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An Adaptive ANN-Based Hybrid ROCOF–DWT Islanding Detection Method for Solar–Wind Grid-Connected Distributed Generation Systems

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Islanding detection, distributed generation, solar–wind systems, rate of change of frequency (ROCOF), discrete wavelet transform (DWT), artificial neural network (ANN), hybrid detection method, power system stability, renewable energy integration, non-detection zone (NDZ), MATLAB/Simulink, adaptive control.

ABSTRACT

The increasing global energy demand has accelerated the deployment of distributed generation (DG) systems, particularly solar–wind hybrid systems. However, ensuring safe operation of grid-connected DG requires reliable islanding detection, where a portion of the system continues to energize local loads after disconnection from the main grid. According to IEEE 1547 standards, islanding must be detected within 2 seconds. This paper presents an improved hybrid islanding detection method based on the Rate of Change of Frequency (ROCOF), combining both passive and active detection techniques. To enhance detection speed and accuracy, the Discrete Wavelet Transform (DWT) is employed for time–frequency signal analysis. In addition, an adaptive Artificial Neural Network (ANN) controller is integrated to improve system stability and dynamic performance under varying operating conditions. The proposed method is implemented on a solar–wind hybrid DG system and validated using MATLAB/Simulink simulations. Results demonstrate that the technique can detect zero power-balanced islanding within 200 ms and unbalanced islanding within 100 ms, significantly outperforming conventional methods in terms of speed and reliability.

1. INTRODUCTION

The continuous rise in global energy demand, coupled with the depletion of conventional fossil fuel resources and growing environmental concerns, has led to a significant shift toward renewable energy-based Distributed Generation (DG) systems [1], [2]. Among various renewable sources, solar photovoltaic (PV) and wind energy systems have gained widespread adoption due to their sustainability, availability, and declining installation costs [3], [4]. The integration of these renewable energy resources into modern power systems enhances energy efficiency, reduces transmission losses, and improves overall system reliability [5]. However, the increasing penetration of DG units into the grid also introduces several operational and protection challenges that must be addressed to ensure safe and stable system performance [6]. One of the most critical issues associated with grid-connected DG systems is islanding [7]. Islanding occurs when a portion of the distribution network becomes electrically disconnected from the main utility grid but continues to be energized by local DG sources [8]. This condition can pose serious risks, including safety hazards to maintenance personnel, damage to sensitive equipment, degradation of power quality, and improper operation of protection devices [9], [10]. Moreover, unintentional islanding can lead to instability in voltage and frequency, particularly in systems with high renewable energy penetration [11]. Therefore, reliable and rapid detection of islanding is essential for maintaining system security and operational integrity. To address these concerns, regulatory standards such as IEEE 1547 have been established, which mandate that islanding conditions must be detected and mitigated within 2 seconds of occurrence [12]. This requirement has motivated extensive research into the development of effective islanding detection techniques. These techniques are broadly categorized into remote and local methods [13]. Remote methods, including communication-based schemes such as Supervisory Control and Data Acquisition (SCADA) and transfer trip techniques, provide high detection accuracy but involve high implementation cost and complex infrastructure [14]. As a result, local detection methods are more commonly used in practical applications due to their simplicity and cost-effectiveness [15].

Local islanding detection techniques are further classified into passive, active, and hybrid methods [16]. Passive methods rely on monitoring system parameters such as voltage, frequency, phase angle, and Rate of Change of Frequency (ROCOF) to identify abnormal conditions [17]. These methods are simple to implement and do not disturb system operation; however, they suffer from large Non-Detection Zones (NDZ), especially under power-balanced conditions where parameter variations are minimal [18], [19]. Among passive techniques, ROCOF is widely utilized due to its fast response to sudden frequency changes during islanding events [20]. Nevertheless, its performance may degrade in cases where the mismatch between generation and load is negligible [21]. Active methods, on the other hand, introduce intentional perturbations into the system and observe the resulting response to detect islanding conditions [22]. While these methods can significantly reduce the NDZ, they may negatively impact power quality and system stability due to the injected disturbances [23]. To overcome the limitations of both passive and active approaches, hybrid islanding detection methods have been proposed, combining the advantages of both techniques to achieve improved detection performance [24]. In recent years, advanced signal processing techniques have been incorporated into islanding detection schemes to enhance accuracy and reliability. One such technique is the Discrete Wavelet Transform (DWT), which provides excellent time–frequency resolution for analyzing transient signals [25]. DWT enables the detection of subtle disturbances in voltage and current waveforms that are often associated with islanding events, even under challenging operating conditions. By capturing both high-frequency transients and low-frequency components, DWT significantly improves detection sensitivity and reduces the NDZ.

