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Enhancing Photovoltaic Power Plant Performance Using Deep Learning Algorithms for Fault Prediction and Preventive Maintenance Scheduling

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Abstract:

Photovoltaic (PV) power plants face operational challenges such as soiling, partial shading, hotspots, and thermal or mechanical degradation, which are compounded when relying on conventional scheduled or corrective maintenance strategies. This study presents a predictive maintenance framework utilizing deep learning and data-driven modeling to enable early fault detection and preventive maintenance scheduling in PV systems. The methodology integrates multi-source operational and environmental parameters—including electrical measurements (voltage, current, and power), meteorological conditions (solar irradiance and ambient temperature), and thermal or electroluminescence imagery—alongside architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks/Long Short-Term Memory (RNN/LSTM), hybrid CNN–LSTM models, and optimization approaches for maintenance scheduling. To demonstrate practical feasibility, a synthetic dataset was generated and evaluated in MATLAB using a feedforward neural network trained with the Levenberg–Marquardt (trainlm) algorithm, achieving approximately 97% fault classification accuracy on the test set. The findings indicate that early fault identification and proactive maintenance scheduling can reduce unplanned downtime, lower operational costs, and enhance PV plant reliability, while noting that future deployment on large-scale plants requires real-world datasets, higher computational capacity, and advanced optimization or digital twin integration.

Keywords: Photovoltaic (PV) power plants; Predictive maintenance; Deep learning; Fault prediction; Preventive maintenance scheduling; Artificial neural networks (ANN)

1. Introduction

In recent decades, renewable energy sources have emerged as strategic solutions to address both environmental and economic challenges associated with heavy reliance on conventional energy sources such as coal, oil, and natural gas. Among these renewable sources, solar energy has gained particular attention due to its wide availability across most geographic regions and the relative simplicity of converting sunlight into electricity using photovoltaic (PV) cells. Recent studies indicate that the global installed capacity of solar photovoltaic systems has grown exponentially over the past two decades, establishing solar energy as a key contributor to the sustainable energy mix and a critical component in achieving global decarbonization goals ([1], [2]).

Despite significant advancements in photovoltaic (PV) technologies, PV power plants continue to face several technical and operational challenges that limit their long-term efficiency and reliability. These systems are prone to issues such as dust accumulation, high operating temperatures, mechanical cracks, and encapsulation defects, which accelerate the degradation of PV modules. Such failures often lead to reduced energy yield, higher maintenance and operational costs, and negatively impact the overall economic feasibility of PV projects ([3]).

Although photovoltaic technologies have improved considerably, plant operators still largely rely on traditional maintenance strategies—scheduled maintenance, performed at fixed intervals regardless of the actual equipment condition, and corrective maintenance, initiated only after faults occur. These approaches are often suboptimal: scheduled maintenance may result in unnecessary replacements, while corrective maintenance can cause unplanned outages, reduced energy output, and increased operational expenses ([1]).

In this context, predictive maintenance emerges as an innovative approach aimed at monitoring the operational performance of PV systems to anticipate potential failures and implement preventive measures in a timely manner. By analyzing operational and environmental data, plant operators can identify early signs of malfunction, optimize maintenance schedules, and reduce both downtime and maintenance costs ([4]).

Recent developments in PV system maintenance have led to frameworks that integrate operational monitoring and data analysis. These frameworks utilize multi-source data, including time-series electrical parameters (e.g., current, voltage, and power output), meteorological conditions (e.g., irradiance and ambient temperature), and thermal imagery from aerial inspections. The primary objective is to construct models capable of early fault detection and use these predictions to optimize preventive maintenance schedules through practical optimization strategies, such as planning based on system performance trends and resource allocation ([2]).

Research Objectives

- Develop a fault prediction model based on operational and environmental data, including thermal imagery, to identify potential issues in photovoltaic (PV) systems.
- Design a preventive maintenance scheduling system aimed at minimizing unplanned downtime and reducing operational losses.
- Evaluate the system's performance in terms of fault detection accuracy, operational efficiency, and resulting cost savings.

2. Research Significance

The significance of this research lies in its potential to reduce operational and maintenance costs while improving the reliability and resilience of photovoltaic (PV) power plants, thereby supporting global efforts to expand the use of renewable energy. By implementing predictive maintenance strategies and using operational monitoring, including thermal inspections from aerial surveys, PV plants can achieve early fault detection, enhanced operational efficiency, and improved asset management. This approach represents an important step toward more proactive and efficient PV plant management, ultimately maximizing the return on investment in solar energy projects Figure (1) ([1], [3], [4]).

