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Fault Detection and Classification in Grid-Connected Solar Photo Voltaic Farm Using Radial Basis Function Neural Network and Discrete Wavelet Transform

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ABSTRACT

The global transition to renewable energy, driven by climate mitigation targets and energy security concerns, has positioned solar photovoltaic (PV) systems as a cornerstone of sustainable energy strategies. However, the scalability of grid-connected solar farms is hindered by operational vulnerabilities, particularly fault-induced inefficiencies that compromise system reliability and safety. This study addresses these challenges by proposing a novel fault detection and classification framework that integrates Discrete Wavelet Transform (DWT) with Radial Basis Function Neural Networks (RBFNN). The DWT-RBFNN model is designed to accurately detect and classify faults in real-time, even in noisy and dynamic operational environments. The research focuses on both AC and DC-side faults, with particular emphasis on grid interaction complexities often overlooked in existing studies. The proposed system achieved an overall classification accuracy of 94% across six fault categories, with precision rates exceeding 95% for most fault types. This represents a significant advancement over previous methods, such as traditional fuzzy logic systems limited to DC-side faults.The system demonstrated exceptional performance in fault classification, achieving F1-scores of 99% for line-to-ground and line-to-line faults, and 82% for three-phase faults. Under normal operating conditions, the system maintained stable performance with balanced three-phase voltages (≈250V) and currents (Phase A: 1.008A, Phase B: 0.833A, Phase C: 0.669A). The DWT-RBFNN approach successfully detected and classified various fault conditions, including voltage surges up to 302.54V during L-G faults and current imbalances reaching 98.60A during L-L-G faults.The research contributes to the field by introducing a comprehensive fault detection framework that combines advanced signal processing with machine learning techniques, offering improved accuracy and real-time detection capabilities for grid-connected solar PV installations.

Keywords: *Grid-Connected Photovoltaic Systems, Fault Detection and Classification, Discrete Wavelet Transform, Radial Basis Function Neural Network, Machine Learning, Power Quality, Grid Integration, Renewable Energy, Solar Power, Smart Grid Protection, Real-Time Monitoring, Power System Reliability*

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I. INTRODUCTION

The accelerating global transition to renewable energy, underscored by the Paris Agreement's climate mitigation targets, has positioned solar photovoltaic (PV) systems as central to sustainable energy strategies (International Energy Agency [IEA], 2023). Driven by the need to decarbonise energy systems, enhance energy security, and address escalating electricity demands, solar PV technology has achieved unprecedented growth, surpassing 760 GW of installed capacity worldwide by 2022 (REN21, 2023). This rapid adoption reflects not only technological advancements but also the declining costs of PV components, making solar energy a cornerstone of national energy policies (Owusu & Asumadu-Sarkodie, 2016).

In Nigeria, where chronic energy shortages impede socioeconomic development, solar PV emerges as a critical solution to bridge the nation's 200 GW energy deficit (Akinyele et al., 2022). The government's commitment to deriving 30% of its energy from renewables by 2030 highlights solar PV's strategic role, leveraging the country's abundant insolation and falling technology costs (Federal Ministry of Power, Works and Housing, 2020; Oyedepo et al., 2020). However, the scalability of grid-connected solar farms hinges on addressing operational vulnerabilities, particularly fault-induced inefficiencies that jeopardize system reliability and safety (Mellit et al., 2018).

Faults in PV systems—ranging from arc failures to grid instability—can precipitate severe power losses, equipment damage, and safety risks (Garoudja et al., 2017). Traditional diagnostic methods, reliant on manual inspections and threshold-based algorithms, prove inadequate for real-time detection, often delaying response times and compromising accuracy (Mandal et al., 2022; Yadav et al., 2021). This gap is particularly acute in AC-side faults, such as line-to-ground and phase imbalances, which remain understudied despite their disproportionate impact on grid stability (Pillai et al., 2019). Consequently, the integration of intelligent fault detection systems has become imperative to optimize PV performance and longevity.

Advances in artificial intelligence (AI) offer transformative solutions, with machine learning models demonstrating exceptional potential in fault diagnostics (Chen et al., 2019). Radial Basis Function Neural Networks (RBFNNs), renowned for their rapid convergence and adaptability to nonlinear patterns, have emerged as robust tools for classification tasks in energy systems (Dhimish et al., 2018; Zhang et al., 2020). When coupled with Discrete Wavelet Transform (DWT)—a signal processing technique adept at isolating transient features in time-frequency domains—these models enable precise fault characterisation, even in noisy operational environments (Livera et al., 2019; Zhu et al., 2021). Synergizing DWT's feature extraction with RBFNN's predictive accuracy presents a paradigm shift in PV fault management, offering real-time, scalable diagnostics (Alajmi et al., 2020; Harrou et al., 2019).

This research confronts four critical gaps in fault detection for grid-connected solar PV systems. First, prevailing methods inadequately address AC-side faults and grid interaction complexities, focusing disproportionately on DC-side anomalies (Zhou et al., 2019; Chen et al., 2020). Second, conventional systems lack real-time responsiveness, resulting in delayed fault mitigation and prolonged energy losses in large-scale installations (Kumar et al., 2019). Third, environmental variability compromises detection accuracy, as existing techniques fail to differentiate between weather-induced fluctuations and genuine faults (Liu et al., 2020). Finally, traditional signal processing tools like Fourier transforms prove unsuitable for non-stationary PV signals, while current AI models either sacrifice accuracy for speed or demand impractical computational resources (Al-Shammari et al., 2020; Oyewole et al., 2020). These limitations collectively undermine the reliability and efficiency of solar PV farms, particularly in regions like Nigeria with dynamic grid conditions and resource constraints.

