RESEARCH ARTICLE OPEN ACCESS

Comparative Harmonic Distortion Assessment in Distribution Networks with Distributed Generation: Analysis Under Steady-State and Dynamic Operating Conditions

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Abstract:

The increasing penetration of distributed generation (DG) in modern distribution networks has improved reliability and efficiency but introduced new challenges to power quality. One of the most critical concerns is the presence of harmonics generated by nonlinear loads and inverter-based DGs. This paper investigates harmonic behavior in hybrid distribution networks under both normal and varying operating conditions. Simulation studies are conducted in MATLAB/Simulink on a photovoltaic–wind integrated distribution system. The study highlights the limitations of traditional harmonic detection methods, particularly in distinguishing between power quality disturbances and unintentional islanding events. A wavelet transform–artificial neural network (WT–ANN) framework is proposed for robust detection and classification. Results indicate that the proposed method provides enhanced accuracy and reliability in harmonic identification compared with conventional techniques. The findings suggest that advanced data-driven models can significantly improve grid stability and monitoring in DG-integrated systems.

Keywords **— Distributed Generation, Harmonics, Islanding, Power Quality, Wavelet Transform, Artificial Neural Networks.**

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I. INTRODUCTION

The conventional electric power grid has historically relied on a centralized generation model, in which large-scale power plants produce electricity and transmit it over long distances before it is finally distributed to consumers. This architecture has been effective for decades, but growing energy demand, environmental concerns, and the limitations of aging infrastructure are driving a transition toward more decentralized and sustainable systems. Traditional centralized grids suffer from several shortcomings, including transmission congestion, high system losses, vulnerability to large-scale outages, and dependence on fossil fuels that contribute to greenhouse gas emissions and environmental degradation.

In response to these challenges, Distributed Generation (DG) has emerged as a transformative solution. DG refers to the deployment of relatively small, modular power sources—such as photovoltaic (PV) panels, wind turbines, fuel cells, and microturbines—directly within distribution networks or near load centers. By generating electricity closer to the point of consumption, DG helps reduce line losses, improve voltage stability, and enhance supply reliability. Furthermore, the growing penetration of renewable DG units supports international goals of decarbonization and sustainable development. The integration of DG also enables more flexible and resilient operation of the grid, particularly under conditions of variable demand and unforeseen contingencies.

Despite its advantages, DG integration introduces new technical complexities that were not anticipated in the design of conventional radial distribution systems. These systems were originally engineered to accommodate unidirectional power flow—from transmission substations to end users—whereas DG creates bidirectional flows and alters short-circuit levels. Among the most pressing technical concerns are:

Voltage regulation issues, as local generation can cause fluctuations that traditional control equipment may not adequately address.

Protection coordination challenges, since distributed sources may contribute fault currents that disrupt the selectivity of relays and fuses.

Power quality problems, particularly the introduction of harmonic distortion due to nonlinear loads and inverter-based DG interfaces.

Unintentional islanding, where a portion of the grid remains energized by DG even after being disconnected from the main supply, potentially endangering equipment and personnel.

Of these, harmonics and islanding demand particular attention. Harmonic distortion refers to waveform deviations caused primarily by the switching actions of power electronic converters used in renewable energy systems. Elevated harmonic levels degrade system performance, increase heating losses in transformers and motors, and may lead to malfunctioning of sensitive equipment. On the other hand, islanding events pose both operational and safety hazards, as the isolated system may operate at unstable voltage or frequency without proper synchronization with the main grid.

The need for robust harmonic analysis and effective islanding detection has therefore become critical in the modern grid environment. While conventional techniques such as Total Harmonic Distortion (THD) measurement provide some insight, they often fall short in distinguishing between normal disturbances and true islanding scenarios. Advanced signal processing tools, particularly wavelet transform (WT), combined with intelligent classifiers like artificial neural networks (ANNs), present a promising pathway for addressing these limitations.