Furthermore, the integration of renewable energy sources introduces nonlinearities, uncertainties, and dynamic variations in power system operation. Conventional control methods often struggle to handle such complexities effectively. In this context, Artificial Neural Networks (ANNs) have emerged as powerful tools for intelligent control and decision-making in power systems. ANNs possess the ability to learn from data, adapt to changing conditions, and model complex nonlinear relationships. When applied to DG systems, ANN-based controllers can regulate key parameters such as voltage and frequency, thereby enhancing system stability and dynamic performance. Motivated by these considerations, this paper proposes an adaptive hybrid islanding detection method that integrates ROCOF and DWT techniques with an ANN-based controller for solar–wind grid-connected DG systems. The proposed approach aims to achieve fast and accurate islanding detection while minimizing the NDZ and improving system stability under varying operating conditions. The effectiveness of the proposed method is validated through MATLAB/Simulink simulations under different scenarios, including load variations and renewable energy fluctuations. The results demonstrate superior performance in terms of detection speed, accuracy, and system stability compared to conventional methods.

II. SYSTEM CONFIGURATION

The proposed system is a grid-connected hybrid Distributed Generation (DG) system that integrates solar photovoltaic (PV), wind energy, and battery storage through a common DC bus as shown in Fig.1. The utility grid is connected via a circuit breaker, which enables both grid-connected and islanded modes of operation. An LCL filter is used at the grid interface to reduce harmonics and ensure smooth power transfer. On the AC side, an asynchronous motor and an RLC load are included to represent practical load conditions. The wind energy system consists of a wind turbine coupled with a Permanent Magnet Synchronous Generator (PMSG), whose output is converted to DC using a rectifier and supplied to the DC bus. The solar PV system is connected through a DC–DC boost converter to regulate voltage and extract maximum power. A battery energy storage system is integrated via a bidirectional converter to support power balance and improve system stability during transients. All sources are linked through the DC bus and interfaced with the grid using a voltage source inverter (VSI). Control and measurement units monitor system parameters such as voltage, current, and frequency, which are essential for islanding detection. This configuration enables coordinated operation of multiple energy sources and provides a reliable platform for implementing the proposed hybrid ROCOF–DWT islanding detection method with ANN-based control.