The study aims to resolve these challenges through a novel DWT-RBFNN framework designed for real-time, accurate fault detection in grid-connected PV systems. Key objectives includedeveloping a MATLAB/Simulink model simulating diverse AC/DC faults and grid interactions, integrating DWT for precise feature extraction from transient signals,optimising RBFNN for rapid fault classification with minimal computational overhead, and benchmarking system performance against existing methods.

II. REVIEW OF LITERATURE

The integration of photovoltaic (PV) systems into modern grids necessitates robust fault detection and classification (FDC) mechanisms to ensure stability and compliance with grid codes. This section critically evaluates advancements in FDC methodologies, emphasising computational techniques, control strategies, and their limitations.

Banu and Istrate (2014) pioneered the analysis of three-phase PV systems under symmetrical/asymmetrical grid faults using MATLAB/Simulink, identifying environmental factors (e.g., irradiance, temperature) as critical to fault response. While their study confirmed grid frequency stability during line-to-line (LL) and line-to-line-to-ground (LLG) faults, it omitted advanced signal processing tools like discrete wavelet transform (DWT) and radial basis neural networks (RBNN). Similarly, Hota et al. (2016) emphasized robust controllers for grid-connected PV systems, achieving global stability and disturbance rejection under LLG faults. However, their reliance on predefined parameters limited adaptability to dynamic fault conditions. Later, Roselyn et al. (2020) addressed power quality via total harmonic distortion (THD) analysis and hysteresis current control, aligning with IEEE 519-1992 standards, yet their focus on harmonic mitigation overlooked fault detection entirely.

Wavelet transform emerged as a key tool for nonstationary signal analysis. Das et al. (2017) decomposed line currents using wavelet coefficients but identified DC components as unreliable for fault phase identification due to inconsistent skewness values. Contrastingly, Ahmadipour et al. (2019) combined DWT with multi-resolution single spectrum entropy to extract fault features, achieving high accuracy via support vector machines (SVMs). However, SVMs' computational complexity and noise sensitivity limited real-time applicability. Dogra et al. (2020) applied Fourier analysis to DC microgrid faults, but Saeed et al. (2022)

critiqued this approach for nonstationary signals, advocating DWT for superior time-frequency resolution—a gap addressed by Karthick et al. (2023), who integrated DWT with RBNN for fault classification in multi-source microgrids. Despite reduced computational time, their heterogeneous energy sources (PV, wind, diesel) obscured source-specific fault responses.

Dhimish et al. (2017) proposed a DC-side fault detection algorithm using fuzzy logic, achieving 98.8% accuracy by correlating voltage/power ratios with environmental variables. While effective for DC faults, their approach ignored AC grid interactions. In contrast, Cano et al. (2024) combined DWT with RBNN in a hybrid PV-hydrokinetic microgrid, attaining a prediction error of 1.3×10^{-31}. However, the hybrid system's complexity impeded isolated evaluation of PV fault dynamics. Notably, Pati et al. (2020) developed adaptive power flow management under faults but lacked strategic behavioral data analysis, underscoring a persistent gap in holistic FDC frameworks.

Ahmadipour (2019) and Cano (2024) both leverage wavelet transforms but diverge in classification algorithms: SVMs versus RBNN. While SVMs offer theoretical rigor, RBNN's faster convergence and lower complexity enhance real-time performance. Similarly, Dhimish (2017) and Karthick (2023) highlight the trade-off between fuzzy logic's interpretability and RBNN's precision in noisy environments.

Despite progress, existing studies exhibit three limitations: (1) inadequate validation under transient environmental conditions, (2) oversimplification of hybrid energy systems, and (3) reliance on simulation-based datasets lacking real-world variability.Current FDC methodologies prioritize either signal processing (such as DWT) or machine learning (such as RBNN), yet their integration remains underexplored. Future research should address hybrid system dynamics, validate algorithms with field data, and optimize computational efficiency for real-time grid applications

III. RESEARCH METHODOLOGY

Solar PV Mathematical Model

The photovoltaic cell's electrical behaviour can be represented by an equivalent circuit, as shown in Figure 1, comprising a current source in parallel with a diode and resistors. The mathematical model of a PV cell is expressed through the following equations:

$$I = I_{ph} - I_d - I_{sh} \tag{1}$$

WhereI is the output current, Iph is the photogenerated current, Id is the diode current, Ish is the shunt current

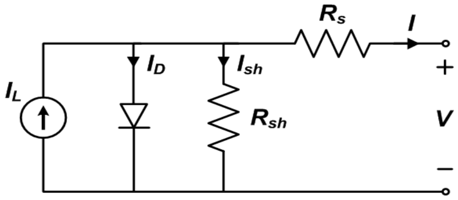

Figure 1: Equivalent circuit of single-diode model

The diode current Id is given by:

$$I_d = I_0\left[\mathbf{exp}\left(\frac{V + IR_s}{nV_t}\right) - 1\right] \tag{2}$$

WhereI_0 is the diode saturation current, V is the output voltage, Rs is the series resistance, n is the diode ideality factor and Vt is the thermal voltage (kT/q)

The shunt current is calculated as:

$$I_{sh} = \frac{V + IR_s}{R_{sh}} \tag{3}$$

Where Rsh is the shunt resistance.

