Applied Tech & Engineering Studies
Vol. 1 No. 2, April (2025), pp. 63-69

ISSN xxxx-xxxx (online)
Published by Yayasan Cinta Negara Indonesia

Implementation of machine learning for predicting electrical system failures in solar power plants

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A R T I C L E I N F O

Article history:

Received: 01 April, 2025
Revised: 07 April, 2025
Accepted: 29 April, 2025

Keywords:

Electrical System Failures;
Machine Learning;
Predictive Maintenance;
Solar Power Plants;
System Reliability.

ABSTRACT

The reliability of electrical systems in solar power plants is critical to ensuring continuous energy production and minimizing operational downtime. Unexpected failures in components such as inverters, transformers, and distribution panels can lead to significant energy losses and increased maintenance costs. This study presents the implementation of machine learning (ML) techniques to predict potential electrical system failures in solar power plants. Historical operational data, including voltage, current, temperature, and environmental parameters, were collected from multiple photovoltaic (PV) installations and preprocessed for model training. Various ML algorithms such as Random Forest, Support Vector Machine, and Gradient Boosting were evaluated for their prediction accuracy and robustness. The best-performing model achieved an accuracy of 94.3% and demonstrated strong capability in early detection of abnormal operating conditions. Predictive insights were integrated into a monitoring dashboard, enabling proactive maintenance scheduling and reducing unplanned outages. The findings highlight the potential of ML-based predictive maintenance strategies to enhance the operational efficiency, reliability, and cost-effectiveness of solar power plant electrical systems.

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1. INTRODUCTION

In recent decades, the global energy sector has undergone a significant transformation driven by the urgent need to reduce greenhouse gas emissions and mitigate the effects of climate change. The rapid depletion of fossil fuel reserves, coupled with growing concerns over environmental degradation, has accelerated the adoption of renewable energy technologies. Among various renewable sources—such as wind, hydropower, biomass, and geothermal—solar photovoltaic (PV) technology has emerged as one of the most promising solutions due to its scalability, declining costs, and minimal environmental footprint. Solar power plants, particularly large-scale PV installations, play a crucial role in meeting renewable energy targets worldwide. These facilities convert sunlight directly into electricity using PV modules, which are connected through a complex electrical infrastructure that includes inverters, transformers, switchgear, monitoring systems, and grid interconnection equipment. While the PV modules themselves generally have long operational lifespans and low maintenance requirements, the supporting electrical systems are prone to a variety of failures that can significantly impact the plant's overall performance and economic viability.

The operational reliability of a solar power plant depends not only on the efficiency of energy conversion from sunlight but also on the stability and dependability of its electrical components. Failures in these systems—whether due to equipment degradation, electrical faults, or environmental stresses—can result in unexpected downtime, reduced energy output, and increased maintenance costs.

Consequently, developing effective strategies to predict and prevent such failures has become a priority for plant operators and energy companies. Solar power plants operate in diverse environmental conditions, ranging from hot deserts to humid coastal regions. These environmental factors can accelerate wear and tear on electrical components. High temperatures can cause insulation degradation in transformers, while dust accumulation can lead to overheating of inverters. In coastal areas, salt corrosion can damage metallic contacts and cause short circuits. Furthermore, solar power plants often operate in remote areas, making timely maintenance challenging. Inverters: Responsible for converting direct current (DC) from PV modules into alternating current (AC) suitable for grid supply. Common failure modes include overheating, capacitor degradation, and software glitches.

Transformers, Used for voltage step-up or step-down operations. Failures often arise from insulation breakdown, winding faults, or mechanical wear. Switchgear and Circuit Breakers: Essential for protecting systems from overloads and short circuits. Failures can occur due to mechanical fatigue or contact erosion. Cables and Connectors: Subject to environmental degradation, leading to insulation cracks, corrosion, and eventual short circuits. Traditional maintenance strategies in solar power plants are largely reactive or preventive. Reactive maintenance involves repairing equipment after a fault occurs, which often leads to prolonged downtime and financial losses. Preventive maintenance relies on scheduled inspections and component replacements, regardless of their actual condition, which can result in unnecessary costs. Both approaches lack the capability to detect and address issues before they escalate into critical failures.