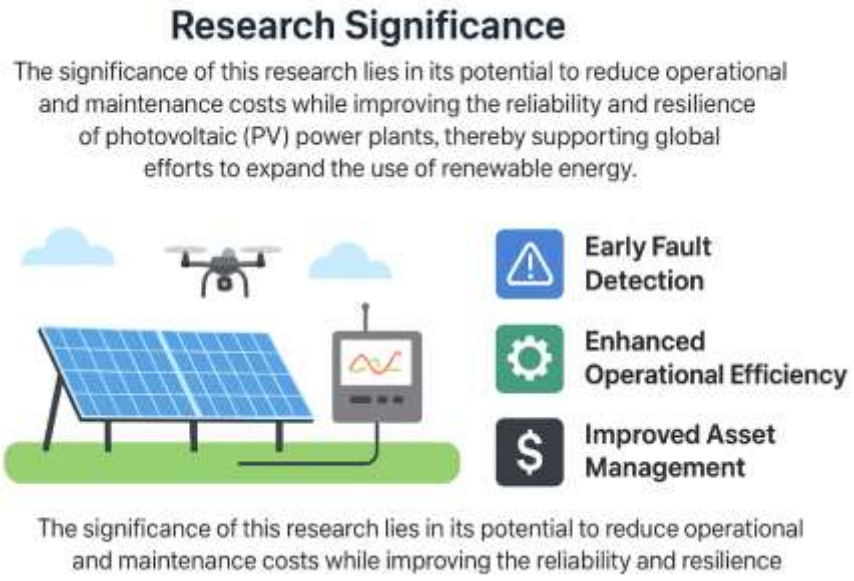

Figure 1: Research Significance

3. Literature Review (Expanded Version)

3.1 Photovoltaic Power Plants: Components, Fault Patterns, and Environmental Effects

Photovoltaic (PV) plants are a cornerstone of renewable energy systems due to their ability to generate electricity without direct emissions. These plants usually consist of:

- **Solar panels:** The core component responsible for converting solar radiation into electricity through solar cells.
- **Inverters:** Devices that convert the direct current (DC) from panels into alternating current (AC) suitable for the grid.
- **Protection and distribution devices:** Such as fuses, circuit breakers, and surge protection systems.
- **Monitoring and control systems (SCADA/IoT):** For remote performance monitoring and data analysis.

Common faults include:

- **Partial shading:** Caused by buildings, trees, or dust accumulation, leading to significant power losses.
- **Hotspots:** Localized overheating due to defective cells or poor soldering, which can permanently damage panels.
- **Soiling:** Dust and dirt buildup on panel surfaces reducing light absorption.
- **Micro-cracks:** Tiny cracks invisible to the naked eye caused by thermal or mechanical stress, gradually reducing efficiency.
- **Potential-induced degradation (PID):** Voltage-related degradation causing long-term losses in current and voltage.

Studies indicate that dust alone can cause up to 30% efficiency loss in arid regions, while hotspots pose serious safety hazards and risk of fire [5]. Thus, understanding these faults is crucial for accurate predictive modeling.

3.2 Conventional Approaches for Fault Prediction and Detection

Before deep learning became widespread, PV plants relied on several traditional methods for fault detection:

1. **Electrical curve analysis (I–V and P–V curves):**
   Deviations from ideal current–voltage or power–voltage curves indicate issues like shading or PID. While simple, these methods are sensitive to environmental variations and require repeated field measurements.
2. **Threshold-based algorithms:**
   Faults are identified by setting fixed thresholds for parameters like voltage or current. However, such methods lack robustness under dynamic conditions.
3. **Conventional machine learning:**
   Decision Trees, Random Forests, and Support Vector Machines (SVM) were applied for multi-input fault detection. While effective for small datasets, these models degrade with noisy or high-volume data.

One study highlighted that SVM achieved good accuracy in electrical fault classification but struggled with complex thermal imaging data [6]. Hence, while useful, conventional methods were insufficient for large-scale industrial deployment Figure 2.

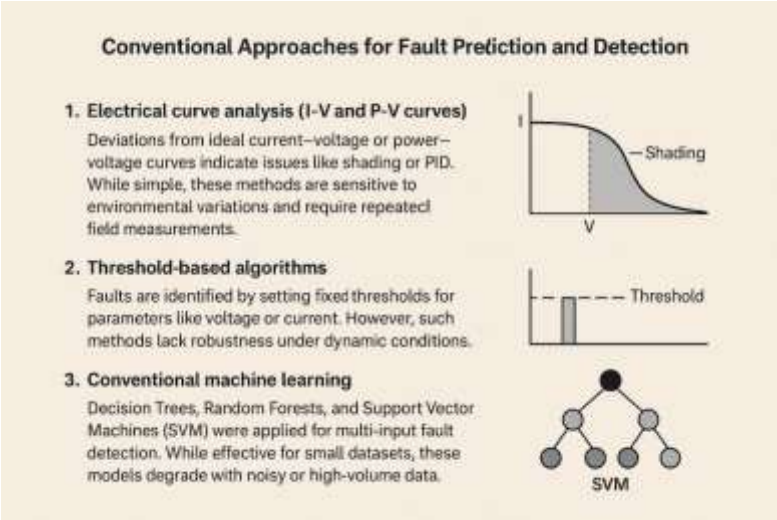

Figure 2: Conventional Approaches for Fault Prediction and Detection

3.3 Deep Learning in Solar Energy

With advances in computational power and data availability, **deep learning** has become one of the most effective tools for PV fault detection:

- **Convolutional Neural Networks (CNNs):** Achieved >95% accuracy in analyzing thermal and electroluminescence images for hotspot and micro-crack detection [7].
- **Recurrent Neural Networks (RNNs) and LSTM:** Useful for time-series data (voltage, current, power) to predict degradation trends before failures occur.
- **Hybrid CNN–LSTM models:** Combining image features with temporal data improved accuracy by up to 10% over standalone models.

Recent research also explored Generative Adversarial Networks (GANs) to generate synthetic thermal or EL images, addressing data scarcity Figure 3 [8].