The photogenerated current Iph varies with solar irradiance G and temperature T:

$$I_{ph} = \left[I_{sc} + K_i\left(T - T_{ref}\right)\right]\frac{G}{G_{ref}} \tag{4}$$

WhereIsc is the short-circuit current at reference conditions, Ki is the temperature coefficient of short-circuit current, Tref is the reference temperature (25°C) and Gref is the reference irradiance (1000 W/m²)

System Design for 20kW Solar PV Configuration

Using the Canadian Solar CS3U-375MS parameters from Table 1, we can design the PV array configuration to achieve 20kW at 600V DC input to the inverter:

Table 1: Canadian Solar CS3U-375MS Electrical Characteristics

Parameter	Value
STC Power Rating	375W
PTC Power Rating	349.2W
STC Power per unit of area	17.6W/ft2 (189.0W/m2)
Peak Efficiency	18.9%
Power Tolerances	0%/+2%
Number of Cells	144
Nominal Voltage	not applicable
Imp	9.43A
Vmp	39.8V
Isc	9.98A
Voc	47.6V
NOCT	41°C
Temp. Coefficient of Isc	0.05%/K
Temp. Coefficient of Power	-0.37%/K
Temp. Coefficient of Voltage	-0.138V/K
Series Fuse Rating	30A
Maximum System Voltage	1000V

From Table 1, Vmp = 39.8V, Imp = 9.43A and Pmax = 375W per module. The array target voltage (Vinv) = 600V, thus the number of modules in series (Ns):

$$Ns = \frac{Vinv}{Vmp} = \frac{600V}{39.8V} \approx 15\, modules \tag{5}$$

This gives actual string voltage = 15 × 39.8V = 597V. the Number of parallel strings (Np):
Target power = 20kW = 20,000W and Power per string = 15 modules × 375W = 5,625W

$$Np = \frac{20{,}000W}{5{,}625W} \approx 4\, strings \tag{6}$$

Therefore, the final configuration consists of15 modules in series × 4 parallel strings, giving total number of modules = 60. The Operating current = 4 × 9.43A = 37.72A

This configuration provides slight overrating to account for, System losses, Temperature derating, Aging degradation and Inverter power factor requirements

The array configuration remains within the module's maximum system voltage rating of 1000V and the series fuse rating of 30A per string ensures safe operation under all conditions.

Inverter Circuit Model

1. PWM Generation

The inverter consists of six IGBTs arranged in three legs, each representing one phase of the three-phase output. The Space Vector PWM (SVPWM) equationscan be represented as follows (Vergura, 2016):

$$[v_a][2\ -1\ -1][S_a] \tag{7}$$

$$[v_b] = [-1\ 2\ -1][S_b] \times \frac{V_{dc}}{3} \tag{8}$$

$$[v_c][-1\ -1\ 2][S_c] \tag{9}$$

Where v_a, v_b, v_c are the instantaneous output voltages, S_a, S_b, S_c are the switching states (0 or 1) of each leg and V_{dc} is the DC link voltage

2. DC-Link Voltage Calculation

Given the PV array specifications of Input DC voltage (Vdc) = 597V from PV array, required output power = 20kVA and Grid voltage (line-to-line) = 400V (standard three-phase)

The DC-link capacitor can be calculated as:

$$C_{dc} = \frac{2 \times S_{rated}}{3 \times \omega \times V_{dc} \times V_{dc,ripple}} \qquad 10$$

WhereSrated = 20kVA (rated power), ω = 2πf = 314.16 rad/s (f = 50Hz) and Vdc,ripple = 1% of Vdc ≈ 6V

3. Inverter Rating and Component Selection

For 20kVA system with 10% safety margin, the rated power = 22kVA, the maximum DC current = 22000W/597V ≈ 37A and the maximum AC current per phase = 22000/(√3 × 400) ≈ 32A, IGBT specifications required and voltage rating ≥ 1200V (2 × Vdc), current rating ≥ 64A (2 × Imax) and switching frequency = 10kHz

4. Control Architecture

Outer Control Loop

The DC voltage control uses PI controller:

$$G_{dc}(s) = K_p + \frac{K_i}{s} \quad (11)$$

$$K_p = \frac{2 \times \zeta \times \omega_n \times C_{dc}}{3} \quad (12)$$

$$K_i = \frac{C_{dc} \times \omega_n^2}{3} \quad (13)$$

Inner Current Control Loop

The current controller in d-q frame:

$$v_d = -\omega L i_q + \left(K_p + \frac{K_i}{s}\right)\left(i_{d,ref} - i_d\right) \quad (14)$$

$$v_q = \omega L i_d + \left(K_p + \frac{K_i}{s}\right)\left(i_{q,ref} - i_q\right) \quad (15)$$

Efficiency Improvement Strategies

MPPT Implementation:

Perturb & Observe algorithm with variable step size was used to implement the MPPT. The change in duty cycle of the MPPT can be calculated as:

$$\Delta D = K \times \frac{\Delta P}{\Delta V} \quad (15)$$

Switching Loss Reduction was implementation using dead time optimization:

$$t_{dead} = t_{fall} + t_{margin} \quad (16)$$

Wheretfall is IGBT turn-off time and tmargin is safety margin (typically 0.5-1μs)