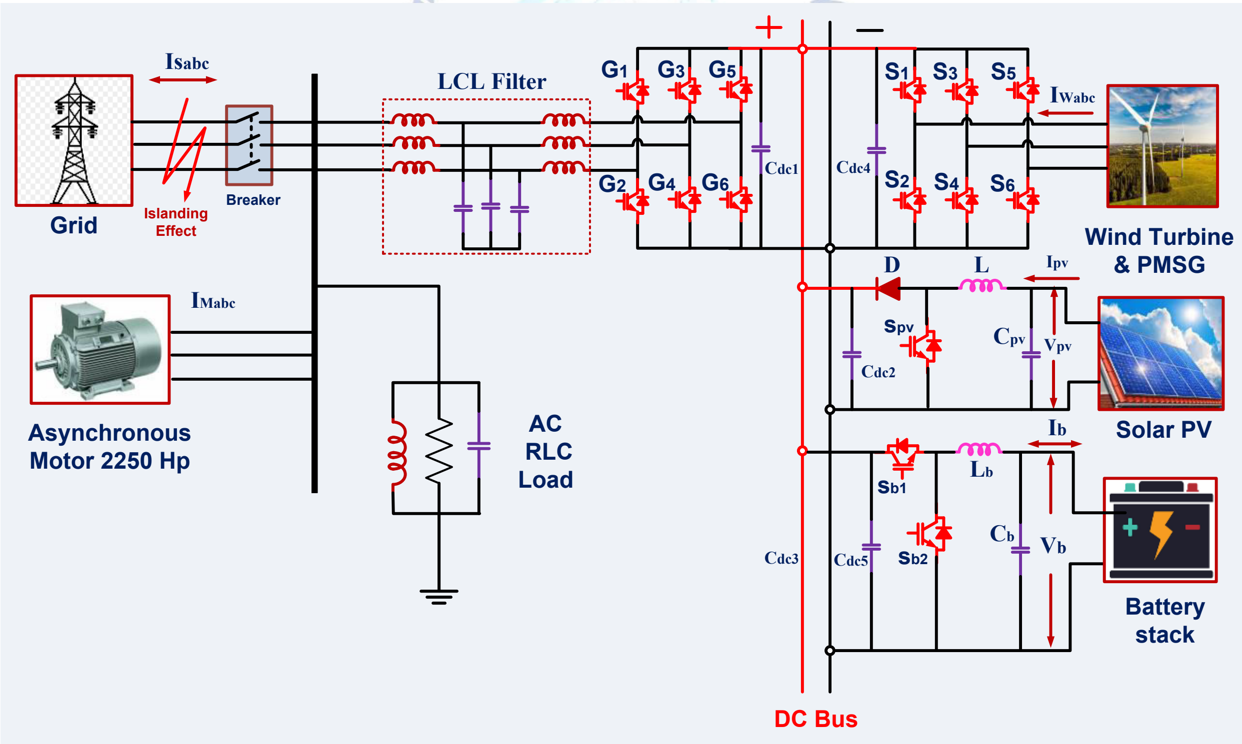


Fig. 1 System configuration grid-connected solar–wind hybrid distributed generation system with battery storage.

III. OVERVIEW OF DC/AC MICROGRID SYSTEM

A. Solar PV System

The solar configuration in the proposed hybrid microgrid consists of a photovoltaic array arranged in a series-parallel structure to achieve the desired voltage and current levels. The photovoltaic system is connected to the DC bus through a DC-DC boost converter that steps up the voltage and regulates the output as shown in Fig.2. To maximize the energy harvested from the solar panels under varying irradiance and temperature conditions, a Maximum Power Point Tracking (MPPT) algorithm is employed, typically using the incremental conductance method as shown in Fig.4. The converter operates efficiently to track the maximum power point and supply a stable DC voltage to the bus. This stabilized DC output is then available for powering DC loads directly, charging the energy storage system, or being inverted and supplied to AC loads through the grid-connected converter. The solar subsystem plays a critical role in supporting the energy demands of the microgrid, particularly during daytime operation, while also contributing to overall system stability and sustainability.

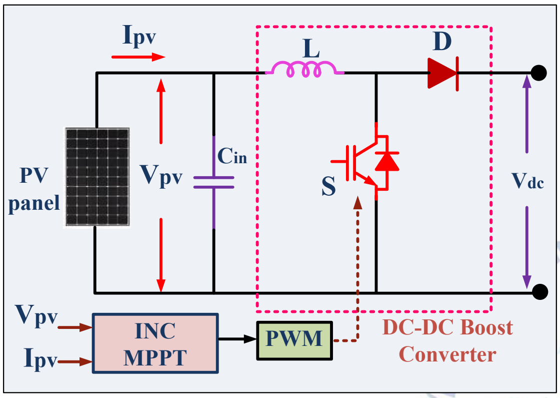


Fig. 2 solar PV INC MPPT DC-DC boost converter

The modeling and designing of the solar photovoltaic (PV) system involve selecting appropriate modules, configuring series and parallel connections, and integrating a DC-DC converter with MPPT to ensure optimal energy harvesting. Each PV module is modeled using the single-diode equivalent circuit as shown in Fig.3, where the output current is:

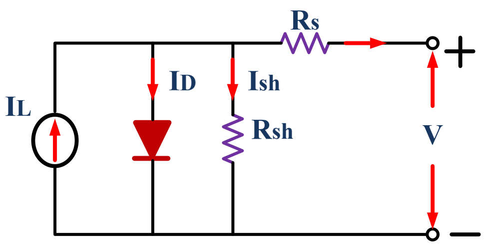


Fig. 3 equivalent model of PV solar.

$$I = I_{Ph} - I_0\left(e^{\frac{q(V+IR_S)}{nkT}} - 1\right) - \frac{V+IR_S}{R_{sh}} \qquad (1)$$

Here, I_{Ph} is the photocurrent, I_0 is the reverse saturation current, R_s and R_{sh} are the series and shunt resistances respectively, V is the terminal voltage, n is the ideality factor, T is the cell temperature in Kelvin, and q and K are the electronic charge and Boltzmann constant. The total power output is:

$$P_{PV} = V_{PV} \cdot I_{PV} \qquad (2)$$

To match the DC bus voltage, a boost converter is designed with the transfer function:

$$V_{out} = \frac{V_{in}}{1-D} \qquad (3)$$

Where D is the duty cycle, The MPPT controller, typically an Incremental Conductance algorithm, is applied to track the maximum power point by adjusting the duty cycle in response to changes in solar irradiance G and temperature T. The converter is designed to operate in Continuous Conduction Mode (CCM), and its inductor L and capacitor C values are selected based on:

$$L = \frac{V_{in} \cdot (V_{out} - V_{in})}{\Delta I \cdot f_s \cdot V_{out}} \qquad (4)$$

$$C = \frac{I_{out} \cdot D}{\Delta V \cdot f_s} \qquad (5)$$

Where ΔI is the desired ripple in inductor current, ΔV is the ripple in output voltage, and f_s is the switching frequency. The output of the converter connects to the DC bus, supplying both DC loads and feeding into the grid through an inverter when needed. This model ensures optimal PV performance across varying environmental conditions.

