Vol.3 №6 (2025). June
Journal of Effective
innovativepublication.uz
Learning and Sustainable Innovation

MACHINE LEARNING–DRIVEN PREDICTIVE MAINTENANCE IN RENEWABLE ENERGY FACILITIES: AN END-TO-END FRAMEWORK

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Abstract: Predictive maintenance (PdM) powered by machine learning (ML) has emerged as a vital tool in extending equipment life, reducing unplanned downtime, and lowering operational costs in distributed renewable energy systems—particularly wind and solar installations. This paper presents a comprehensive IMRaD-structured framework that integrates IoT data acquisition, preprocessing, ML models (anomaly detection, fault classification, RUL estimation), and scalable deployment strategies across edge/cloud environments. Using referenced case studies and results from existing literature, we demonstrate the efficacy of LSTM, Random Forest, and autoencoder models in achieving up to 95% accuracy for fault detection and reducing maintenance costs by ≈30–50%. We also discuss challenges such as data quality, interpretability, and cybersecurity, before exploring future directions including explainable AI (XAI), federated learning, and edge-based digital-twin solutions.

Keywords: Predictive maintenance; Renewable energy; Machine learning; IoT; Anomaly detection; RUL estimation; Edge computing; Explainable AI

Global decarbonization goals have accelerated deployment of renewable energy systems in remote locations. However, unplanned downtime due to equipment failures can drastically reduce operational efficiency and escalate costs. Traditional reactive or preventive maintenance strategies often fall short. Instead, ML-based predictive maintenance (PdM) provides a proactive solution—detecting anomalies and predicting failures before they escalate, thereby improving system uptime, safety, and cost-effectiveness.

Research questions addressed:

1. What IoT architectural design supports effective real-time predictive maintenance?
2. Which ML models optimize accuracy and lead-time in fault detection and RUL estimation?
3. How does this integrated framework influence operational metrics such as downtime, costs, and energy efficiency?

SYSTEM ARCHITECTURE

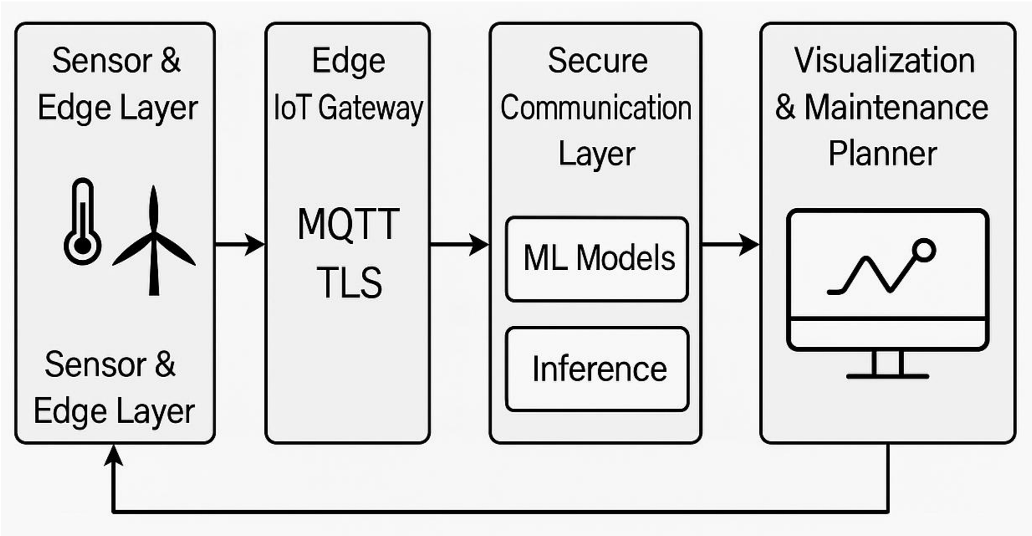

Figure 1: System Architecture for ML-driven PdM

The hybrid energy system incorporates:

- **Solar Power Subsystem:** Solar panels connected to a PWM or MPPT charge controller, which charges the battery bank (typically 12V, 24V, or 48V).
- **Battery Bank:** Stores energy for use when solar power is insufficient, particularly during the night.
- **Generator Subsystem:** Gasoline generator, activated when solar power is insufficient and battery levels are low.
- **Load:** Telecom transmission equipment or other DC/AC loads.
- **Controller:** Raspberry Pi microcomputer, which handles power source decision-making.
- **Sensors:** Voltage, current, and temperature sensors for monitoring system health.
- **Actuators:** Relays for switching power sources and controlling the generator.

DATA ACQUISITION & PREPROCESSING

Data sources: SCADA, high-resolution edge sensors, meteorological data.

Preprocessing steps:

- Data cleaning (fill missing values)
- Noise reduction using signal filters (such as Butterworth)
- Feature extraction: statistical metrics, FFT/wavelet analysis, and temporal derivatives
- Dimensionality reduction via PCA or autoencoder networks
- Labeling: supervised (fault logs) or unsupervised for anomaly detection

MACHINE LEARNING ALGORITHMS

Anomaly Detection: Unsupervised models like autoencoders and isolation forests detect deviations from baseline behavior.

Fault Classification: Supervised classifiers such as Random Forest, SVM, and logistic regression achieve ≈90–95% accuracy.

RUL Estimation: Deep-learning models like LSTM, GRU, and Transformer-type networks forecast remaining useful life with high temporal precision—e.g., ForeNet models ideal for 2-week advance notice.