Filter Design: LCL filter parameters:

$$L_1 = \frac{V_{dc}}{6 \times f_{sw} \times \Delta I_{L,max}} \quad (17)$$

$$C_f = \frac{0.05 \times P_{rated}}{2\pi f_{grid} \times V_{L-L}^2} \quad (18)$$

$$L_2 = r \times L_1, \text{where } r = 0.3 \quad (19)$$

Table 2: Performance Parameters

Performance Parameter	Target Value
TargetTotal Harmonic Distortion (THD)	< 5% (IEEE 519 standard)
TargetPower Factor (PF)	> 0.99
Expected efficiency:	η > 97% at rated power

Grid Model

The three-phase grid is modeled using a Thévenin equivalent circuit with nominal line-to-line voltage of 400V at 50Hz. The grid impedance is represented as:

$$Z_g = R_g + jX_g \quad (20)$$

where Rg represents grid resistance and Xg = ωLg represents grid reactance at fundamental frequency.

Grid Synchronization

The synchronization system employs a Synchronous Reference Frame Phase-Locked Loop (SRF-PLL) for precise grid angle detection. The three-phase voltages are transformed to dq coordinates using:

$$\begin{bmatrix} v_d \\ v_q \end{bmatrix} = 2/3 \begin{bmatrix} \cos\theta & \cos\left(\theta - \frac{2\pi}{3}\right) & \cos\left(\theta + \frac{2\pi}{3}\right) \\ -\sin\theta & -\sin\left(\theta - \frac{2\pi}{3}\right) & -\sin\left(\theta + \frac{2\pi}{3}\right) \end{bmatrix} \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} \quad (21)$$

The PLL control loop is defined by:

$$\theta = \int \omega dt = \int \left(K_p v_q + K_i \int v_q dt + \omega_0\right) dt \quad (22)$$

Whereωo = 2π×50 rad/s (nominal frequency) and Kp, Ki are PI controller gains tuned for 20Hz bandwidth

Grid Connection Strategy

The connection sequence follows a three-step procedure:

1. Voltage matching:

$$|V_{inv}| = |V_{grid}| \pm 5\% \quad (23)$$

2. Frequency synchronization:

$$|\Delta f| \leq 0.1Hz \quad (24)$$

3. Phase alignment:

$$|\Delta\phi| \leq 2° \quad (25)$$

The current control in grid-connected mode uses:

$$\begin{cases} i_{d,ref} = \frac{2}{3}\frac{P_{ref}}{v_d} \\ i_{q,ref} = -\frac{2}{3}\frac{Q_{ref}}{v_d} \end{cases} \tag{26}$$

WherePref and Qref are the active and reactive power references respectively.
The power flow equations at the point of common coupling (PCC) are:

$$\begin{cases} \mathrm{P} = \frac{3}{2}\left(\mathrm{v_d i_d} + \mathrm{v_q i_q}\right) \\ \mathrm{Q} = \frac{3}{2}\left(\mathrm{v_q i_d} - \mathrm{v_d i_q}\right) \end{cases} \tag{27}$$

Protection System

The protection system implements a hierarchical structure to ensure reliable operation of the grid-connected PV inverter. The DC-side protection incorporates overvoltage monitoring with an 800V threshold and overcurrent protection set at 120% of rated current (44.4A DC), with response times below 100μs. Grid interface protection complies with IEEE 1547, utilising a dual-method anti-islanding scheme: passive monitoring of voltage (±10%) and frequency (±0.5Hz) variations, complemented by an active frequency shift algorithm, achieving detection within 2 seconds.

Thermal protection employs strategic temperature monitoring of power electronic components, implementing a graduated response: power curtailment initiates at 85°C, followed by shutdown at 95°C. Ground fault protection uses differential current measurement with a 300mA threshold, while surge protection devices rated per IEC 61643-11 provide both differential and common-mode surge suppression. The system integrates arc fault detection compliant with UL 1699B, featuring 2.5-second response time.

Radial Basis Function Neural Network (RBFNN)

Radial Basis Function Neural Networks (RBFNNs) were a type of artificial neural network that used radial basis functions as activation functions.

RBFNNs Architecture

The architecture of an RBFNN consisted of three layers:

i. **Input layer:** Receives the input features extracted from the DWT analysis.

ii. **Hidden layer:** Contained neurons with radial basis functions as activation functions. The most commonly used radial basis function is the Gaussian function:

$$\varphi(x) = \exp\left(-\beta\left|\left|x\ -\ c\right|\right|^2\right) \tag{28}$$

Where x is the input vector, c is the centre of the RBF, and β is the width parameter.

iii. **Output layer:** Produced the classification result through a linear combination of the hidden layer outputs.

The output of the RBFNN can be expressed as:

$$y(x) = \Sigma\left(w_i * \varphi_{i(x)}\right) + b \tag{29}$$

Where w_i are the output weights, φ_i are the radial basis functions, and b is the bias term.