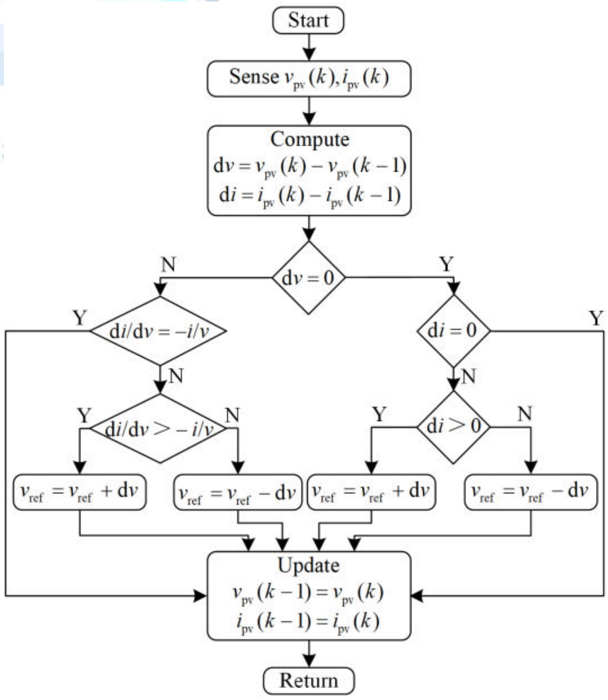


Fig. 4. Flow chat of modified incremental conductance maximum power point algorithm

B. Wind Energy System Configuration using PMSG

In this configuration, a wind turbine is mechanically coupled to a Permanent Magnet Synchronous Generator (PMSG). The electrical output of the PMSG is a variable-frequency AC that is first rectified to DC and then converted back to AC through a Voltage Source Inverter (VSI) for AC load/grid interface or directly supplied to the DC bus of the microgrid.

1. Wind Turbine Power Output:

The mechanical power extracted from wind is given by:

$$P_{wind} = \frac{1}{2} \cdot \rho \cdot A \cdot v^3 \cdot C_P(\lambda, B) \qquad (6)$$

Where: ρ = Air density (kg / m^3), $A = \pi R^2$ swept area of turbine blades, v = wind speed (m/s), C_P = power coefficient (function of tip speed ratio λ and pitch angle β)

2. Tip Speed Ratio λ:

$$\lambda = \frac{\omega_t R}{v} \qquad (7)$$

Where: ω_t: Turbine angular speed (rad/s), R: Blade radius (m)

3. PMSG Modeling (dq-axis):

PMSG electrical dynamics in dq-frame:

$$V_d = R_s i_d + \frac{d\psi_d}{dt} - \omega_e \psi_q \qquad (8)$$

$$V_q = R_s i_q + \frac{d\psi_q}{dt} - \omega_e \psi_d \qquad (9)$$

$$T_e = \frac{3}{2} P(\psi_d i_q - \psi_q i_d) \qquad (10)$$

Where: R_s: Stator resistance, ψ_d, ψ_q: d and q-axis flux linkages, ω_e : Electrical angular speed, T_e : Electromagnetic torque, P: Number of pole pairs

4. Control on the Machine Side

The machine-side control relies heavily on wind speed reference generation in order to get the most power out of the wind turbine. Figure 5 shows the control circuit of an active rectifier-connected PMSG. The ideal ratio of tip speed to actual wind speed is used to determine the reference rotor speed. This is the reference speed:

$$\omega_m^{opt} = \frac{\lambda'_{opt} v_w}{R} \qquad (11)$$

The speed of the reference rotor is represented by ω_m^{opt}. The PI speed controller is used to limit the speed error, which is calculated from the ideal wind speed and the actual speed of the PMSM, as reference electromagnetic torque. This means:

$$\omega_r^{error} = \omega_m^{opt} - \omega_r \qquad (12)$$

$$T_e^* = k_{p,s}(\omega_r^{error}) + k_{i,s} \int (\omega_r^{error})\, dt \qquad (13)$$

The variables ω_r^{error}, T_e^*, $k_{p,s}$, and $k_{i,s}$ denote the rotor speed error, reference electromagnetic torque, proportional gain, and integral gain, respectively, of the speed controller.

