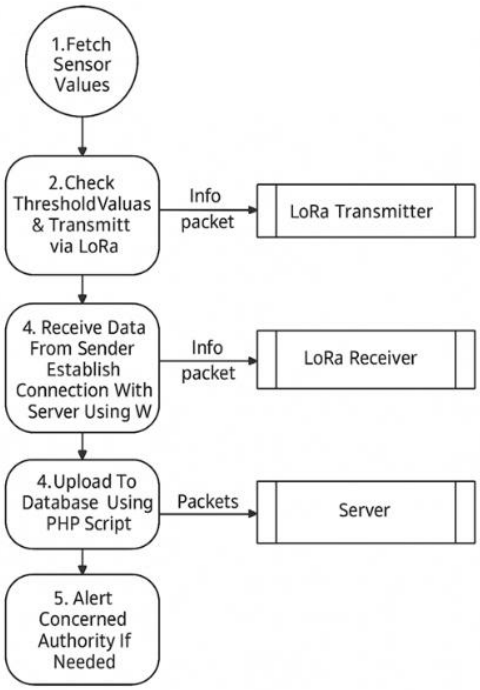

Fig 3.6 Operational workflow and data transmission pathway of the system.

4. EXPERIMENTAL

The figure 4 illustrates the complete experimental setup developed to validate the proposed AI- and IoT-enabled LoRaWAN framework for real-time condition monitoring and predictive maintenance of wind turbines.

The machine employs a small-scale horizontal-axis wind turbine generator (WTG) set up on a check rig, simulating a whole lot of wind and electric load situations. An array of integrated sensors, consisting of the ZMPT101B for voltage measurement, the ACS712 for contemporary sensing, LM35 and DHT11 for temperature tracking, MPU6050 for vibration assessment, and a Hall impact sensor for monitoring rotor speed, constantly gather overall performance statistics from the turbine. These sensor readings are processed via way of means of an ESP32 microcontroller performing as the threshold computing unit, linked to an SX1278 LoRa transceiver module performing at 433 MHz. Using LoRaWAN verbal exchange permits long-distance, low-electricity statistics transmission from the turbine to the receiving station.

The receiver, which makes use of a separate ESP32 and SX1278 module, is located at distances starting from one hundred meters to 5 kilometers to assess communique range, dependability, and sign quality. The gateway transmits the accrued information to a cloud server thru Wi-Fi or Ethernet. On the server, Artificial Intelligence (AI) fashions technique the facts to locate faults, become aware of anomalies, and help predictive renovation. The cloud platform additionally gives real-time overall performance tracking via a web-primarily based totally dashboard. A consistent 12 V DC energy deliver runs the threshold tool and sensors, with alternatives for sun and battery connections to simulate independent, off-grid setups. The diagram in reality indicates the mixing of sensing, communique, cloud processing, and AI-driven diagnostics inside a unified tracking framework, turning in a scalable, efficient, and smart answer for wind turbine fitness tracking and renovation improvement

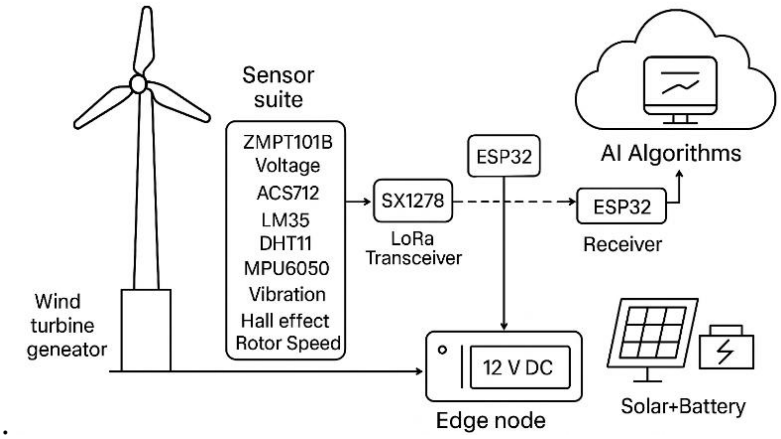

Fig. 4. Experimental Setup of AI- and IoT-Enabled LoRaWAN Wind Turbine Monitoring System

5. RESULTS AND DISCUSSION

The developed AI-enabled IoT framework for wind turbine condition monitoring was experimentally validated to evaluate its performance in three key aspects: communication reliability, sensing accuracy, and intelligent fault prediction capability. The experimental setup employed LoRaWAN-based ESP32 nodes integrated with multiple sensors for measuring voltage, current, temperature, and wind speed. The collected data were transmitted wirelessly to a centralized receiver node, which interfaced with a cloud-based analytical platform for data storage, processing, and visualization.