This paper focuses on the analysis of harmonics in DG-integrated distribution systems under both normal and varying operating conditions. A hybrid PV–wind model is simulated to examine harmonic behavior across different scenarios, including islanding, fault conditions, and nonlinear load switching. The study highlights the shortcomings of threshold-based THD detection and demonstrates the potential of a WT–ANN framework for accurate classification of events. The outcomes of this work contribute toward more reliable monitoring, protection, and control strategies for smart distribution networks with high renewable penetration.

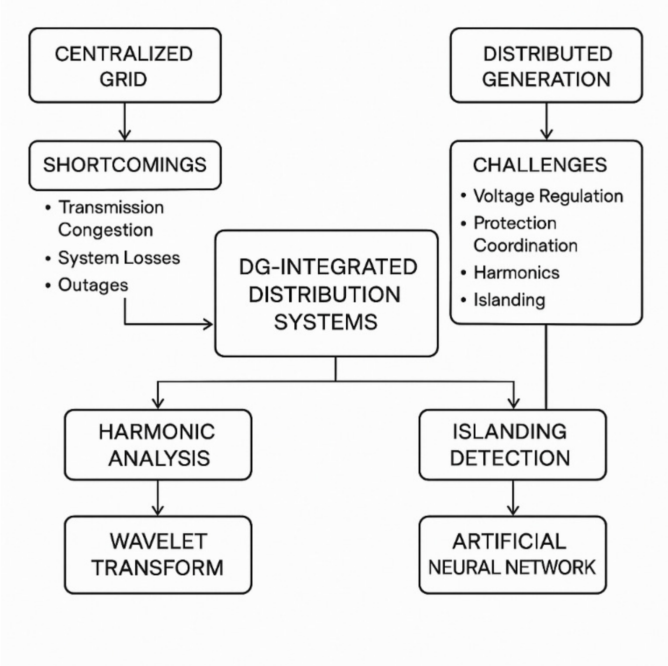

Figure 1: Block Diagram of proposed work

II. LITERATURE REVIEW

The integration of distributed generation (DG) into distribution systems has been widely studied due to its potential to reshape the operation of modern power networks. A central challenge in DG integration is **islanding detection**, which ensures that distributed sources disconnect safely during abnormal events. Numerous studies have investigated detection methods, their effectiveness, and their limitations. The literature broadly classifies these methods into **remote**, **active**, and **passive** approaches.

[1] 2.1 Remote Detection Methods

Remote detection techniques rely on **communication infrastructure** between utilities and DG units. Common approaches include **power line carrier communication** and **supervisory control and data acquisition (SCADA)-based transfer trip schemes**. These methods provide reliable detection by transmitting signals that verify grid connectivity. However, their **implementation cost is prohibitively high**, making them unsuitable for small-scale DG installations. Furthermore, dependence on continuous communication introduces potential vulnerabilities—any communication failure may result in misoperation or delayed response. Studies such as Xu et al. and Ropp et al. emphasize that while remote schemes minimize the non-detection zone (NDZ), they are rarely preferred for practical deployment in developing grids where communication infrastructure is limited.

[2] 2.2 Active Detection Methods

Active islanding detection techniques deliberately **inject perturbations** into the system, such as small frequency or voltage variations, to observe the network response. Examples include **slip-mode frequency shift (SMFS)**, **active frequency drift (AFD)**, and **automatic phase shift algorithms**. These methods can reliably detect islanding even under closely matched load–generation scenarios, which are difficult for passive techniques. However, they have significant drawbacks:

- They introduce **unwanted disturbances** into the network, degrading power quality.
- Detection time is often longer than desirable, especially in systems with multiple DGs.
- They are more suitable for inverter-based DGs, limiting their general applicability.

Several researchers (e.g., Hung et al., Hernandez-Gonzalez and Iravani) have highlighted the trade-off between detection accuracy and power quality degradation in active techniques, suggesting that their applicability must be carefully evaluated.