The reference q-axis current (i_{qm}^*) is:

$$i_{qm}^* = \frac{4T_e^*}{3P} \qquad (14)$$

An inner loop current controller regulates the machine side converter, which in turn generates the reference voltage. The coordinates on the d-q axis are:

$$v_{dm}^* = k_{p,mc}(i_{dm}^* - i_{ds}) + k_{i,mc} \int (i_{dm}^* - i_{ds})\, dt - \omega_e L_s i_{qs} \qquad (15)$$

$$v_{qm}^* = k_{p,mc}(i_{qm}^* - i_{qs}) + k_{i,mc} \int (i_{qm}^* - i_{qs})\, dt + \omega_e (L_s i_{ds} + \lambda_m) \qquad (16)$$

The variables v_{dm}^* and v_{qm}^* on the d-q axis represent the reference machine voltage, i_{dm}^* and i_{qm}^* on the d-q axis represent the reference stator current, and the variables $k_{p,mc}$ and $k_{i,mc}$ represent the component gains of the machine current controller, respectively.

The voltage references on the d-q axis are converted into three-phase machine voltage references via inverse park transformation so that the wind turbine can produce its maximum output. Pulse width modulation (PWM) generators use these three-phase machine voltage references and use them to operate the active rectifier on the machine side.

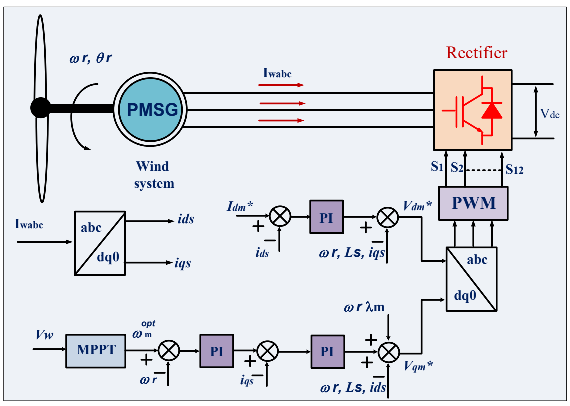


Fig.5 Wind conversion controller

C. Battery Energy Storage System (BESS) Configuration

Microgrids that include renewable energy sources like wind turbines and solar PV depend on energy storage devices that store energy, which is crucial during periods of low production or high demand. An array of batteries, a bidirectional DC-DC converter, and a BMS constitute the system. Alterations to the load and generation cause the BESS to transition between charging and discharging modes of operation. The process of charging entails transferring power from the DC bus to the battery, whereas the reverse is true during discharging, when the DC bus voltage is maintained by pulling power from the battery. By allowing this energy to flow in both directions, the bidirectional converter achieves proper voltage regulation. The converter, designed to run in Continuous Conduction Mode (CCM), is equipped with an inductor and a capacitor according to the power requirements and the allowable ripple constraints. Maintaining optimal performance is the working of battery management systems (BMSs), which monitor the battery's state of charge (SOC), voltage, current, and temperature. By its contributions to reducing peak loads, improving power quality, and providing backup power, the solution increases the microgrid's overall reliability and flexibility.

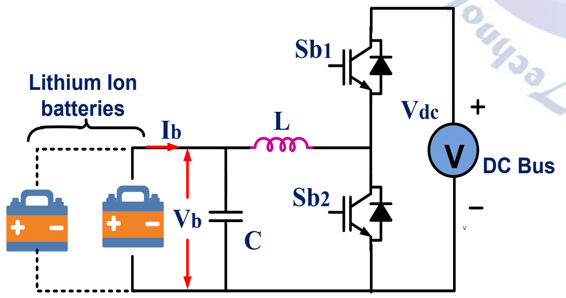


Fig.6 principle operation bidirectional dc-dc buck boost converter

1. Battery Terminal Voltage:

$$V_{bat} = V_{oc} - I_{bat} \cdot R_{bat} \quad (17)$$

2. State of Charge (SOC):

$$soc(t) = soc(0) - \frac{1}{C_{bat}} \int_0^t I_{bat}(t)\, dt \quad (18)$$

Where C_{bat} is the battery capacity in Ah.