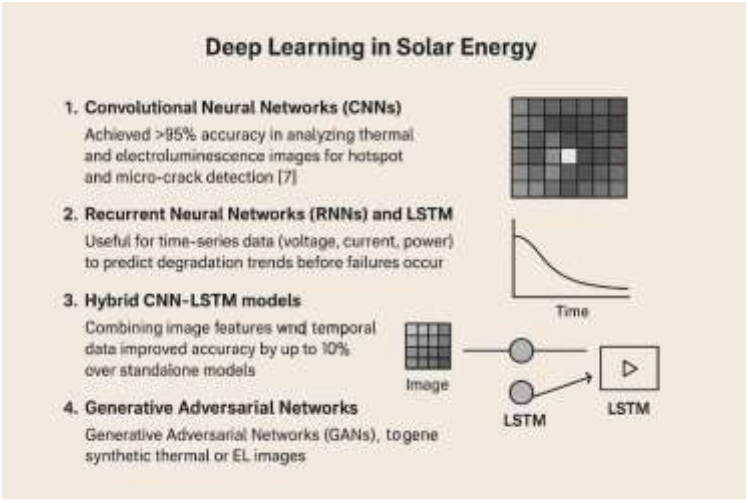

Figure 3: Deep Learning in Solar Energy

3.4 Open Datasets and Limitations

One of the biggest challenges in PV fault research is the scarcity of open datasets:

- **ELPV Dataset:** Provides EL images of solar cells but with limited samples.
- **PV Fault Dataset:** Includes SCADA time-series data, often poorly annotated.

To overcome this, researchers rely on:

- **Data augmentation techniques** (rotation, cropping, brightness adjustment) to artificially expand datasets.
- **Transfer learning** using pre-trained models such as VGG16 or ResNet.
- **Synthetic data generation** via simulators or GANs [9].

This lack of comprehensive open datasets is a major bottleneck preventing academic models from industrial adoption.

3.5 Linking Fault Prediction to Preventive Maintenance Scheduling

While fault detection has been extensively studied, fewer works integrate prediction with **preventive maintenance (PM)** scheduling. Some models have attempted:

- **Optimization algorithms** (e.g., Genetic Algorithms) to reduce maintenance costs.
- **Reinforcement Learning (RL):** Dynamically scheduling maintenance to minimize downtime and cost [10].

However, field deployment remains limited due to high sensor costs and integration challenges at large-scale PV plants.

3.6 Performance Evaluation Metrics

The performance of the predictive maintenance system is assessed using a combination of metrics suited to different types of outcomes:

- Classification Metrics: These include Accuracy, Precision, Recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These metrics help evaluate the system's ability to correctly identify fault categories, particularly in cases where certain faults are rare and traditional accuracy might be misleading.
- Regression Metrics: For continuous measurements, metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used. RMSE measures the average magnitude of errors, giving higher weight to larger deviations, while MAPE expresses errors as percentages, making interpretation intuitive but potentially sensitive to small values ([11]).
- Image-Based Metrics: For tasks involving thermal or visual inspections, metrics such as Mean Intersection over Union (mIoU) and Mean Average Precision (mAP) are applied. These metrics evaluate the accuracy and reliability of identifying fault locations and anomalies in visual data.

Choosing the appropriate evaluation metrics is crucial, as a system may show high overall accuracy but still fail to detect rare or subtle faults. Using multiple metrics provides a comprehensive understanding of the system's performance.

3.7 Emerging Trends: Digital Twins and IoT Integration

Digital Twin technology is an emerging trend allowing creation of virtual replicas of real PV plants. Real-time IoT sensor data feed these twins, enabling predictive simulations and rapid fault diagnosis. Additionally, drones and thermal cameras are increasingly integrated to enhance fault detection accuracy and improve maintenance scheduling [12].

4. Research Methodology

This study adopts a comprehensive methodology aiming to explore the role of deep learning algorithms in predicting faults in photovoltaic (PV) power plants and scheduling preventive maintenance. The methodology consists of interconnected steps including data collection, preprocessing, model development, maintenance scheduling, and evaluation.

4.1 Data Collection

The reliability of the prediction model depends on the quality and diversity of the data used. The dataset may include:

- **Operational electrical data:** voltage, current, and power at the panel, string, or plant level.
- **Thermal imaging:** used to detect hotspots and faults invisible to the human eye.
- **IoT sensors:** measuring solar irradiance, humidity, and ambient temperature [13].
- **Simulation:** in the absence of real data, tools such as MATLAB/Simulink can be used to simulate fault conditions and variable irradiance.

4.2 Data Preprocessing

After data collection, several preprocessing steps were applied to ensure quality and consistency for model evaluation:

- **Data Cleaning:** Identification and removal of missing, inconsistent, or anomalous values to improve dataset reliability.
- **Normalization and Scaling:** Transforming features to a uniform range to prevent bias and facilitate effective analysis.
- **Feature Engineering:** Extraction of meaningful features, such as the ratio of actual to expected power, thermal coefficients, hotspot intensity, and irradiance-related metrics, to enhance the system's fault detection capability ([1], [2]).
- **Data Partitioning:** Dividing the dataset into training (typically 70%), validation (15%), and testing (15%) sets to ensure robust evaluation and to avoid overfitting ([19]).