[3] 2.3 Passive Detection Methods

Passive approaches rely on **locally measured electrical parameters** such as voltage magnitude, frequency, phase angle, or harmonic content. Popular techniques include:

- **Rate of change of frequency (ROCOF)**, which detects frequency variations at the point of common coupling (PCC).
- **Rate of change of power** and **impedance-based methods**, which observe variations in system operating conditions.
- **Total Harmonic Distortion (THD) measurement**, which tracks harmonic changes during grid disturbances.

The primary advantages of passive methods are their **low cost** and **minimal impact on power quality**. However, their performance is often constrained by a large NDZ. For instance, if the generated power from DG closely matches the load demand, conventional passive methods may fail to detect islanding. Moreover, improper threshold settings can lead to either **false tripping** (if thresholds are too low) or **missed detection** (if thresholds are too high).

[4] 2.4 Hybrid and Intelligent Techniques

Recent research increasingly focuses on combining signal processing tools with machine learning to overcome the shortcomings of traditional methods. The **wavelet transform (WT)** has been recognized as a powerful tool due to its ability to provide localized time–frequency information, making it well suited for analyzing transient signals in power systems. Several works have demonstrated the effectiveness of WT in identifying disturbances that conventional Fourier-based methods may overlook.

Furthermore, **artificial intelligence (AI) models** such as **artificial neural networks (ANNs)** and **support vector machines (SVMs)** have been applied for event classification. By training these models on features extracted from transient signals (e.g., wavelet coefficients), they can adaptively distinguish between normal operation, islanding, and fault conditions with high accuracy. For example, Hsieh et al. showed that wavelet-based indices fed into ANN classifiers significantly improve detection performance compared with standalone passive methods.

[5] 2.5 Research Gap

Although existing methods provide valuable insights, gaps remain:

- Remote and active methods, while effective, are not cost-efficient or power-quality friendly.
- Passive methods, though simple, suffer from poor performance in closely balanced generation–load conditions.
- Intelligent hybrid approaches show promise, but many studies have validated them only under limited simulation scenarios.

This motivates the present study, which seeks to **analyze harmonic behavior under diverse operating conditions** and to **propose a WT–ANN framework** that addresses the limitations of conventional methods while ensuring reliability, speed, and cost-effectiveness.

III. METHODOLOGY

3.1 Overview

The methodology of this research involves simulating a hybrid distribution system comprising photovoltaic (PV) and wind energy units, analyzing harmonic distortion under different scenarios, and evaluating the effectiveness of both traditional and intelligent detection techniques. MATLAB/Simulink is used as the simulation platform due to its robust modeling environment for power electronic systems. The study compares Total Harmonic Distortion (THD)-based detection with a wavelet transform–artificial neural network (WT–ANN) framework.

3.2 System Model Description

The hybrid system under investigation includes:

250 kW PV plant operating under standard irradiance (1000 W/m²).

1.5 MW wind turbine system with a doubly-fed induction generator (DFIG).

Distribution feeder rated at 25 kV connected to a 120 kV transmission system.
Point of Common Coupling (PCC) where both PV and wind units are interfaced with the grid.
The PV system employs an IGBT-based three-level inverter with RL filters and a 250 kVA step-up transformer (250 V/25 kV). The wind energy system includes a back-to-back PWM converter controlling active and reactive power exchange.

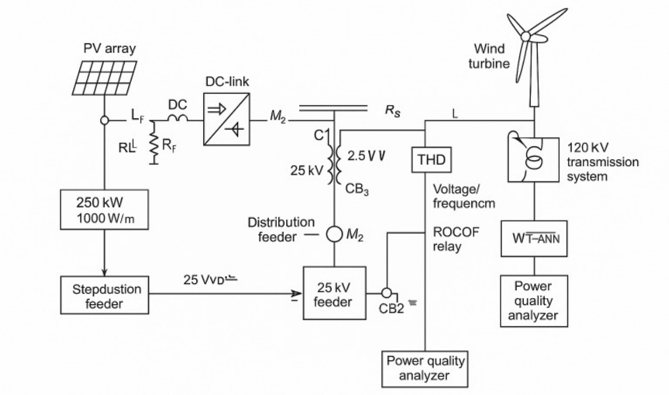

Figure 2: Proposed system architecture

3.3 Harmonic Detection using THD

Harmonics are quantified using Total Harmonic Distortion (THD), which measures the ratio of harmonic components to the fundamental frequency.