3. Inductor Design for Bidirectional Converter (Buck/Boost):

$$L = \frac{V_{in} \cdot (1-D)}{f_s \cdot \Delta I_L} \quad (19)$$

Where V_{in}: input voltage, D: duty cycle, f_s: switching frequency, ΔI_L: inductor ripple current

4. Capacitor Design:

$$C = \frac{I_o \cdot D}{f_s \cdot \Delta V_o} \quad (20)$$

Where I_o: output current, ΔV_o: allowable output voltage ripple

D. Controller Designing for BESS

The double-loop control strategy is widely used for Battery Energy Storage Systems (BESS) to ensure accurate and stable regulation of both DC bus voltage and battery current, especially during dynamic charging and discharging events. This method consists of two control loops: the outer voltage control loop and the inner current control loop. The outer voltage loop is responsible for regulating the DC bus voltage V_{dc} by generating a reference current I_{ref} for the inner loop. It compares the measured DC bus voltage with the reference voltage V_{dc}^*, and the error is processed through a PI controller to maintain bus stability and support power balancing across sources and loads. The inner current loop, being faster, tracks the reference current I_{ref} by adjusting the converter's duty cycle D. This ensures the battery charges or discharges precisely according to system requirements, enhancing dynamic response and reducing voltage fluctuations. Both loops are typically implemented using PI controllers for their simplicity and reliable steady-state performance. The output of the inner loop modulates the duty cycle of a bidirectional DC-DC converter (often a buck-boost or bidirectional interleaved converter), ensuring stable operation in both charging and discharging modes.

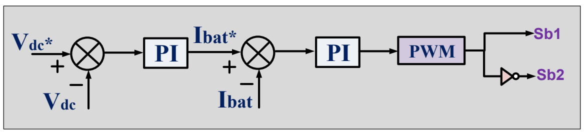


Fig. 7 double loop ev charging controller

1. Voltage Error Calculation:

$$e_v(t) = V_{dc}^* - V_{dc} \quad (21)$$

2. PI Voltage Controller Output (Reference Current):

$$I_{ref}(t) = K_{pv} \cdot e_v(t) + K_{iv} \int_0^t e_v(\tau) d\tau \quad (22)$$

3. Current Error Calculation:

$$e_i(t) = I_{ref}(t) - I_{bat}(t) \qquad (23)$$

4. PI Current Controller Output (Duty Cycle Signal):

$$D(t) = k_{pi} \cdot e_i(t) + k_{ii} \int_0^t e_i(\tau)d\tau \qquad (24)$$

IV. Islanding Detection Method

Islanding detection is a crucial requirement in grid-connected Distributed Generation (DG) systems to ensure system safety, reliability, and compliance with grid standards. Islanding occurs when a portion of the power system becomes electrically isolated from the main grid while DG units continue to supply power to local loads. To address this issue, hybrid detection techniques based on the Rate of Change of Frequency (ROCOF) are widely used. ROCOF serves as an effective parameter for identifying sudden changes in system frequency at the Point of Common Coupling (PCC), which typically occurs during islanding events. The hybrid ROCOF method combines both passive and active detection approaches to enhance detection performance. Passive methods rely on monitoring natural variations in system parameters such as frequency, while active methods introduce small disturbances into the system to observe its dynamic response. By integrating these two techniques, the hybrid approach improves detection accuracy, reduces the non-detection zone, and ensures reliable operation under different loading and generation conditions. This makes it a suitable and efficient solution for islanding detection in modern renewable energy-based DG systems.

A. Passive ROCOF Islanding Detection Method

In the passive ROCOF based method, islanding is detected by monitoring the rate of change of frequency at the PCC. The system frequency is measured using a Phase Locked Loop, and its rate of change is calculated. If the ROCOF value exceeds a predefined threshold, islanding is detected. This method is simple and provides fast detection; however, it has certain limitations. It fails to detect islanding under zero power mismatch conditions, where the generation and load are balanced. In such cases, the frequency variation is minimal, and the ROCOF value does not exceed the threshold. Additionally, this method has a detection delay of approximately 500 ms.

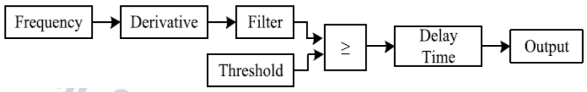


Fig.8 Passive ROCOF Relay

B. Active ROCOF Islanding Detection Method

In the active ROCOF method, a low frequency current signal is continuously injected into the system through the inverter controller. This injected signal causes variations in system parameters, which are used to detect islanding. If the signal is injected through the d-axis controller, it results in voltage variations at the PCC. If it is injected through the q-axis controller, it leads to frequency variations. Under normal grid connected conditions, the system suppresses these variations. However, during islanding, the variations become significant and can be used for detection.