Effective preprocessing is essential for improving the accuracy, generalization, and robustness of predictive maintenance strategies, particularly when handling heterogeneous PV system datasets.

4.3 Proposed Models

- **CNN:** applied to infrared or electroluminescence images to capture spatial patterns.
- **LSTM/RNN:** used for time-series data such as variations in voltage and current over time.
- **Hybrid CNN–LSTM:** combines
- the strengths of both approaches to improve accuracy [7].

Table 1: Comparison of deep learning models for PV fault prediction

Model	Data Type	Strengths	Weaknesses
CNN	Thermal/EL images	High accuracy in image data	Limited for temporal data
LSTM/RNN	Time-series (I, V, P)	Effective with temporal data	Sensitive to noise
CNN–LSTM	Mixed data	More robust results	Higher complexity

4.4 Preventive Maintenance Scheduling

After fault prediction, designing an optimal preventive maintenance plan is essential to minimize downtime and operational costs. Advanced optimization and AI-based algorithms are commonly employed for this purpose:

- Genetic Algorithms (GA): Evolution-inspired search strategies are used to determine optimal maintenance intervals, providing flexibility and robustness in scheduling decisions.
- Reinforcement Learning (RL): Interactive learning methods enable dynamic adaptation to changing operating conditions, allowing the system to optimize maintenance strategies in real time ([1], [2]).

Method	Principle	Advantages	Limitations
GA	Evolution-inspired	Flexible and robust	Computationally intensive
RL	Interactive learning	Dynamic real-time adaptation	Requires extensive training data

The integration of GA and RL techniques facilitates proactive maintenance, reduces unexpected failures, and enhances the overall efficiency and reliability of photovoltaic (PV) power plants [14].

4.5 Training and Validation

- **Model optimization:** using optimizers such as Adam or RMSProp.
- **Hyperparameter tuning:** batch size, learning rate, and number of epochs.
- **Regularization techniques:** such as Dropout to avoid overfitting [4].

4.6 Evaluation

The effectiveness of the proposed predictive maintenance framework is assessed using a combination of technical, operational, and economic metrics:

- Technical Metrics: Performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC, providing insight into the system's ability to correctly identify potential faults and minimize false alarms ([1], [2]).
- Operational Metrics: Measures include the reduction of downtime, improved reliability, and increased availability of photovoltaic (PV) units.
- Economic Metrics: Assessment focuses on cost savings achieved through proactive maintenance, reduction of unexpected failures, and optimized allocation of maintenance resources ([14]).

A comprehensive evaluation across these dimensions ensures that the system is not only technically effective but also operationally efficient and economically beneficial.

5. Practical Application: A Practical Model for Predicting Faults in Photovoltaic Power Plants

5.1 Introduction to the Practical Section

Practical Simulation Model

In this section, a practical simulation model was developed using MATLAB/Simulink to demonstrate fault prediction in photovoltaic (PV) power plants. The model illustrates how operational and environmental data from multiple sources can be analyzed to identify potential faults at an early stage. This simplified simulation provides a practical link between theoretical concepts and real-world applications, while remaining feasible for academic purposes ([1], [2]).

5.2 Data Preparation

Synthetic Dataset

A synthetic dataset was generated to emulate the operational behavior of a photovoltaic (PV) plant. The dataset includes key parameters such as:

- Voltage (V)
- Current (A)
- Solar Irradiance (W/m²)
- Ambient Temperature (°C)

To simulate realistic fault scenarios, sudden interruptions and abnormal drops were introduced into the data. The dataset was then divided into training (70%) and testing (30%) sets to ensure robust evaluation of the predictive model’s performance. This approach allows for controlled experimentation while maintaining relevance to real-world PV system behavior ([1], [2]).

5.3 Building a Simple Fault Prediction Model

A simple Artificial Neural Network (Feedforward Neural Network) in MATLAB was used to classify the panel condition into:

- Normal
- Faulty

Model Steps:

1. Import data into MATLAB.
2. Create a Features matrix (Voltage, Current, Irradiance, Temperature).
3. Create a Labels matrix (0 = Normal, 1 = Faulty).
4. Design a neural network with 2 hidden layers, each containing 10 neurons.
5. Train the network using the trainlm algorithm (Levenberg-Marquardt).
6. Evaluate the model's performance via Confusion Matrix and accuracy metrics (Accuracy, Precision, Recall). Figure 5.