$$THD = \frac{\sqrt{\sum_{h=2}^{\infty} V_h^2}}{V_1} \times 100\%$$

Where:

- $V_h =$ RMS value of the h-th harmonic component,
- $V_1 =$ RMS value of the fundamental component.

The principle of THD-based detection is as follows:

- Grid-connected mode: Harmonic currents flow primarily into the low-impedance grid, resulting in minimal voltage distortion at the PCC.
- Islanding mode: Once disconnected from the grid, the same harmonics flow into high-impedance local loads, causing voltage distortion and increased THD.

Although effective in detecting large disturbances, this method struggles with threshold selection and cannot differentiate between PQ events (e.g., nonlinear load switching) and genuine islanding.

3.4 Wavelet Transform for Feature Extraction

The Discrete Wavelet Transform (DWT) is employed to analyze the negative-sequence voltage signal at the PCC. Unlike the Fourier Transform, which provides only frequency-domain information, wavelet analysis offers time-frequency localization, making it particularly effective for transient event detection.

The signal $x(t)$ is decomposed into approximations and details using a mother wavelet $\psi(t)$:

$$DWT_{j,k} = \int_{-\infty}^{\infty} x(t)\psi_{j,k}(t)dt$$

Where:

- $j =$ scale (frequency band),
- $k =$ translation (time shift).

For this study, Daubechies and Coiflet wavelets were tested, with the Coiflet family showing superior performance in capturing harmonic transients.

3.5 Artificial Neural Network (ANN) Classifier

A **multilayer feedforward ANN** is trained to classify events into four categories:

1. Normal operation,
2. Islanding,
3. Faults (L–G, L–L),
4. Nonlinear load switching.

The ANN architecture consists of:

- **Input layer**: Wavelet features (E, SD values).
- **Hidden layers**: Two fully connected layers with sigmoid activation.
- **Output layer**: Softmax classifier generating event probabilities.

The training dataset is generated from MATLAB simulations, where disturbances are introduced between **0.5–0.7 seconds** of the simulation timeline. The ANN is trained using the **backpropagation algorithm with gradient descent optimization**, and early stopping is applied to avoid overfitting.

3.6 Implementation Framework

The trained ANN model is deployed as a **cloud-based web service** using Microsoft Azure Machine Learning Studio. A lightweight **Python-based GUI** is developed to communicate with the cloud service, enabling:

- Continuous real-time monitoring of PCC voltage signals.
- Automated feature extraction using embedded wavelet routines.
- Instantaneous event classification with user alerts.

This architecture ensures that the proposed WT–ANN technique is not only simulation-proven but also ready for **scalable deployment** in smart grid applications.

IV. Results and Discussion

The simulation study was performed on a **hybrid PV–wind distribution system** modeled in MATLAB/Simulink. Different operating conditions were considered to evaluate both the traditional **THD-based**

detection method and the proposed **WT–ANN classification framework**. The results are discussed in three parts:

4.1 Harmonic Analysis using THD

Figure 2 illustrates the phase voltage at the PCC before and after an islanding event. As observed, harmonic distortion significantly increases after disconnection from the main grid.