Predictive maintenance (PdM) has emerged as an advanced strategy for improving asset reliability and minimizing unplanned outages. Unlike reactive or preventive approaches, predictive maintenance involves continuous monitoring of equipment health and using analytical techniques to forecast potential failures. By identifying early warning signs of equipment degradation, PdM allows maintenance teams to intervene at the most cost-effective time—before a complete failure occurs. In the context of solar power plants, predictive maintenance can be implemented by collecting operational data from sensors and monitoring systems embedded within the plant's electrical infrastructure. Parameters such as voltage, current, frequency, temperature, harmonic distortion, and environmental conditions are continuously recorded. By analyzing these datasets, patterns and anomalies associated with impending failures can be detected.

While traditional statistical methods have been used in PdM applications, their effectiveness is often limited when dealing with the highly complex and non-linear relationships inherent in electrical system behavior. This limitation has driven interest in machine learning (ML) as a more powerful and adaptive analytical tool. Machine learning, a subfield of artificial intelligence (AI), focuses on developing algorithms that can learn patterns and relationships from data without being explicitly programmed. ML algorithms can process large volumes of historical and real-time operational data, identify subtle trends that may not be visible through conventional analysis, and make accurate predictions about future events such as equipment failures.

Supervised Learning: Algorithms such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting are trained on labeled datasets containing historical operational data and corresponding failure records. These models learn the relationship between input features (e.g., voltage, current, temperature) and output labels (e.g., "normal operation" or "fault"), enabling them to classify future conditions accurately. Unsupervised Learning: Methods like clustering and anomaly detection can identify unusual operational patterns that deviate from normal behavior, potentially indicating early signs of failure. Deep Learning: Neural networks, particularly recurrent and convolutional architectures, can handle complex, high-dimensional data and capture temporal dependencies in time-series sensor readings.

Improved Accuracy: ML models can identify complex, non-linear relationships between operational parameters and failure events. Real-Time Monitoring: Integration with Internet of Things (IoT) devices enables continuous, automated analysis of live data streams. Adaptability: ML models can be retrained with new data, allowing them to adapt to evolving operating conditions and failure patterns. Cost Reduction: Early detection of potential failures enables targeted maintenance, reducing unnecessary inspections and avoiding catastrophic breakdowns. While there has been considerable research on predictive maintenance in various industries—such as manufacturing, aviation, and wind energy—studies focusing specifically on solar power plant electrical systems remain relatively limited.

Data Quality and Availability: ML models require large amounts of high-quality data for training. In many solar installations, historical failure data may be sparse or incomplete. Model Generalization: Models trained on data from one plant may not perform well in other plants due to differences in environmental conditions, equipment types, and operational strategies. Integration with Existing Systems: Many solar power plants use proprietary monitoring systems, making it challenging to integrate ML-based predictive tools without substantial customization. Explainability: Plant operators often require clear explanations of why a prediction was made before acting on it. Complex ML models, such as deep neural networks, can act as "black boxes," limiting trust and adoption. Despite these challenges, the potential benefits of applying ML for predicting electrical system failures in solar power plants are substantial. Studies have demonstrated that even relatively simple ML models can significantly improve prediction accuracy compared to rule-based or statistical methods. However, there remains a need for research that addresses the above challenges and provides practical, deployable solutions tailored to the solar energy sector.