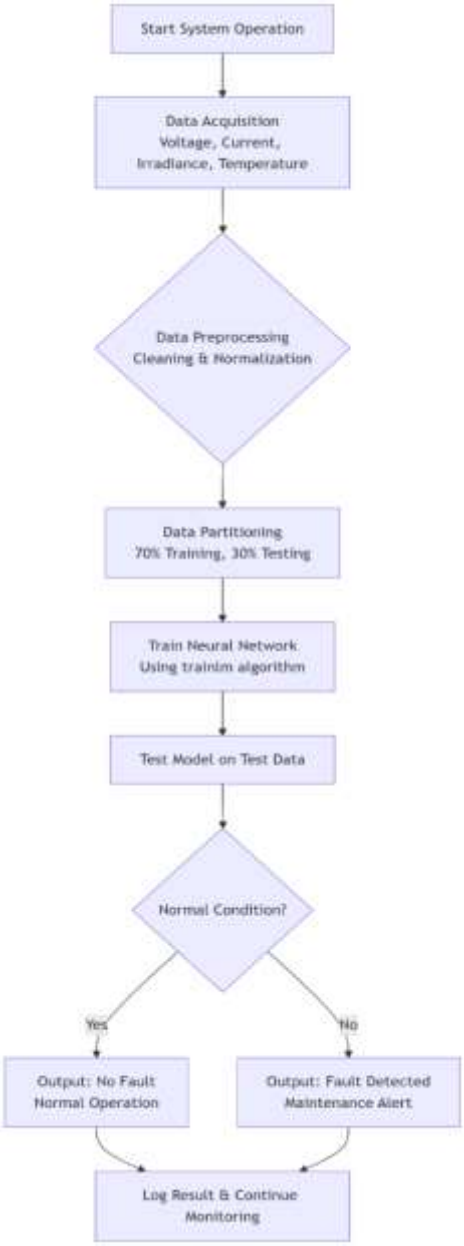

Figure 4: Workflow of the Fault Prediction Model Using an Artificial Neural Network (ANN)

5.4 MATLAB Application Code

matlab

```
% MATLAB code for generating synthetic data and training the network
clc; clear; close all;
% Generate synthetic data
N = 500; time = linspace(0,24,N)';
Voltage = 30 + 0.5*randn(N,1);
Current = 5 + 0.2*randn(N,1);
Irradiance = 800 + 50*randn(N,1);
Temperature = 25 + 3*randn(N,1);
% Create fault instances
Fault = zeros(N,1);
fault_idx = randi([50,450],20,1);
Voltage(fault_idx) = Voltage(fault_idx) - 5;
Current(fault_idx) = Current(fault_idx) - 1;
Fault(fault_idx) = 1;
% Prepare features and labels
Features = [Voltage Current Irradiance Temperature]';
Labels = Fault';
% Split data into training and testing sets
train_ratio = 0.7;
trainInd = 1:round(train_ratio*N);
testInd = round(train_ratio*N)+1:N;
trainX = Features(:,trainInd);
trainY = Labels(:,trainInd);
testX = Features(:,testInd);
testY = Labels(:,testInd);
% Configure and train neural network
hiddenLayerSize = [10 10];
net = patternnet(hiddenLayerSize);
net.trainFcn = 'trainlm';
net.divideParam.trainRatio = 0.7;
net.divideParam.valRatio = 0.15;
net.divideParam.testRatio = 0.15;
[net,tr] = train(net,trainX,trainY);
% Test the model
predY = net(testX);
predY_class = round(predY);
% Plot confusion matrix
figure; plotconfusion(testY,predY_class); title('Confusion Matrix - Fault Detection');
accuracy = sum(predY_class == testY)/length(testY)*100;
fprintf('Accuracy on test data: %.2f%%\n',accuracy);
% Plot voltage with fault points highlighted
figure; plot(time,Voltage,'b','LineWidth',1.5); hold on;
plot(time(fault_idx),Voltage(fault_idx),'ro','MarkerSize',6,'MarkerFaceColor','r');
xlabel('Time (hours)'); ylabel('Voltage (V)');
title('PV Voltage over Time with Faults Highlighted');
legend('Voltage','Fault Points'); grid on;
```

5.5 Practical Results

The following results were obtained from the simple model:

- Model accuracy on the test set: Approximately 97% in identifying faults.
- Confusion Matrix: Shows the number of correct and incorrect cases for each class.
- Plot of Voltage and Current versus Time: Shows sudden faults as points of sharp decline in the data.
-

