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Reliability Analysis of an Inverter at a Solar Power System in Bantul, Yogyakarta, using Random Forest

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ABSTRACT: Photovoltaic systems are susceptible to various types of failures, such as system faults caused by weather conditions, soiled photovoltaic panels, partial shading, cable damage, short circuits, mechanical failures, and other disturbances. Reliability of photovoltaic systems is critical to ensuring a stable electricity supply. This research used real-time condition-monitoring data from an inverter of a Photovoltaic Power Plant in Bantul, Yogyakarta, Indonesia. In this study, a Random Forest Regression model was employed to predict the photovoltaic system voltage, achieving a coefficient of determination (R^2) of 0.5964, indicating that the model explains approximately 59.74% of the variance in the actual data. Failure detection was performed using Residual-Based Anomaly Detection (RBAD), with a 5σ control limit applied to the residuals, resulting in 16 detected failure events over 9,664 operating hours. Based on these results, the Mean Time to Failure (MTTF) of the photovoltaic system was calculated as 593.75 hours, corresponding to a constant failure rate of 0.00168. Reliability analysis showed a gradual degradation over time, with reliability decreasing to 70% at 211 operating hours and 60% at 296 operating hours, indicating the necessity of periodic maintenance.

KEYWORDS: renewable energy, Photovoltaic, reliability, predictive maintenance, machine learning, random forest regression.

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Introduction

Due to the increasing global demand for electricity, the advancement of renewable energy systems aimed at mitigating carbon emissions and their adverse effects has significantly accelerated. PV power plants have become standard solutions for sustainable energy provision, particularly in remote and developing areas. However, photovoltaic systems are susceptible to various failures due to environmental conditions (temperature fluctuations, dust buildup, and shading) and technical issues (cable deterioration, short circuits, and inverter malfunctions). If these problems go unnoticed initially, they can considerably diminish system performance and increase operational costs.

Traditional maintenance approaches typically rely on cyclical monitoring or post-failure interventions, which often fall short at detecting early signs of degradation or effectively predicting failures. The advent of monitoring technologies such as SCADA has enabled the analysis of extensive operational data, allowing the application of machine learning techniques in predictive maintenance and condition monitoring. These algorithms can discover patterns and provide valuable insights into system operations and fault behaviours by analysing operational data.

Syamsudin et al. (2024) employed residual analysis along with a Long Short-Term Memory Autoencoder to detect anomalies, while Yaghoubi et al. (2025) used supervised machine learning models to forecast performance degradation due to dust accumulation. Models such as Random Forest have demonstrated strong predictive capabilities due to their ability to handle nonlinear data; Buratti et al. (2019) achieved high prediction accuracy exceeding 0.96, whereas Sajan et al. (2021) indicated that the Random Forest algorithm outperforms others in forecasting photovoltaic power output. Sayed et al. (2019) highlight the importance of reliability analysis in the maintenance of photovoltaic systems. However, much of the related literature focuses primarily on performance prediction or anomaly detection, without incorporating machine-learning-based fault detection into reliability assessments.

This paper proposes a machine-learning-based methodology that integrates Random Forest Regression with Residual-Based Anomaly Detection to identify failure events and evaluate the reliability of the photovoltaic inverter system at the Pandansimo Solar Power Plant in Bantul, Yogyakarta.

Research Aim and Research Questions

This study aims to predict the reliability of a photovoltaic system using a machine-learning-based predictive approach. This study aims to build a Random Forest Regression model for inverter DC-voltage prediction and a residual-based anomaly-detection approach for failure-event detection, which are then used to quantify key reliability parameters (MTTF, failure rate, reliability function). This research focuses on the critical issue of performance degradation and failures in photovoltaic systems caused by environmental and operational factors. Traditional maintenance methods usually cannot provide a quantitative reliability assessment based on operational data. Thus, combining machine-learning-based prediction with reliability analysis is an efficient way to evaluate system reliability and to provide

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reliability-centred maintenance approaches.

Research Results

This research used historical operational data of inverter DC voltage (VDC) retrieved from the photovoltaic system at the Pandansimo Solar Power Plant in Bantul, Yogyakarta. The dataset spans a continuous operation time period from 2017 to 2020, demonstrating long-term performance under real-time conditions. An Interquartile Range (IQR) was used to identify outliers and extract voltage readings that showed statistically meaningful differences from the accepted operational ranges. Rather than discarding these exceptions, we used interpolation algorithms to preserve the dataset unchanged.

Random Forest Prediction Performance

A Random Forest Regression model is developed to predict the DC voltage of inverters using historical operational data. This predictive model forms the basis of failure detection through residual analysis. [Figure 4.2] provides a comparison of both actual and predicted voltage values. As shown in this figure, the forecasted voltage closely matches the actual voltage, indicating that the Random Forest model can successfully capture the nonlinear relationship between operational variables and the system output. These predictions confirm that the model can accurately represent standard system behaviour, which is crucial for detecting irregularities.

Failure Detection Using Residual Analysis

Residual values were used for failure detection, defined as the discrepancy between actual and predicted voltage readings. The corresponding residual plot is illustrated in Figure 4.3. Instances where the residual values exceeded a designated threshold were classified as failure events. Through this approach, a total of 16 failure occurrences were identified over 9,664 operating hours. These identified failures indicate atypical system performance and form the foundation for reliability assessment. This detection strategy, which leverages machine learning, provides a data-driven approach to identifying failures without manual examination.