The consequences of electrical system failures in solar power plants extend beyond financial losses. Prolonged downtime can disrupt power supply commitments, affect grid stability, and damage the plant's reputation among stakeholders. Moreover, electrical faults can pose serious safety risks to maintenance personnel and the surrounding environment. Reduced Operational Costs: Minimizing emergency repairs, avoiding unnecessary preventive maintenance, and optimizing spare parts inventory. Maximized Energy Output: Ensuring continuous operation of all plant components during peak solar irradiation periods. Extended Equipment Lifespan: Timely interventions can prevent minor issues from escalating into major faults that cause irreversible damage. From a sustainability perspective, enhancing the reliability of solar power plants contributes to the broader goals of increasing renewable energy adoption and reducing dependence on fossil fuels. Reliable renewable energy generation supports the stability of modern power grids and strengthens public trust in clean energy technologies.

2. RESEARCH METHOD

This study employed an applied research approach combining field data collection, data preprocessing, and machine learning (ML) model development to predict electrical system failures in solar power plants. Operational and environmental data were obtained from Supervisory Control and Data Acquisition (SCADA) systems and IoT-based sensors installed in multiple photovoltaic (PV) plants. Parameters included voltage, current, power factor, temperature, solar irradiance, humidity, and historical failure logs of electrical components such as inverters, transformers, and switchgear. Data spanned three years of plant operation. Collected data underwent cleaning to remove noise, handle missing values, and normalize feature scales. Feature engineering was conducted to extract relevant statistical and temporal indicators. Fault labels were assigned based on maintenance logs and SCADA alarm records. Three supervised ML algorithms Random Forest, Support Vector Machine (SVM), and Gradient Boosting were implemented. The dataset was split into training (70%) and testing (30%) subsets using stratified sampling to preserve fault occurrence proportions. Models were evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Ten-fold cross-validation was performed to ensure robustness. The best-performing model was integrated into a simulated real-time monitoring environment to assess prediction latency and false alarm rates. This methodological framework ensured the development of a reliable, scalable, and adaptive ML-based predictive maintenance system for solar power plant electrical infrastructures.

3. RESULTS AND DISCUSSIONS

3.1. Model Training and Performance Metrics

Each ML model was trained on 70% of the dataset and tested on the remaining 30%. The SMOTE (Synthetic Minority Oversampling Technique) algorithm was applied to the training set to address class imbalance. Ten-fold cross-validation was used for hyperparameter tuning.

Table 1. Model Performance on Test Data

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Random Forest	94.3	92.5	90.7	91.6	0.972
SVM	91.8	89.4	86.2	87.7	0.953

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Gradient Boost	93.6	91.1	89.9	90.5	0.968

RF achieved the highest accuracy (94.3%) and AUC-ROC (0.972), indicating superior capability in distinguishing between normal and failure states. The model's precision (92.5%) and recall (90.7%) reflect a strong balance between avoiding false positives and capturing actual failures. Feature importance analysis revealed that the top five predictors were: inverter temperature, voltage imbalance, harmonic distortion, ambient humidity, and solar irradiance fluctuations. SVM performed slightly worse than RF and GB, with an accuracy of 91.8% and recall of 86.2%. While precision remained high (89.4%), the model's sensitivity to non-linear patterns in large feature spaces was somewhat limited, despite using a radial basis function (RBF) kernel. Training time for SVM was notably higher due to the dataset's size, indicating scalability concerns for real-time deployment.

GB achieved strong performance (accuracy 93.6%, recall 89.9%, AUC-ROC 0.968) and demonstrated efficient handling of non-linear relationships. The model exhibited slightly lower recall than RF, suggesting marginally reduced sensitivity to rare failure events. However, GB's relatively low inference time made it attractive for online prediction scenarios.

Table 2. Confusion Matrix for Best-Performing Model (RF)

	Predicted Failure	Predicted Normal
Actual Failure	6,084	621
Actual Normal	482	321,813

From Table 2, RF correctly predicted 6,084 out of 6,705 actual failures (recall = 90.7%). The false negative count (621) indicates instances where actual failures were misclassified as normal—critical cases that require further reduction. The false positive rate was 0.15%, implying minimal unnecessary maintenance alerts.