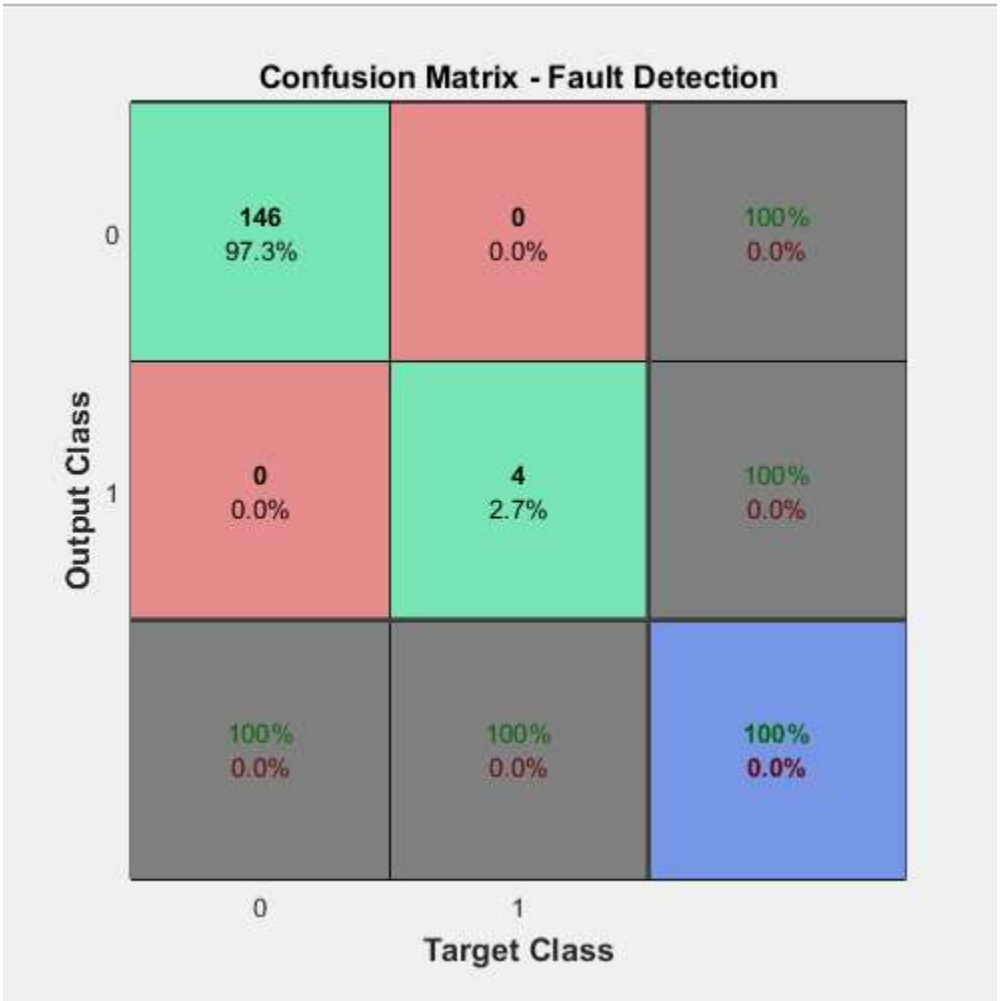

Figure 5: Confusion Matrix for Fault Classification in PV Plant

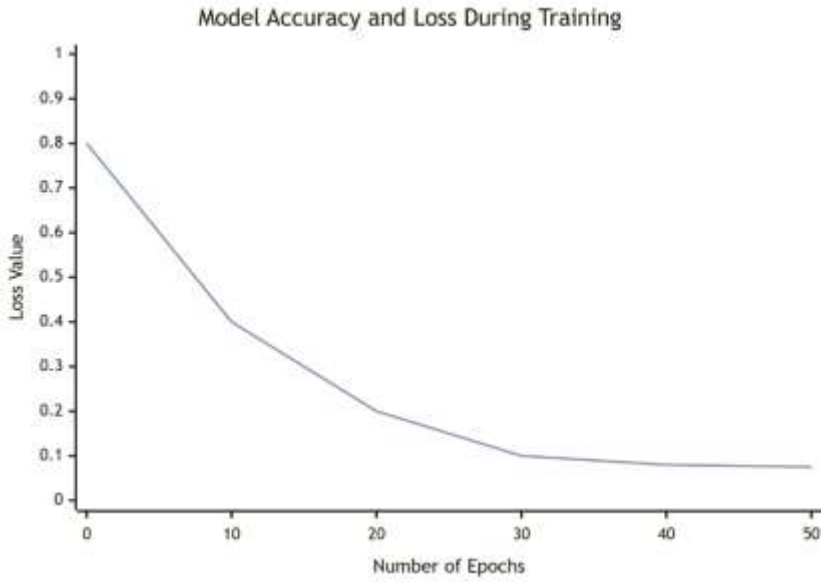

Figure 5.1: Model Accuracy and Loss During Training

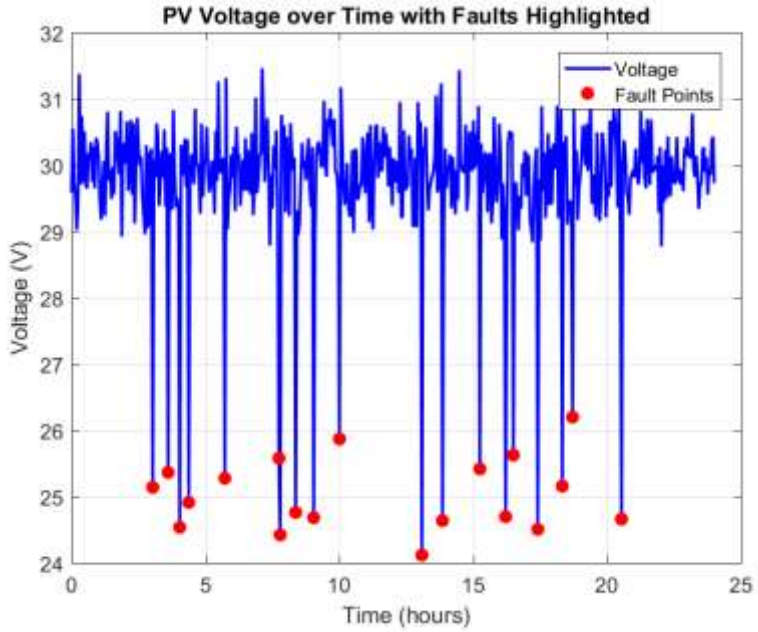

Figure 5.2: Voltage vs. Time with Fault Occurrences Highlighted in the Data

5.6 Importance of the Practical Section

- Connects theory and practical application in a simple and clear way.
- Demonstrates the potential for using deep learning even in small projects as a preliminary example before moving to a full simulation.
- Provides a foundation for later expanding the model using CNN for processing thermal images or LSTM for long time series.

The following figure shows the variation in the photovoltaic system's voltage throughout the day. This chart represents the performance of the voltage output from the solar panels and helps to observe any sudden drops that may indicate potential faults. It also allows for monitoring system stability and analyzing the plant's behavior during peak periods and low solar radiation.