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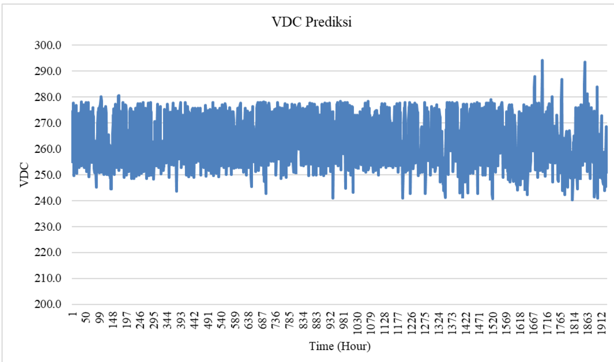
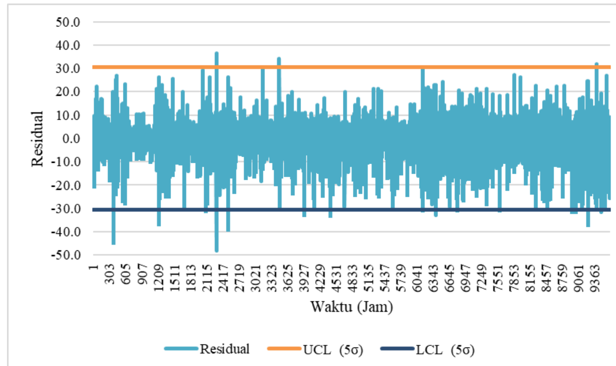
Figure 2

(a) Comparison between actual and predicted voltage, (b) Residual plot for failure detection

(a)



(b)



Reliability Analysis

An estimated reliability was calculated from the detection of failure events to assess the probability that the system operates without failure over time. Mean Time to Failure. For TTF, MTTF = 593.75 hours. This demonstrates that the photovoltaic system operates, on average, for approximately 593.75 hours before failure. This value provides a quantitative measure of overall system reliability—failure Rate. The failure rate is determined using the exponential reliability model $\lambda = 0.00168$ failures per hour. This represents the failure frequency during system operation. Reliability performance is generally acceptable due to the low failure rate, but system degradation is also evident. [Figure 4.3] shows the reliability curve. With respect to the reliability curve, it declines over time. At 211 hours, the reliability scores were 70%; at 296 hours, 60%. This indicates that increased operating time increases the likelihood of failure. This degradation in reliability is common in photovoltaic systems operating under real-world environmental conditions. The reliability curve gives important information to both maintenance planning and evaluating system performance.

Figure 3

Reliability Curve

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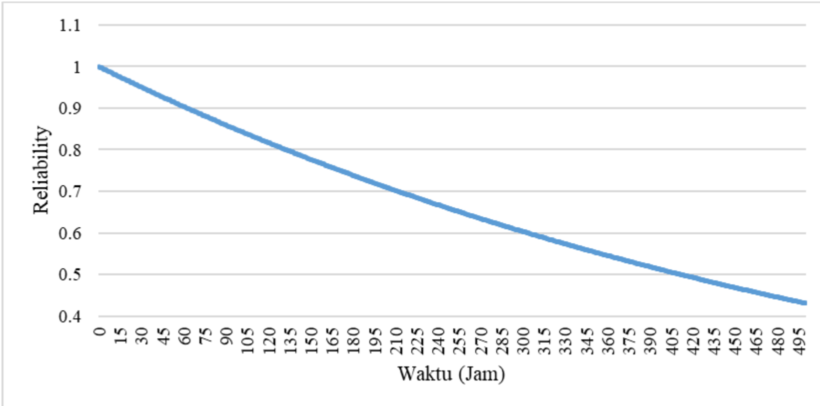

Conclusions

Machine learning method for evaluation of the reliability of a photovoltaic system using Random Forest Regression and residual-based anomaly detection. The developed model was able to detect failure cases using historical inverter DC-voltage data and quantify reliability under true operating conditions. Based on failure-detection data, 16 failure events were identified over 9,664 hours of operation. From these failure intervals, the mean time to failure (MTTF) of the photovoltaic system was calculated to be approximately 593.75 h, representing the average operating period between consecutive failures. It was found that the failure rate was 0.00168 per hour, assuming a constant failure rate model.

The system's operational performance gradually decreases, implying it is unreliable. In addition, reliability decreases with increasing operating time, as revealed by the reliability analysis. At about 211 operating hours, reliability falls to about 70%, and at 296 operating hours, it decreases to about 60%. This finding shows that the likelihood of system failure significantly increases well after this operating time period, underscoring the significance of reliability-based maintenance planning to avoid unexpected system failure. Machine learning, predictive modelling, and reliability analysis combine to offer an empirically powered system-level approach to failure characteristics identification and system reliability assessment in a more efficient way than traditional methods. This approach provides access to operating data to determine reliability variables, thereby eliminating the need to keep detailed physical failure lists, enabling the approach to be adopted in more modern photovoltaic systems with monitoring.

The inclusion of additional operational parameters, such as current, temperature, and irradiance, could enhance the accuracy of failure detection and reliability estimation. Secondly, the introduction of advanced machine learning models (e.g., hybrid and/or deep learning methods) might improve predictive performance. It is necessary to extend this work to include non-constant failure-rate models, such as the Weibull distribution, to analyse the degradation path of photovoltaic systems more accurately over long-term operation. Developments will improve reliability assessment and pave the way for implementing predictive maintenance strategies in photovoltaic power plants.

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