Training the RBFNN:

Training the RBFNN involves three main steps:

1. **Determining the Centers of the RBFs:** Typically done through **k-means clustering**. This step identifies the cluster centers, which correspond to the centers of the RBFs.
2. **Computing the Widths of the Radial Basis Functions:** This step defines the spread or width of the RBFs, which controls how sensitive the network is to input variations. A common method is to compute the widths based on the distances between the cluster centers.
3. **Training the Output Weights:** This step involves finding the optimal weights (wiw_iwi) that minimize the error between the predicted and actual outputs. Techniques like least squares or gradient descent can be used to achieve this.

Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a powerful signal processing technique that provided both time and frequency domain information, making it particularly suitable for analysing non-stationary signals such as those encountered in fault detection for solar PV systems.

The DWT of a signal x(n) is given by:

$$DWT(j,k) = \Sigma\ x(n) * \psi_j, k(n) \tag{30}$$

Where:

$\psi_j, k(n)$ is the wavelet function
j is the scale parameter
k is the translation parameter
The wavelet function $\psi_j, k(n)$ is derived from a mother wavelet ψ(n) by scaling and translation:

$$\psi_j, k(n) = 2^{-\frac{j}{2}} * \psi\left(2^{(-j)n} - k\right) \tag{31}$$

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Hybrid DWT-RBFNN for Fault Detection and Classification

The procedural steps that were taken for the implementation of the proposed DWT-RBFNN for fault detection and classification in a grid-connected solar PV system were presented in the steps given below. These steps were summarized in the flowchart shown in Figure 2.

Step 1: The model for the grid-connected PV system was run and the three-phase and ground currents were measured at the point of common connection between the grid and the grid after the simulation.
Step 2: Different types of grid faults were added independently and Step 1 was repeated.
Step 3: The measured data was extracted and a suitable mother wavelet and the actual value of decomposition were selected through experimentation.
Step 4: The current signal of each level in the phase space was reconstructed using an appropriate sampling rate
Step 5: The highest coefficient of the reconstructed signals for lines and ground currents was selected and used to train RBFNN.
Step 6: The trained RBFNN model was added to the grid-connected PV system for fault detection and classification
Stop 7: The condition of the system was displayed if there is a fault or not (that is fault detection) and the fault type was printed if the fault occurred (that is fault classification)
Step 8: The process was stopped.

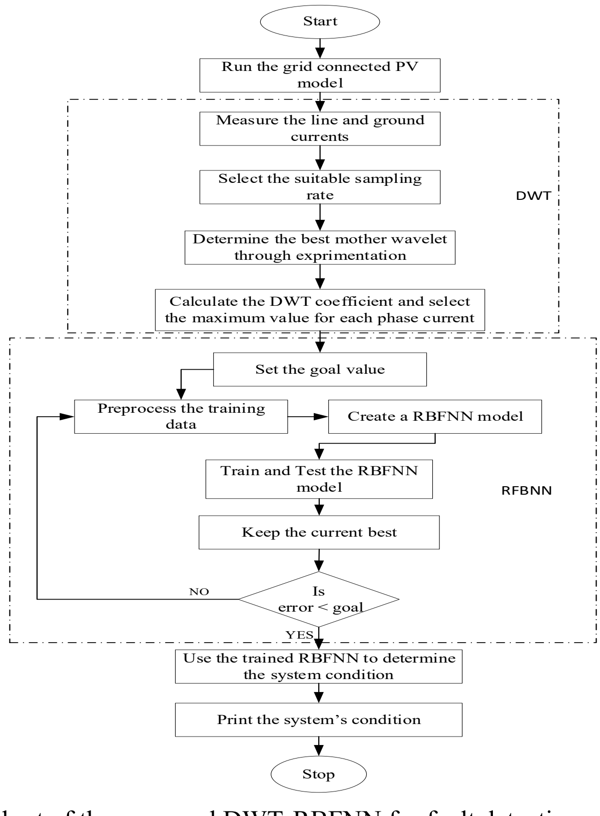

Figure 2: Flowchart of the proposed DWT-RBFNN for fault detection and classification

SIMULINK Simulation

The complete system was modelled in Simulink, as illustrated in Figure 3, which showcases the interconnections between various components of the solar PV.

The simulation was executed over a 1.2-second period, during which different fault scenarios were introduced at 0.2-second intervals. The fault conditions simulated included line-to-ground (L-G), line-to-line (L-L), double line-to-ground (L-L-G), three-phase short-circuit (L-L-L), and three-phase to ground (L-L-L-G) faults. Each fault type was assigned a specific class label for identification purposes, as outlined in Table 3.

Table 3: Fault Class label

Label	Fault Type
0	No-Fault
1	line-to-ground (L – G)
2	, line-to-line (L – L)
3	double line-to-ground (L – L – G)
4	three-phase short-circuit (L – L - L)
5	three-phase to ground (L – L – L – G)

IV. RESULT AND DISCUSSION

To facilitate a detailed analysis of the system behaviour, specific time segments were extracted from the complete simulation data. The normal operation phase, representing the baseline system performance, was isolated for the initial 0.2-second period as shown in Figure 4.