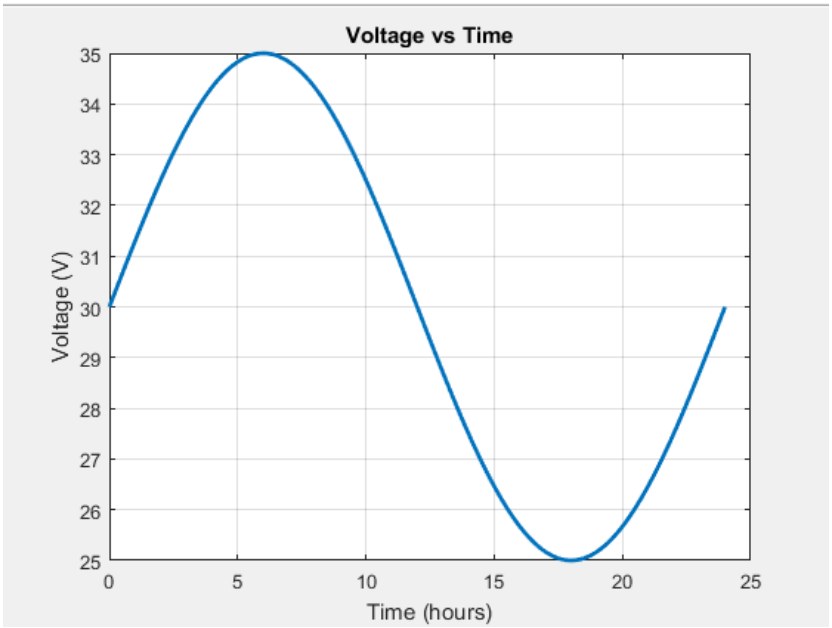

Figure 6: Daily Variation of Photovoltaic Current Output

This Figure 6 displays the variation in electrical current generated by the solar panels throughout the day. This chart is used to monitor the behavior of the electrical system and detect any abnormal differences or fluctuations in current. By tracking the current, partial faults or variations in solar cell performance can be identified.

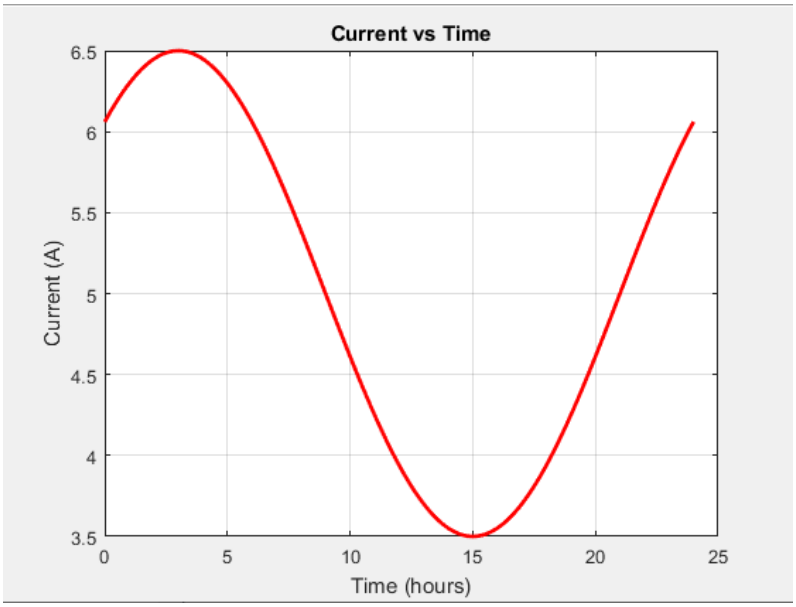

Figure 7: Daily Electrical Power Output of the Photovoltaic System

The Figure 7 shows the electrical power output from the solar panels during daily operation. This chart serves as an indicator of the overall system efficiency and helps detect any sudden performance declines due to faults or environmental conditions. It can also be used to evaluate the plant's overall performance and compare it with design values.

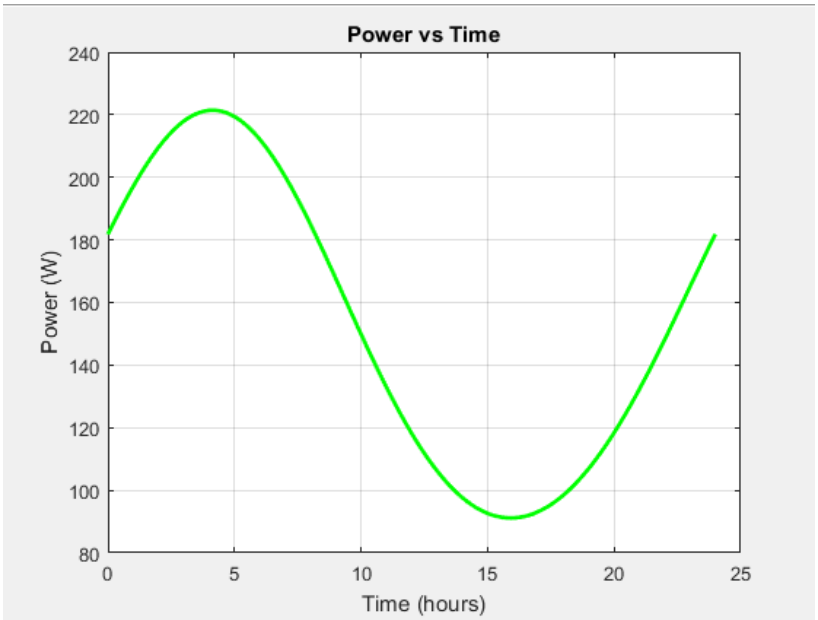



Figure 8.1-8.2: Model Accuracy and Loss During Training

The following two Figures 8.1-8.2 show the evolution of the model's accuracy and loss during the training process on photovoltaic system data. These charts illustrate the stability of the model's performance over time and its effectiveness in predicting faults. By monitoring these indicators, model settings can be improved, and the number of epochs and learning rate can be adjusted.