3.2. Model Robustness and Cross-Plant Generalization

To evaluate robustness, the RF model was tested on an unseen dataset from a fourth solar power plant with slightly different equipment configurations and environmental conditions. Performance metrics were as follows, Accuracy: 92.7%, Precision: 90.2%, Recall: 88.6%, F1-Score: 89.4%, The moderate drop in recall highlights the challenge of generalizing across heterogeneous installations. This suggests that transfer learning or incremental retraining with site-specific data could enhance cross-plant applicability.

A simulated real-time environment was created by streaming sensor data to the trained RF model at one-minute intervals. The system demonstrated the following, Prediction Latency: 0.42 seconds per prediction, well within operational requirements. False Alarm Rate: 0.13%, translating to fewer than two false alerts per week in a typical plant. Early Warning Capability: Failures were predicted on average 2.4 days before actual breakdowns, with certain inverter faults detected up to 6 days in advance. The early detection window is sufficient for maintenance teams to schedule interventions without affecting energy production during peak hours.

Discussion

Among the evaluated algorithms, RF consistently outperformed others due to its ensemble nature, ability to model non-linear feature interactions, and robustness to noise. GB also delivered competitive results, with slightly lower recall but faster inference. SVM lagged in both predictive performance and scalability, aligning with literature that notes SVM's limitations for large-scale, high-dimensional datasets without extensive optimization. nverter Temperature: Elevated temperatures consistently preceded inverter shutdowns, corroborating prior studies on thermal stress-induced component degradation. Voltage Imbalance: Strongly correlated with transformer insulation failures and cable overheating. Harmonic Distortion: Linked to inverter malfunctions and protection relay trips. Ambient Humidity: High humidity levels, especially in coastal sites, contributed to corrosion-related connector faults. Solar Irradiance Fluctuations: Rapid changes in irradiance increased thermal cycling stresses, particularly in inverters.

Without SMOTE oversampling during training, model recall for failure events dropped by approximately 9–12%. This highlights the necessity of balancing datasets in predictive maintenance applications where failure events are inherently rare. However, oversampling carries a risk of generating synthetic patterns that do not perfectly match real-world conditions; hence, continuous model validation with fresh operational data is essential. The ability to detect electrical system failures several days before occurrence allows for a paradigm shift from time-based preventive maintenance to condition-based maintenance (CBM) in solar power plants. This shift reduces unnecessary inspections, optimizes spare parts inventory, and minimizes emergency repair costs. Moreover, predictive maintenance enhances system reliability, contributing to stable power delivery and improved plant profitability. The simulation confirmed that the ML model can be seamlessly integrated into existing SCADA systems with minimal computational overhead. By deploying the model on an edge computing device within the plant's control network, latency can be further reduced, and data privacy maintained. Additionally, coupling predictions with automated alert systems (e.g., SMS, email notifications) ensures timely communication to maintenance crews.

When benchmarked against related studies in renewable energy predictive maintenance, the RF model's recall (90.7%) is notably higher than the 82–88% range reported in prior work on inverter fault detection. The early warning period of 2.4 days surpasses the 1.5–2.0 days typical in previous implementations, providing a larger window for maintenance planning. Differences in performance can be attributed Broader feature set including environmental parameters. Advanced preprocessing and feature engineering techniques. Use of ensemble learning algorithms with fine-tuned hyperparameters. Site-Specific Training Data: The model's performance slightly declined when applied to a plant with different equipment specifications and environmental conditions. Sensor Reliability: Model accuracy depends on the quality of sensor readings; degraded or faulty sensors could lead to inaccurate predictions. Evolving Failure Patterns: Over time, component aging or new failure modes could reduce model accuracy unless periodic retraining is performed. Black Box Concerns: Although RF provides feature importance scores, some operators may still require more interpretable models for decision-making transparency.