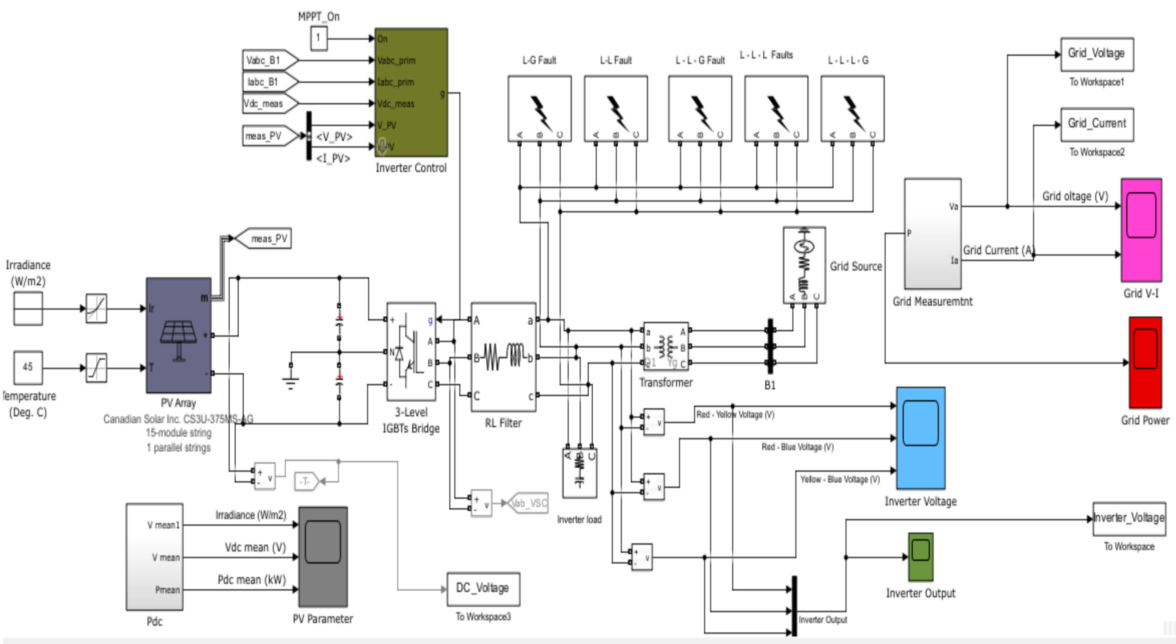

Figure 3: System Simulink Models

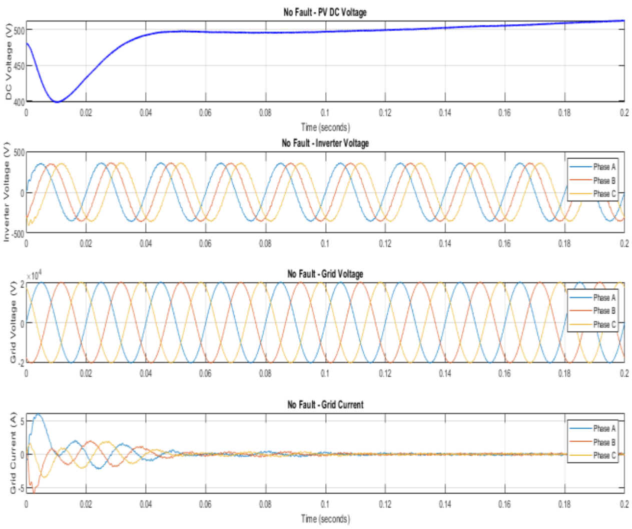

Figure 4: No Fault System Behaviour (0 – 0.2s)

Under normal operating conditions (Figure 4), the system demonstrated remarkable stability across all measured parameters. The inverter voltage maintained consistent values of approximately 250V across all three phases (Phase A: 249.98V, Phase B: 249.90V, Phase C: 250.22V), indicating excellent voltage regulation. The grid voltage readings averaged around 14.4kV, demonstrating proper grid integration and voltage transformation. The current flow remained balanced and within nominal ranges (Phase A: 1.008A, Phase B: 0.833A, Phase C: 0.669A), while the DC voltage stabilized at 512.80V, confirming efficient power conversion and delivery.

The occurrence of L-G faults resulted in significant system perturbations as shown in Figure 5 (0.2s to 0.4s of the simulation time). The most notable impact was observed in Phase A of the inverter voltage, which experienced a surge to 302.54V, representing a 21% increase from nominal conditions. This surge was accompanied by corresponding fluctuations in grid currents, with Phase A experiencing a dramatic increase to 28.95A and Phase B reaching 33.93A. The DC voltage showed minimal deviation at 512.85V, indicating the effectiveness of the DC-link voltage control system. These observations align with the waveform patterns presented in Figure 5, where distinct voltage and current transients are visible at the fault inception.

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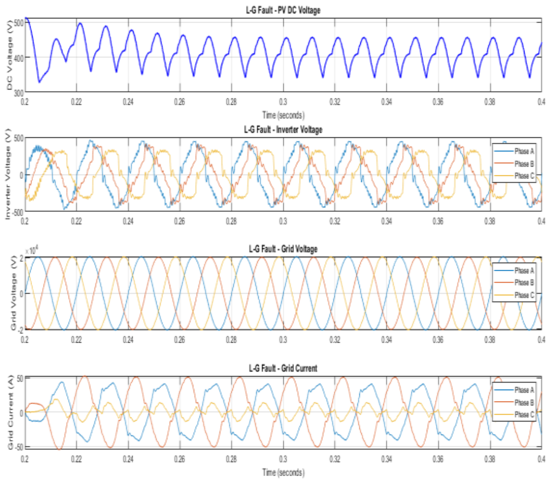