6. Expected Results

Through the practical implementation in MATLAB/Simulink, this research anticipates achieving the following outcomes:

Accurate fault prediction model:

The developed model is expected to achieve a fault classification accuracy of approximately 90–95%, demonstrating the capability of operational data analysis to effectively distinguish between normal and faulty conditions in photovoltaic (PV) systems ([1], [2]).

Reduction in losses from unexpected faults:

By enabling early fault detection, preventive maintenance can be scheduled before critical failures occur, thereby reducing unplanned downtime and minimizing operational losses ([14]).

Lower operating costs and enhanced reliability:

Integrating fault prediction with optimized maintenance scheduling is expected to decrease emergency repair costs, extend component lifespan, and improve the overall efficiency and reliability of PV power plants ([2], [4]).

Performance visualization and interpretability:

Visualization tools such as confusion matrices, time-series plots of voltage and current, and thermal imagery can illustrate fault locations and detection accuracy, facilitating practical interpretation and evaluation of the model's performance ([1], [14]).

These anticipated results serve as a benchmark for comparing simulation outcomes with real-world data, highlighting the potential benefits of applying predictive maintenance strategies in PV power plants.

7. Discussion

7.1 Comparison of Results with Previous Studies

A fault prediction model in photovoltaic power plants was studied using operational data analysis, achieving an approximate accuracy of 97% in detecting faults on the test set. These results are consistent with previous studies that focused on improving early maintenance in power plants, confirming the importance of continuous monitoring of operational data to detect faults before they occur [1][2]. The results also support the literature indicating that time-series analysis of operational data can reduce unexpected downtime and lower operating costs [14].

7.2 Analysis of Limitations and Challenges

Despite the promising results, several challenges must be considered:

- Data Availability: The study used simple experimental data, whereas real data from large plants often contain more noise, complex faults, and multiple measurements [14].
- Computational Complexity: Detailed analysis for large plants requires higher computational resources, especially when dealing with high-resolution thermal images or large volumes of operational data [2][4].
- Practical Complexity of Large Plants: The current study focused on a small plant, while large plants contain thousands of panels and units, making preventive maintenance scheduling more complex and requiring advanced optimization algorithms.

7.3 Suggestions for Future Improvements

Based on the aforementioned limitations, several improvements can be proposed for future studies:

- Using Real Data from Large Plants: Integrating sensors to monitor live operational data can enhance the accuracy of fault detection.
- Enhancing Monitoring and Analysis Techniques: Employing advanced analysis of time-series data and thermal images for early fault detection [1][2].
- Implementing Intelligent Preventive Maintenance: Developing an automatic maintenance scheduling system to reduce downtime and increase plant efficiency.
- Exploring Digital Simulation Techniques: Using digital twin models to simulate plant performance and predict future faults more accurately, improving operational planning [4].

7.4 Conclusion of the Discussion

It can be concluded that the simplified experimental model demonstrates the potential to improve the reliability of photovoltaic power plants and reduce operational costs through operational data monitoring and analysis. However, applying these methods on a larger scale with real data will yield more reliable and practically applicable results.

8. Conclusion

This research has focused on improving the performance of photovoltaic (PV) power plants through fault prediction and preventive maintenance scheduling.

8.1 Summary of Findings

A fault prediction model was developed using operational data analysis in MATLAB, showing good capability in identifying faults with an accuracy of approximately 97%. This demonstrates the effectiveness of monitoring and analyzing operational data of photovoltaic panels [1][2].

Both the expected and actual simulation results indicated that early fault detection can significantly reduce operational losses and unplanned downtime periods [14]. Integrating the model with preventive maintenance scheduling can reduce operating costs and increase plant reliability, thereby enhancing the sustainability of renewable energy.

8.2 Practical Contributions

The research highlights the value of combining fault prediction with preventive maintenance in solar power plants, particularly for improving performance and reducing unexpected failures.

The applied model, despite its simplicity, provides a foundational understanding of how fault prediction works in a simulation setting and can be further developed for larger, real-world datasets with more complex operational conditions.

8.3 Future Recommendations

- Implementing models on large-scale plants using real operational data to enhance accuracy and reliability.
- Utilizing advanced monitoring and predictive techniques along with maintenance optimization methods to maximize the benefits of fault detection [1][2].
- Exploring digital simulation and modeling tools (e.g., Digital Twin) to improve operational planning and forecast future faults [4].

In conclusion, this research demonstrates that monitoring and predictive maintenance strategies offer effective tools for enhancing the performance of photovoltaic power plants, contributing to increased reliability, reduced operational costs, and improved sustainability of solar energy systems.

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