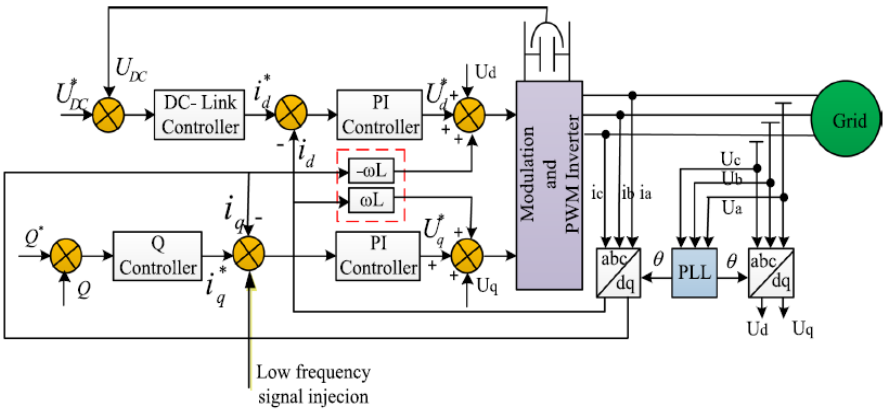


Fig.9 Grid interfacing inverter controller for low-frequency signal injection

C. Hybrid ROCOF Islanding Detection Method

The hybrid ROCOF method combines both passive and active detection techniques to improve accuracy and reduce non detection zones. Initially, the passive ROCOF method is used for detection. If the ROCOF value is greater than a maximum threshold value, islanding is immediately confirmed, and a trip signal is sent to disconnect the distributed generation system. If the

ROCOF value lies between the maximum and minimum threshold values, the system enters an uncertain region. In this case, the active method is activated. A low frequency current signal, typically around 20 Hz and equal to 1 percent of the DG capacity, is injected into the system through the q-axis controller. This signal causes frequency variations at the PCC, which are then analyzed to confirm islanding. The frequency at PCC is measured using a Phase Locked Loop and differentiated to obtain the ROCOF. During normal operation, ROCOF values remain within threshold limits. However, during islanding, these values increase significantly. The detection process uses a window size of 50 ms. If the ROCOF exceeds threshold T1 for two consecutive intervals, islanding is confirmed using the passive method. If the ROCOF lies between thresholds T1 and T2, the active method is activated. After signal injection, if the ROCOF exceeds threshold T3 for two consecutive intervals, islanding is confirmed.

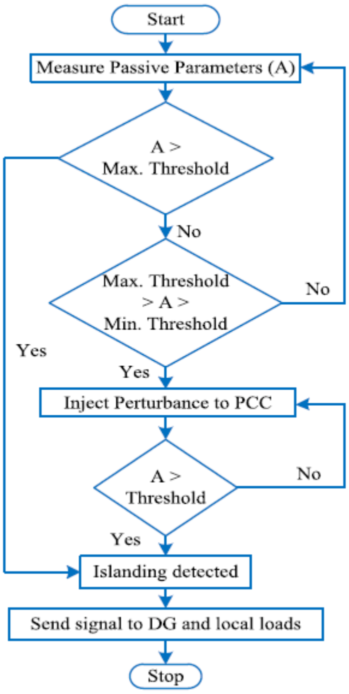


Fig. 10 Flowchart of Hybrid ROCOF based islanding detection method

D. Proposed Discrete Wavelet Transform (DWT) Based Method for Detecting Islanding Effects

The increasing integration of renewable energy sources such as solar and wind into modern power systems has led to the widespread use of distributed generation. Although distributed generation improves system efficiency and reduces environmental impact, it introduces several operational challenges, among which islanding is one of the most critical issues. Islanding occurs when a portion of the power system becomes disconnected from the main grid but continues to be supplied by local generation sources. This condition can lead to unsafe operation, equipment damage, and deviation of voltage and frequency from standard limits. Therefore, fast and accurate detection of islanding is essential to ensure system safety and reliability. Conventional islanding detection methods such as Rate of Change of Frequency are widely used due to their simplicity and fast response. However, these methods suffer from limitations such as non detection zones, sensitivity to disturbances, and reduced accuracy under dynamic operating conditions. In renewable energy based systems, frequent variations in generation and load introduce transient disturbances, which make detection more challenging using conventional techniques. To overcome these limitations, signal processing techniques such as Discrete Wavelet Transform have been proposed. The DWT is an effective tool for analyzing non stationary signals, as it provides both time and frequency information. It decomposes the signal into different frequency components, allowing accurate identification of transient events associated with islanding. By applying DWT to signals such as ROCOF or voltage, the sudden changes caused by islanding can be clearly identified. In this work, a DWT based method is proposed for detecting islanding effects in distributed generation systems. The proposed method enhances detection accuracy by analyzing transient characteristics of the system signals. It reduces non detection zones, improves reliability, and provides better performance under dynamic conditions compared to conventional methods. Therefore, the DWT based approach offers an effective solution for islanding detection in modern renewable energy integrated power systems.

