Machine Learning-Based Islanding Detection in Grid-Connected Photovoltaic Systems

Abstract

The growing integration of grid-connected photovoltaic (PV) systems into distribution networks has made reliable islanding detection a critical safety requirement. Islanding occurs when a PV-connected segment remains energised after utility disconnection, endangering maintenance personnel and risking equipment damage. Traditional passive and active detection methods are constrained by Non-Detection Zones (NDZ) and power quality degradation. This study develops and evaluates a suite of machine learning classifiers, including Random Forest, Support Vector Machine (SVM), Multi-layer Perceptron Neural Network (M), and XGBoost, trained on features extracted from MATLAB/PSIM simulations of a grid-connected PV system. Features were extracted from three-phase voltage signals at the Point of Common Coupling(PCC). Random Forest with an adaptive decision threshold of 0.45 achieved the best overall performance, attaining 98.35% accuracy, 97.23% precision, 94.75% recall, and an F1-score of 95.97%, with a near-zero NDZ and no active signal injection, satisfying the IEEE 1547 two-second detection requirement.

keywords: Islanding detection, Random Forest, adaptive thresholding, grid-connected PV, non-detection zone, machine learning

Introduction

The global expansion of renewable energy has accelerated the deployment of grid-connected PV systems, with approximately 585 GW of new renewable capacity installed in 2024, representing 92.5% of all new generation [1]. Ghana's Renewable Energy Act (Act 832, 2011) reflects this trend, driving increasing PV integration into the national distribution network. A key operational challenge accompanying this growth is islanding, which occurs when a section of the network remains energised by local PV inverters following utility disconnection [2]. IEEE Standard 1547 mandates islanding detection and disconnection within two seconds to protect line workers and prevent equipment damage on reconnection.

Existing detection approaches, including passive threshold-based, active signal injection, and remote communication-based methods, each carry significant limitations such as large NDZs, power quality degradation, or prohibitive infrastructure costs [3]. Computational intelligence methods have emerged as a promising alternative, capable of learning subtle multivariate signal patterns without fixed thresholds. This study systematically trains and compares five machine learning algorithms, identifying Random Forest with adaptive thresholding as the optimal solution for grid-connected PV islanding detection.

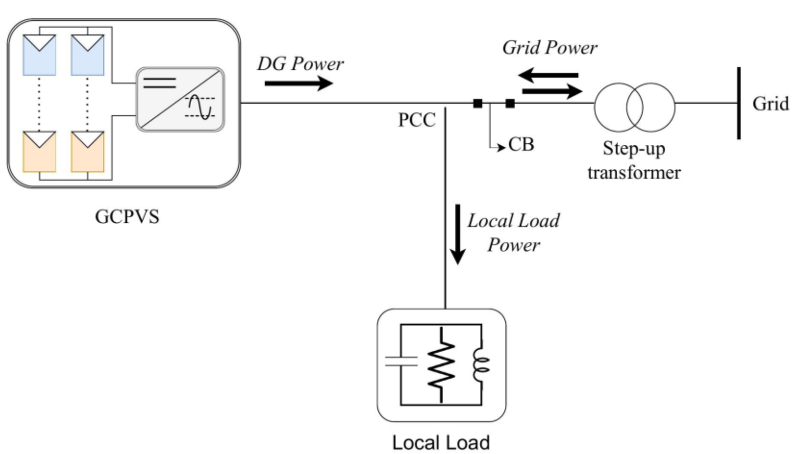

Figure 1: Grid-connected photovoltaic system (GCPVS) showing DG power flow, the Point of Common Coupling (PCC), circuit breaker (CB), step-up transformer, and local RLC load.

Methods

System Modelling. A grid-connected PV system with a parallel RLC local load was modelled in MATLAB. Islanding and non-islanding events were generated across a wide range of power mismatch ratios, load switching, and capacitor switching scenarios, producing a balanced, labelled dataset for both classes.

Feature Extraction. Three-phase voltage signals at the Point of Common Coupling (PCC) were processed using the Discrete Wavelet Transform (DWT) for time-frequency decomposition. 12 key statistical features extracted from each frequency band per phase included kurtosis, rms voltage, peak voltage, shape factor, crest factor, clearance factor, etc

Classifiers. Four algorithms were trained on 60% of the dataset, evaluated on 20% of the data while the rest were tested on 20% of the unseen data using: Random Forest (RF), Support Vector Machine (SVM), Multi-layer Perceptron Neural Network (MPNN), and XGBoost. For Random Forest, the default classification threshold of 0.50 was replaced with an adaptive threshold of 0.45, calibrated to maximise recall and minimise missed islanding events while maintaining high precision.

Results

Table 1 presents the performance metrics of all four classifiers. Random Forest with adaptive threshold 0.45 achieved the highest accuracy and a perfect recall score, correctly identifying every islanding event in the test set with near zero missed detections. Kurtosis and shape factor emerged as the most discriminative features across all models.

Table 1: Performance metrics of ML classifiers for islanding detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	NDZ
Random Forest	98.35	97.23	94.75	95.97	Low
SVM	97.60	97.44	97.76	97.60	Low
MLP	98.80	98.46	99.14	98.80	Near-zero
XGBoost	97.30	91.09	96.48	93.71	Near-zero

Discussion and Conclusion

Random Forest with an adaptive threshold of 0.45 is the best-performing model in this study and the most suitable for practical islanding detection in grid-connected PV systems. Three properties justify this conclusion. First, its 94.75% recall guarantees few missed islanding events, the most safety-critical metric, as any undetected island directly endangers maintenance personnel. Second, its 97.23% precision keeps false-alarm rates reasonable, allowing for a few false alarms. Third, the adaptive threshold mechanism provides a principled, data-driven means of shifting the sensitivity-specificity trade-off without retraining, making it easily recalibrated for different grid configurations or load profiles.

References

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