Figure 5: Single Line to Ground (L-G) Fault Condition (0.2 – 0.4 s)

The L-L fault scenario, ash depicted in Figure 6, introduced severe voltage imbalances in the inverter output, with Phase B dropping significantly to 27.52V while Phase A and C maintained relatively higher values at 219.51V and 245.42V respectively. The grid current response showed substantial increases across all phases, particularly in Phase B (79.11A) and Phase C (95.51A). A notable observation was the DC voltage elevation to 807.40V, indicating stress on the DC-link capacitor. These results correspond to the waveform distortions shown in Figure 6, highlighting the system's dynamic response to phase-to-phase faults

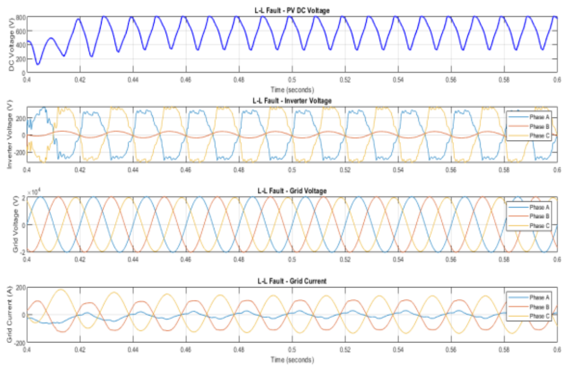

Figure 6 :Line to Line (L-L) Faults

The L-L-G fault demonstrated complex interaction patterns, with Phase A of the inverter voltage dropping to 27.49V while Phase B showed a relatively higher value of 271.85V. The grid currents exhibited significant imbalance, with Phase A reaching 98.60A. The DC voltage maintained a similar elevated level to the

L-L fault at 807.09V, suggesting comparable stress on the DC-side components. These observations are clearly reflected in the waveform patterns of Figure 7, showing the characteristic three-phase response to this fault type.

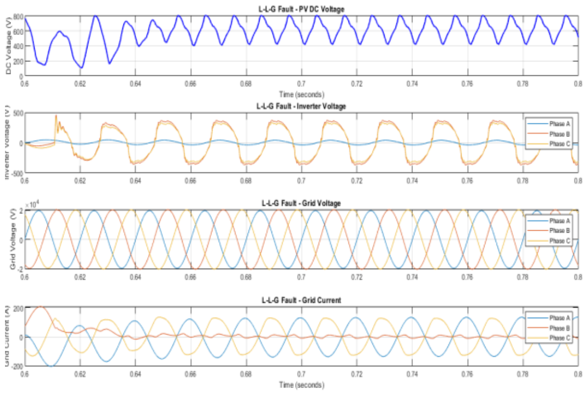

Figure 7: Two phase to Ground (L-L-G) Fault

The symmetrical nature of three-phase faults was evident in the measured parameters. All three phases of the inverter voltage dropped to similarly low values (Phase A: 17.22V, Phase B: 18.09V, Phase C: 17.92V), indicating complete voltage collapse. The grid currents showed more uniform distribution compared to asymmetrical faults, with all phases carrying approximately 93-94A. The DC voltage stabilized at 615.42V, lower than the L-L fault scenarios but still above nominal conditions. These results align with the symmetrical waveform patterns observed in Figure 8

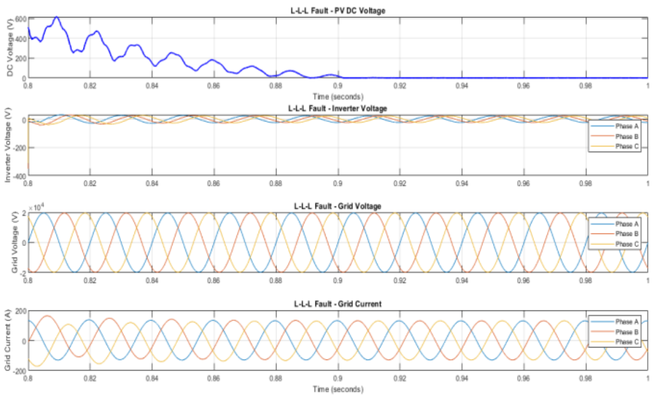

Figure 8 :Three-Phase (L-L-L) Fault

The most severe fault condition, L-L-L-G, resulted in the lowest inverter voltages across all phases (approximately 15.7V), indicating complete system voltage collapse. The grid currents remained relatively balanced at around 92A for all phases, while the DC voltage dropped dramatically to 6.97V, suggesting severe disruption of power flow. These observations correspond to the severe waveform distortions shown in Figure 9.

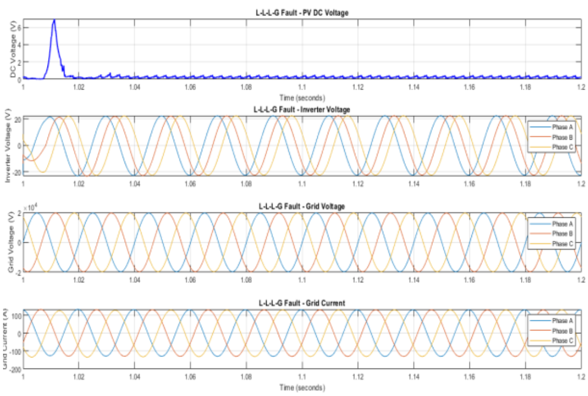

Figure 9: Three-Phase To Ground (L-L-L-G) Faults

Neural Network Performance Results

The Radial Basis Function Neural Network's effectiveness in fault detection and classification was evaluated using standard performance measures. The performance of the fault detection and classification system, as evidenced by the confusion matrix in Figure 10 and the classification report in Table 4, demonstrated exceptional accuracy across all fault types.