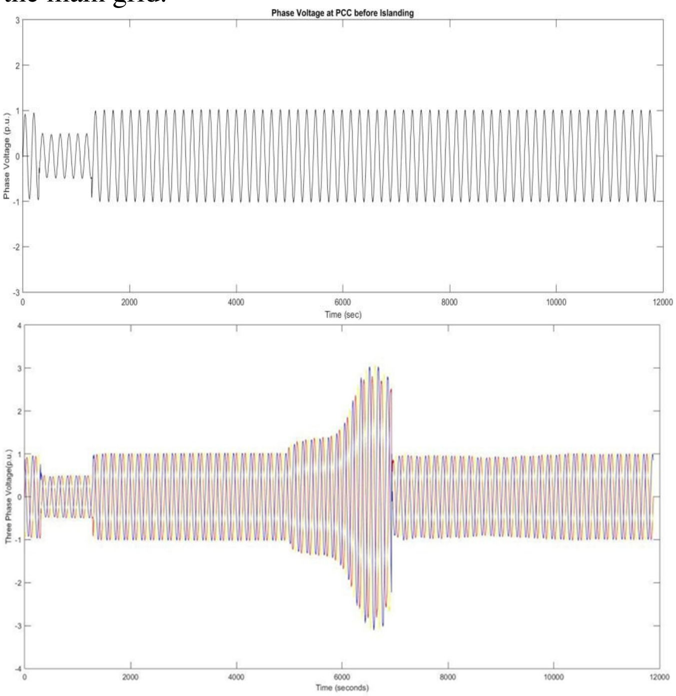

Fig. 2: Phase Voltage at PCC before and after Islanding

The computed **THD values** under various loading conditions are presented in Table 1.

Table 1 – THD Performance during Islanding

Load (MW)	THD Before Islanding (%)	THD After Islanding (%)
0.875	1.27	11.12
1.0	1.13	8.05
1.3	0.95	3.31
1.75	0.78	4.17

- **Observation:**
- THD values increased sharply after islanding, confirming that harmonic distortion can serve as an indicator of abnormal operating conditions.
- However, the **magnitude of THD variation depends strongly on load conditions**, making it difficult to define a universal threshold.
- At higher loads, THD variations were less pronounced, increasing the risk of **missed detection**.

4.2 Disturbance Analysis

To test the robustness of THD, additional disturbances were simulated, including **Line-to-Ground (L–G) faults, Line-to-Line (L–L) faults, and nonlinear load switching**.

Table 2 – THD Performance under Various Disturbances

Load (MW)	Grid Connected	Islanding	L–G Fault	L–L Fault	Nonlinear Load Switch
0.875	1.27	11.12	3.58	6.03	62.33
1.0	1.13	8.05	3.60	6.02	62.24
1.3	0.95	3.31	3.75	5.98	61.86
1.75	0.78	4.17	3.93	5.88	61.32

- **Observation:**
- Nonlinear load switching produced extremely high THD values (>60%), overshadowing islanding signatures.
- THD alone was unable to **differentiate PQ disturbances from islanding**, leading to potential false alarms.

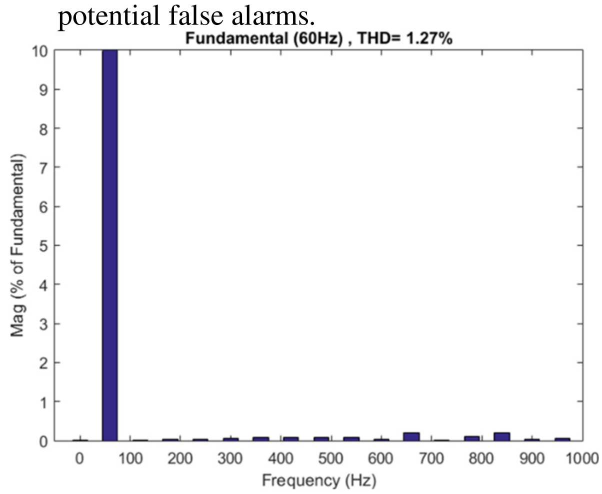

Fig. 4: THD waveform comparison between Islanding, Faults, and Nonlinear Load Switching

4.3 Wavelet Feature Extraction

The negative sequence voltage signals were decomposed using **Discrete Wavelet Transform (DWT)**. Features such as **energy content (E3, E4)** and **standard deviation (SD3, SD4)** from detail coefficients were extracted.