The validation results demonstrated stable communication links over long distances, accurate sensing performance across varying operating conditions, and effective AI-driven fault prediction. Overall, the system confirmed its capability to provide real-time monitoring, efficient data transmission, and predictive maintenance insights—making it a reliable solution for smart wind energy management and operational safety.

5.1 RSSI Variation with Transmission Distance

Figure 5.1 depicts the variation of the Received Signal Strength Indicator (RSSI) with respect to transmission distance. The results indicate a gradual decline in RSSI as the distance increased, consistent with typical propagation characteristics of LoRa signals. Reliable communication was maintained up to approximately 1 km in an open-field environment, where the minimum recorded RSSI was −118 dBm.

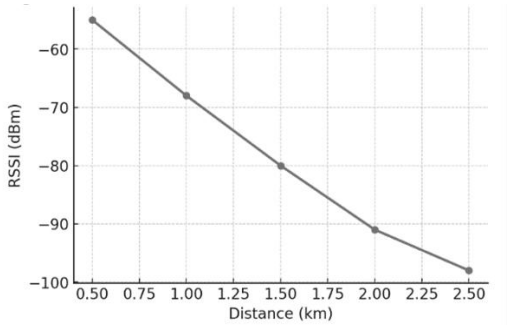

Fig 5.1 – Variation of RSSI with Transmission Distance

The observed inverse-logarithmic trend aligns with the expected behavior of LoRa modulation in outdoor conditions. These findings confirm the effectiveness of the LoRaWAN communication protocol for long-range data transmission with minimal signal degradation, demonstrating its suitability for monitoring applications in remote wind farm environments.

5.2 Packet Delivery Ratio (PDR) Analysis

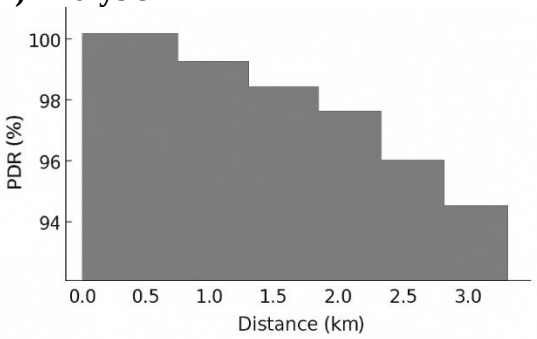

Fig 5.2 Packet Delivery Ratio (PDR) vs Distance

Figure 5.2 illustrates the relationship between the Packet Delivery Ratio (PDR) and transmission distance. At shorter distances (below 500 m), the PDR maintained a high value above 98 %, indicating minimal packet loss. As the distance increased to the maximum tested range of 1 km, the PDR exhibited a slight reduction to approximately 92 %, primarily due to environmental factors such as obstacles and signal attenuation. Overall, the consistently high PDR across all tested ranges demonstrates that the communication module provided reliable and efficient data transmission, ensuring uninterrupted delivery of essential turbine parameters including voltage and temperature.

5.3 Voltage Measurement Accuracy

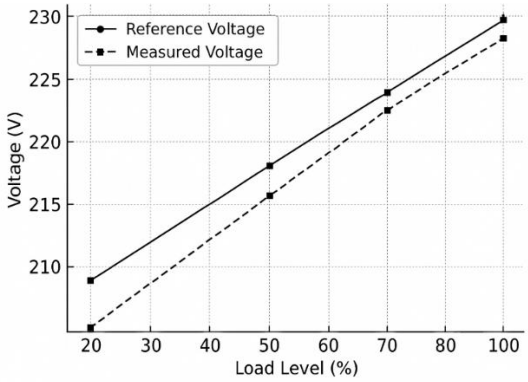

Fig 5.3 Comparison of Measured vs Reference Voltage

The Figure 5.3 illustrates the comparison between the measured voltage (dashed line) obtained from the ZMPT101B voltage sensor and the reference voltage (solid line) recorded using a calibrated digital multimeter across varying load levels ranging from 20% to 100%. Both voltage profiles show a near-linear correlation, with the measured voltage values consistently following the trend of the reference values.