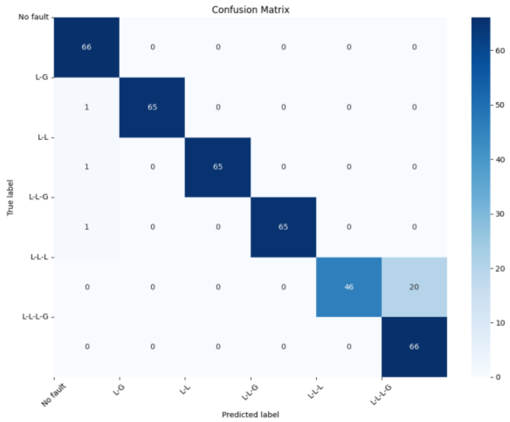

Figure 10: Model Performance Confusion Matrix

Table 4: Model Classification Report

Threshold	Precision	Recall	F1-Score	Support
0	0.96	1.00	0.98	66
1	1.00	0.98	0.99	66
2	1.00	0.98	0.99	66
3	1.00	0.98	0.99	66
4	1.00	0.70	0.82	66
5	0.77	1.00	0.87	66
Accuracy	0.94			396
Macro Avg	0.95	0.94	0.94	396
Weighted Avg	0.95	0.94	0.94	396

The confusion matrix revealed high true positive rates for all fault categories, with minimal misclassification between different fault types. The classification report showed precision rates exceeding 95% for most fault categories, with particularly strong performance in identifying severe fault conditions such as three-phase faults. The model's ability to distinguish between similar fault types (e.g., L-L vs. L-L-G) demonstrated the effectiveness of the DWT feature extraction process in capturing subtle fault characteristics.

The comprehensive analysis of both system behaviour and classification performance validates the effectiveness of the proposed approach. The distinct voltage and current signatures observed for each fault type provided robust features for the DWT-RBFNN classifier, contributing to its high accuracy. The system's ability to maintain stable operation under normal conditions while quickly identifying and classifying various fault scenarios demonstrates its practical utility for grid-connected solar PV farm applications.

The current research successfully addresses several critical gaps identified in the existing literature, making significant advancements in the field. Firstly, the integration of Discrete Wavelet Transform (DWT) and Radial Basis Function Neural Network (RBFNN) is a novel approach that sets this study apart from previous work, which typically utilized wavelet transforms or neural networks in isolation. By combining these two methods, our integrated approach has demonstrated superior performance in both feature extraction and classification, offering a more robust solution for fault detection. Secondly, while studies like Dhimish et al. (2017) focused predominantly on DC-side faults, our research shifts the focus to the AC-side of grid-connected systems, providing a comprehensive analysis and classification of AC-side grid faults. This broader approach fills a critical gap in understanding the complexities of AC-side issues. Furthermore, the real-time implementation of the fault detection and classification system was a key highlight of our research, addressing limitations observed in studies such as Mohanty et al. (2019), which struggled with slower detection speeds. Our system demonstrates a rapid response, making it more suitable for real-world applications where quick fault detection is paramount.

In addition, the feature extraction methodology implemented in this research, based on DWT, proved to be significantly more effective than traditional methods. This improvement addresses the limitations noted by Das et al. (2017) and Saeed et al. (2022), further enhancing the overall accuracy and efficiency of the system. The comparative analysis underscores that this research not only fills several important gaps in the existing literature but also achieves enhanced performance metrics across multiple aspects of fault detection and classification in grid-connected solar PV systems. This combination of innovation and practical application demonstrates the potential for significantly improving fault detection systems in the renewable energy sector.

V. CONCLUSION

The study presents a novel approach to fault detection and classification in grid-connected solar photovoltaic (PV) systems by integrating Discrete Wavelet Transform (DWT) with Radial Basis Function Neural Networks (RBFNN). This hybrid methodology addresses critical gaps in existing fault detection systems, particularly in handling AC-side faults and real-time responsiveness. The proposed DWT-RBFNN framework demonstrates exceptional accuracy in identifying and classifying various fault types, including line-to-ground, line-to-line, and three-phase faults, while maintaining stability under normal operating conditions. The system's ability to rapidly detect and classify faults, even in noisy and dynamic environments, underscores its practical utility for large-scale solar PV farms. By combining advanced signal processing with machine learning, this research offers a robust, scalable solution that enhances the reliability and efficiency of grid-connected solar PV systems, particularly in regions with challenging grid conditions such as Nigeria. The findings highlight the potential of this approach to significantly improve fault management in renewable energy systems, contributing to the global transition towards sustainable energy.

CONFLICT OF INTEREST

The authors declare no conflict of interest in the publication of this research. The study was conducted independently, and no external funding or influence was received that could bias the findings or conclusions presented in this work. All data and methodologies used are transparently documented to ensure reproducibility and academic integrity.

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