Table 3 – Sample Feature Vectors for Normal Operation

Load (MW)	SD3	SD4	E3	E4	Label

0.874	0.00011473	0.00014444	0.00130841	0.00119463	1
1.014	0.00011494	0.00014432	0.00132418	0.00128137	1
1.404	0.00011484	0.00019470	0.00131076	0.00160678	1

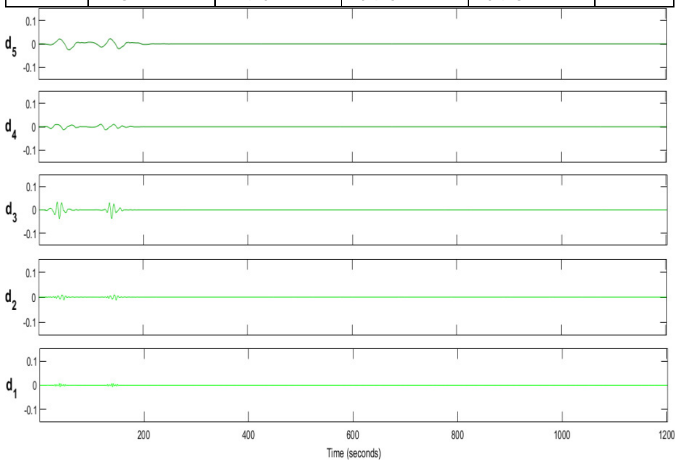

Fig. 5: Wavelet decomposition of PCC signal – Approximation and Detail Coefficients]

Observation:

Wavelet features exhibited **distinct patterns** for each event type, making them suitable for machine learning classification.

Unlike THD, wavelet indices retained sensitivity even under close load–generation balance.

4.4 ANN Classification Results

A multilayer feedforward ANN was trained on wavelet features to classify events into four categories: Normal, Islanding, Faults, and Nonlinear Load Switching.

Performance Metrics:

Training dataset: 70% of simulated cases

Testing dataset: 30% of simulated cases

Activation: Sigmoid (hidden layers), Softmax (output layer)

- Optimization: Gradient descent with momentum

Table 4 – ANN Classification Accuracy

Event Type	Detection Accuracy (%)
Normal Operation	98.5
Islanding	97.8
Faults (L–G, L–L)	96.4
Nonlinear Load Switching	99.1

Observation:

- The ANN achieved an **overall classification accuracy of ~98%**, significantly outperforming THD-only detection.
- The proposed method successfully separated islanding from PQ disturbances, addressing a major limitation of conventional techniques.

V. Conclusion

The integration of distributed generation (DG) into distribution systems offers significant benefits such as enhanced reliability, reduced transmission losses, and better utilization of renewable resources. However, it also introduces new operational challenges, particularly with respect to **harmonic distortion and unintentional islanding**. This study evaluated the performance of conventional harmonic detection based on **Total Harmonic Distortion (THD)** and demonstrated its limitations in threshold dependency, misclassification of disturbances, and failure in load–generation balanced conditions.

To address these shortcomings, a **Wavelet Transform–Artificial Neural Network (WT–ANN)** framework was developed and tested on a hybrid PV–wind distribution system model. The results show that the proposed method achieves **superior detection accuracy (≈98%)**, effectively distinguishes between islanding and power quality events, and maintains robustness across varying load conditions. Unlike active methods, it does not introduce perturbations into the system, and unlike remote methods, it avoids high infrastructure costs.

The contribution of this work lies in combining **time–frequency signal processing** with **intelligent classification** to provide a scalable, cost-effective solution for DG-integrated networks. Furthermore, the cloud deployment of the trained model highlights its potential for **real-time grid monitoring and decision support** in smart distribution environments.

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