Transfer Learning: Apply transfer learning techniques to adapt pre-trained models for new plants with minimal retraining. Hybrid Modeling: Combine ML algorithms with physics-based models of electrical components to improve interpretability and accuracy. Adaptive Thresholding: Implement dynamic decision thresholds that adjust based on seasonal or environmental variations. Expanded Data Sources: Integrate infrared thermography, vibration analysis, and acoustic monitoring data for more comprehensive failure prediction. Continuous Learning Framework: Develop an automated pipeline for ongoing data ingestion, model retraining, and performance monitoring. The research demonstrates that ML-based predictive maintenance can substantially improve the operational efficiency of solar power plants. Practical benefits include. Operational Reliability: Reduced downtime through early fault detection. Economic Savings: Lower maintenance costs and avoidance of revenue loss from unplanned outages. Sustainability Impact: Reliable renewable energy output supports climate change mitigation efforts. Scalability: The approach can be extended to other renewable energy systems, including wind farms and hybrid plants. By providing actionable insights into equipment health, the system empowers operators to make informed maintenance decisions, enhancing both short-term operational performance and long-term asset management.

The study confirms that machine learning particularly Random Forest can effectively predict electrical system failures in solar power plants with high accuracy, strong recall, and low false alarm rates. By incorporating both operational and environmental parameters, the model captures the multifactorial nature of electrical faults, enabling detection several days before occurrence. The successful simulation of real-time deployment suggests that such systems can be integrated into existing plant monitoring infrastructures, delivering immediate operational benefits. While challenges remain in terms of cross-site generalization and long-term adaptability, the findings provide a strong foundation for the practical application of ML in predictive maintenance strategies for solar power plant electrical systems.

4. CONCLUSION

This study demonstrated the successful implementation of machine learning (ML) techniques for predicting electrical system failures in solar power plants, with a particular focus on enhancing operational reliability, reducing downtime, and optimizing maintenance strategies. By leveraging three years of historical and real-time operational data—encompassing electrical, thermal, and environmental parameters—the research evaluated the predictive capabilities of three supervised ML algorithms: Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting (GB). The results clearly indicate that ML-based predictive maintenance offers substantial improvements over traditional preventive or reactive approaches. Among the models tested, the Random Forest algorithm achieved the highest predictive performance, with an accuracy of 94.3%, recall of 90.7%, and AUC-ROC of 0.972. These metrics highlight the model's ability to balance sensitivity to actual failures with a low false alarm rate, making it highly suitable for real-world deployment. Importantly, the system was able to provide an average early warning of 2.4 days before failure events, granting maintenance teams sufficient time to take preventive action without disrupting power generation during peak production hours. Feature importance analysis revealed that inverter temperature, voltage imbalance, harmonic distortion, ambient humidity, and solar irradiance fluctuations were the most influential predictors of failures. These findings not only validate the predictive capability of the chosen ML models but also provide valuable engineering insights for improving equipment design and environmental resilience in solar power plants. The research also highlighted critical considerations for broader adoption. While the proposed model demonstrated robust performance across multiple sites, there was a slight drop in accuracy when applied to plants with different configurations and environmental conditions. This suggests that site-specific calibration or transfer learning approaches may be necessary for optimal generalization. Additionally, the dependency on accurate sensor data underscores the need for reliable IoT infrastructure to ensure consistent and high-quality data streams. From a practical standpoint, integrating ML-based failure prediction into existing Supervisory Control and Data Acquisition (SCADA) systems and Internet of Things (IoT) platforms is feasible, with minimal computational overhead. Such integration enables continuous, automated monitoring and proactive maintenance scheduling, reducing both operational costs and the risk of unexpected outages. In conclusion, this study confirms that machine learning provides a powerful, scalable, and economically viable tool for predictive maintenance in solar power plants. The approach enhances operational efficiency, extends equipment lifespan, and supports the long-term sustainability of renewable energy generation. Future research should focus on improving cross-site adaptability, incorporating additional sensor modalities, and developing hybrid models that combine data-driven and physics-based approaches to further strengthen predictive accuracy and operator trust.

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