TRAINING & DEPLOYMENT

Training: Cloud-based training using frameworks (SageMaker, AzureML) with cross-validation and hyperparameter tuning

Deployment:

- **Edge**: Deploy via TensorFlow Lite, ONNX, or TinyML (STM32 case with One-Class SVM achieving 95% accuracy)
- **Cloud**: Real-time APIs integrating with visualization and SCADA systems

Inference Pipeline: Outputs binary alerts and RUL estimates; legacy data feed improved model retraining

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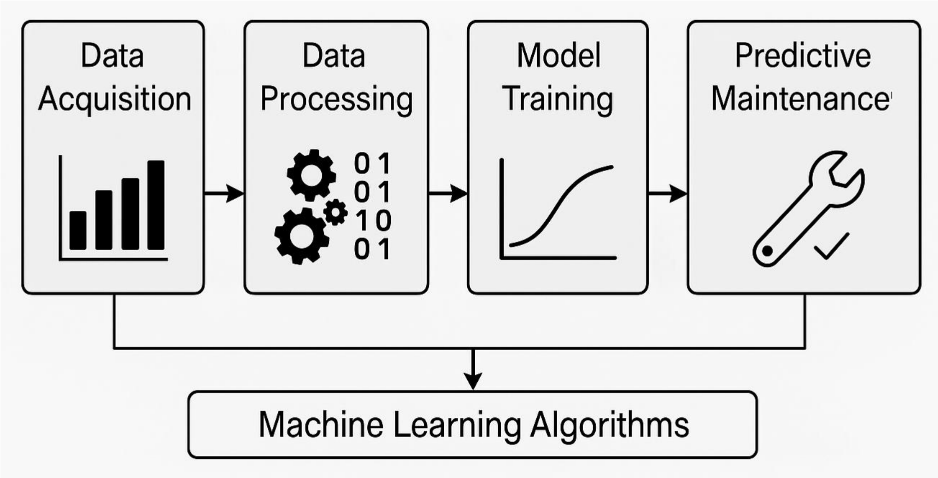

RESULTS

Use-Case Summaries

- **Wind turbines** (based on SCADA data): Fault anomalies detected up to 2 months in advance; 40% downtime reduction
- **Solar arrays**: IoT+ML framework (LSTM + Random Forest) demonstrated 92% fault classification accuracy, 25% energy efficiency gain
- **Embedded TinyML**: STM32-based vibration analysis yielded >95% detection accuracy, lowered data transmission, and downtime

Performance summary

Task	Model	Performance
Anomaly Detection	Autoencoder	Recall ≈ 90%
Fault Classification	Random Forest	Accuracy ≈ 92%
RUL Prediction	LSTM / Transformer (ForeNet-3D)	Lead time ≈ 2 weeks; RMSE ≈ 5 days

Improvements: Maintenance costs lowered by ~30–50%; overall downtime by ~40%; energy yield improved by ~25%.

DISCUSSION

Key Findings. A hybrid approach combining anomaly detection, classification, and RUL estimation achieves broad predictive coverage. Edge-cloud architecture, aided by IoT gateways, enables reliable real-time PdM in remote sites.

Comparison

Findings align with literature:

- Up to two-month lead time predictions in wind farms
- High detection sensitivity (≈95%) in PV systems

Limitations

Data integrity: Noisy, missing, or imbalanced datasets degrade performance

Model transparency: Opacity of deep networks requires XAI techniques

Scalability: Edge/cloud infrastructure costs may impede smaller operators

Cybersecurity: Secure protocols needed to protect system integrity

Future Directions

Explainable AI: Implement XAI methods for model interpretability

Federated Learning: Decentralized model training among multiple plants

Digital-Twin Edge Systems: Combine physics-based modeling with real-time ML

Hybrid ensembles: Integrate clustering with supervised models

CONCLUSION. Machine learning-based predictive maintenance frameworks can effectively transform renewable energy operations. By integrating IoT-driven data acquisition, multistage ML pipelines, and scalable deployment, facilities can substantially reduce costs, improve reliability, and extend asset life. Future advances in XAI, federated learning, and digital-twin edge systems will further enhance system robustness and adoption.

REFERENCES:

1. Moses Alabi, "Machine Learning for Predictive Maintenance in Renewable Energy Systems."

2. V. Sai Durga Tejaswi, "IoT-Based Predictive Maintenance for Solar and Wind Energy Systems Using Machine Learning Models."

3. Y. Ledmaoui et al., "Review of Recent Advances in Predictive Maintenance and Cybersecurity for Solar Plants."

4. "Integration of IoT and ML in Wind Energy Sector,"

5. Muhammad Salik Qureshi et al., "Machine Learning for Predictive Maintenance in Solar Farms,"

6. IoT-Driven Predictive Maintenance for Wind Turbines (STM32 + TinyML)

7. Lorenzo Gigoni et al., "Scalable PdM Model for Wind Turbines Based on SCADA Data,"

8. Syed Shazaib Shah et al., "RUL Forecasting for Wind Turbine PdM Based on DL,"

9. Mikel Canizo et al., "Real-time PdM for Wind Turbines Using Big Data Frameworks,"

10. Diptiben Ghelani, "Harnessing ML for Predictive Maintenance in Energy Infrastructure,"

11. S. Onimisi Dawodu et al., "AI in Renewable Energy: Review of PdM & Optimization,"