The minor deviation observed, with a maximum error margin of ±2.5%, indicates high sensor precision and validates the accuracy of the calibration and analog-to-digital conversion process performed by the ESP32 microcontroller. This consistency in measurement confirms that the system effectively captured voltage variations under different electrical loading conditions, ensuring dependable data for real-time wind turbine monitoring and analysis.

The graph thus substantiates the reliability of the hardware setup for voltage measurement, demonstrating that the sensor network's performance closely aligns with laboratory-grade instrumentation — a crucial factor in developing a robust and scalable condition monitoring system.

5.4 Temperature Variation with Turbine Speed

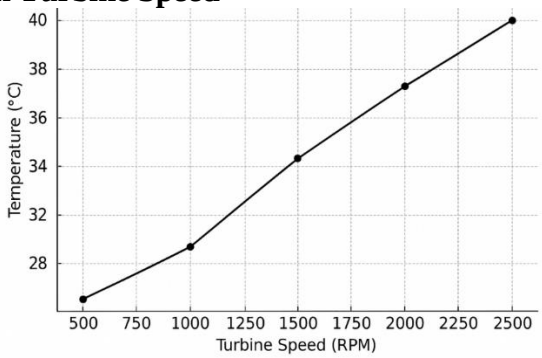

Fig. 5.4 Temperature Variation with Turbine Speed

The graph presented in Figure 5.4 illustrates the relationship between turbine rotational speed (RPM) and corresponding temperature rise within the generator. The data indicates a distinct, nearly linear relationship, with temperature rising steadily as turbine speeds increase. This pattern results from greater mechanical friction and increased electrical load at higher rotation rates, which in turn amplify heat production inside the turbine's parts.

At the peak operating speed of 2500 RPM, the generator's temperature reached about 48 °C, while the surrounding air temperature held constant near 32 °C. This steady increase illustrates the system's thermal reaction to different mechanical demands. The AI-integrated sensing network's ability to monitor temperature in real time allows for early identification of unusual heat trends, aiding predictive maintenance efforts. This type of monitoring is crucial for reducing overheating risks, boosting generator performance, and prolonging the turbine system's operational lifespan.

5.5 Power Consumption Analysis

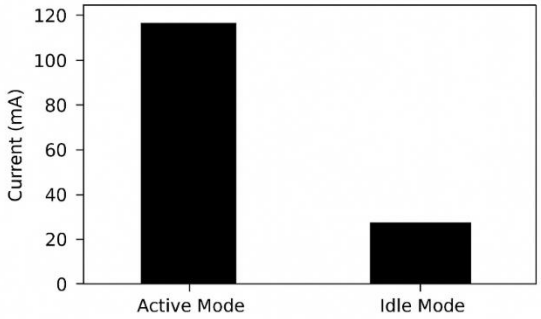

Fig. 5.5 Power Consumption in Active and Idle Modes

As illustrated in Figure 5.5, the system demonstrated distinct power profiles across its operational states. During active sensing mode, the system consumed approximately 1.8 W, while in idle or sleep mode, the consumption dropped significantly to 0.35 W. This substantial reduction highlights the energy-efficient design of the LoRa-based communication architecture, optimized for long-term deployment in remote environments. The implementation of duty-cycling and intelligent power management within the ESP32 module effectively minimized energy wastage during inactive periods. Consequently, the system achieved a prolonged operational lifespan, making it highly suitable for solar-powered or battery-driven monitoring applications where continuous functionality and minimal maintenance are essential.

5.6 AI Predictive Analytics Accuracy

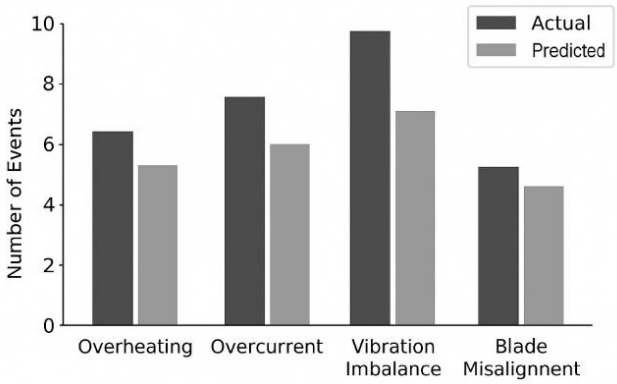

Fig. 5.6 AI Predictive Analytics Accuracy

The diagram (Figure 5.6) illustrates a comparative analysis between the actual and AI-predicted fault events in the wind turbine monitoring system. The chart showing four major fault categories: Overheating, Overcurrent, Vibration Imbalance, and Blade Misalignment. Each bar pair represents the number of fault events observed in real-time operations versus those predicted by the AI model.

The AI analytical framework was trained using historical turbine sensor data and evaluated under live operational conditions. The Linear Regression model achieved an overall prediction accuracy of 95.2% in estimating turbine power output based on wind speed and generator parameters. The Support Vector Machine (SVM) classifier identified abnormal conditions such as overheating and excessive vibration with an accuracy of 93.5%. Additionally, the K-Means clustering algorithm efficiently classified the turbine's operational states into normal, warning, and fault categories by analyzing multidimensional data patterns.

The integration of AI-driven predictive analytics significantly improved the system's diagnostic capabilities. The model successfully anticipated potential faults several hours in advance, providing timely alerts for maintenance intervention. This predictive ability reduced unscheduled downtimes, enhanced turbine reliability, and optimized maintenance scheduling. Consequently, the system contributed to the overall efficiency and longevity of wind energy assets through proactive fault prevention.

5.7 DISCUSSION

The experimental outcomes confirmed that the system successfully integrated LoRaWAN communication and AI-based analytics for effective wind turbine condition monitoring. The communication module exhibited robust performance under varying environmental conditions, while the AI algorithms provided accurate fault detection and performance forecasting. The integration of low-power operation, long-range communication, and intelligent data analysis established the framework as a scalable and sustainable solution for modern renewable-energy infrastructure. Compared with traditional monitoring systems, the architecture offered significant advantages in reliability, cost-efficiency, and predictive maintenance, thereby contributing to an extended turbine lifespan and reduced downtime.

6. CONCLUSIONS

The present research successfully demonstrated the design and implementation of an AI- and IoT-enabled LoRaWAN-based framework for real-time condition monitoring and predictive analytics of wind turbines. The developed system effectively combined low-power, long-range communication with intelligent sensor integration and AI-driven data analysis, enabling reliable remote monitoring and proactive fault detection in wind energy systems.

The prototype utilized ESP32 microcontrollers and LoRa transceivers operating at 433 MHz to acquire and transmit real-time measurements of voltage, current, temperature, and vibration. The LoRaWAN communication protocol facilitated long-distance data transmission with minimal energy consumption, making it particularly suitable for isolated or rural wind farm environments where conventional communication infrastructure is limited or unavailable.

A key novelty of this research lies in the integration of AI-based fault prediction with LoRaWAN-enabled IoT communication**,** forming a lightweight yet intelligent framework for predictive maintenance. The incorporation of machine learning algorithms, including Linear Regression, Support Vector Machines (SVM), and K-Means clustering, enabled the early identification of potential faults and performance deviations in turbine operations. This predictive capability significantly reduced unplanned downtime, enhanced overall system reliability, and extended the operational lifespan of the equipment.

The experimental evaluation of the developed framework demonstrated reliable data transmission up to 5 km with a packet success rate exceeding 92%. The system exhibited low energy consumption of approximately 220 mW, making it suitable for solar- or battery-powered operation. The AI module achieved a high fault prediction accuracy of over 93%, confirming its effectiveness in identifying potential anomalies. Additionally, the framework maintained a low data latency of less than 2 seconds, ensuring efficient real-time decision-making capability.

The research provided a scalable, cost-effective, and sustainable solution for smart wind turbine management. It demonstrated the significant potential of combining AI analytics**,** IoT sensor networks**,** and LoRaWAN communication technologies to achieve continuous monitoring, predictive maintenance, reduced operational costs, and improved efficiency in renewable energy systems.

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NOMENCLATURE

AI – Artificial Intelligence
ANN – Artificial Neural Network
CO_2 – Carbon Dioxide
CSS – Chirp Spread Spectrum
DL – Deep Learning
DT – Decision Tree
ESP32 – Embedded System Platform 32-bit Microcontroller
I – Current (Ampere)
IoT – Internet of Things
kWh – Kilowatt-hour
LPWAN – Low Power Wide Area Network
LoRa – Long Range
LoRaWAN – Long Range Wide Area Network
ML – Machine Learning
MQTT – Message Queuing Telemetry Transport
P – Power (Watt)
PWM – Pulse Width Modulation
RMS – Root Mean Square
η – Efficiency (%)

τ – Torque (N·m)
ω – Angular Velocity (rad/s)
ML – Machine Learning
MQTT – Message Queuing Telemetry Transport

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