E. Signal Extraction

In the initial stage, the three-phase voltage signals Va, Vb , and Vc, along with the corresponding time vector, are extracted from the system output data. Since the data may be stored in different formats, the procedure includes checking whether each variable is in a structured format and, if so, extracting the actual signal values accordingly. After extraction, all variables are converted into column vectors to ensure uniformity. This step is essential because subsequent operations such as differentiation, indexing, and signal processing require consistent vector dimensions for accurate analysis.

a. Voltage Increase Detection

In this step, the system identifies the first abnormal condition by checking whether any of the three-phase voltages exceeds its predefined upper threshold. This method is known as Voltage Increase Detection (VID). Each phase voltage Va, Vb, and Vc is continuously monitored and compared with its corresponding upper limit.

The condition for islanding detection is:

- $|V_a| > V_{a,upper}$
- $|V_b| > V_{b,upper}$ (25)
- $|V_c| > V_{c,upper}$

The algorithm finds the first sample index k island where any of these conditions is satisfied. This is mathematically expressed as:

$$k_{island} = min\begin{cases} k: |V_a(k)| > V_{a,upper} \\ k: |V_b(k)| > V_{b,upper} \\ k: |V_c(k)| > V_{c,upper} \end{cases} \quad (26)$$

The corresponding islanding detection time (IDT) is:

$$t_{island} = t(k_{island}) \quad (27)$$

After detecting the abnormal condition, the three-phase voltages are transformed into two orthogonal components using Clarke Transformation (CT). This transformation converts the three-phase system into a two-axis stationary reference frame **(**α- β**)**, which simplifies further analysis.

The equations are:

$$V_\alpha = \frac{2}{3}\left(V_a - \frac{1}{2}V_b - \frac{1}{2}V_c\right) \quad (28)$$

$$V_\beta = \frac{2}{3}\left(\frac{\sqrt{3}}{2}V_b - \frac{\sqrt{3}}{2}V_c\right) \quad (29)$$

b. Phase Angle Estimation (PAE)

Using the transformed voltages V_α and V_β, the phase angle θ is calculated.

$$\theta = tan^{-1}\left(\frac{V_\beta}{V_\alpha}\right) \quad (30)$$

c. Instantaneous Frequency Calculation (IFC)

The instantaneous frequency (IF) is calculated from the derivative of phase angle.

First, the sampling time Ts is calculated:

$$T_s = mean(\Delta t) \quad (31)$$

The frequency is then calculated as:

$$f(k) = \frac{\theta(k+1)-\theta(k)}{2\pi T_s} \quad (32)$$

This represents the instantaneous frequency of the system.

d. ROCOF Calculation

The Rate of Change of Frequency (ROCOF) is calculated by differentiating the instantaneous frequency.

$$ROCOF = \frac{df}{dt} \quad (33)$$

In discrete form:

$$ROCOF(k) = \frac{f(k+1)-f(k)}{T_s} \quad (34)$$

ROCOF is a very important parameter because islanding causes sudden frequency changes, which appear as sharp peaks in ROCOF.

e. Discrete Wavelet Transform (DWT) Analysis

This is the main enhancement in the proposed method.

The DWT is applied to the ROCOF signal to extract transient features associated with islanding.

DWT Decomposition

The signal is decomposed as:

$$x(t) \to A_n + D_n + D_{n-1} + \cdots + D_1 \quad (35)$$

Where: A_n → Approximation (low frequency), D_n → Detail components (high frequency)

Wavelet Equation

$$W(j,k) = \sum x(n)\psi_{j,k}(n) \quad (36)$$

Where: $x(n)$ → input signal (ROCOF), $\psi_{j,k}(n)$ → wavelet function, j → scale level, k → position

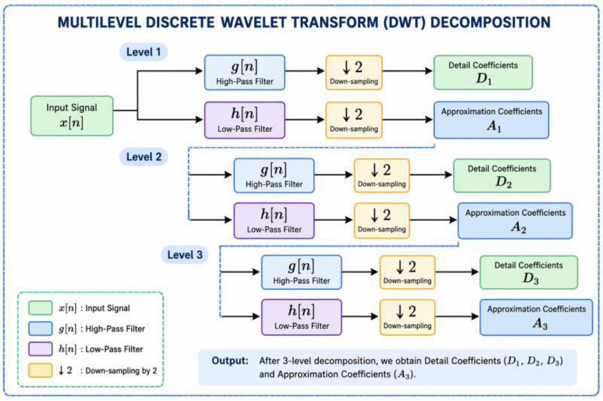


Fig.11Multilevel discrete wavelet transform

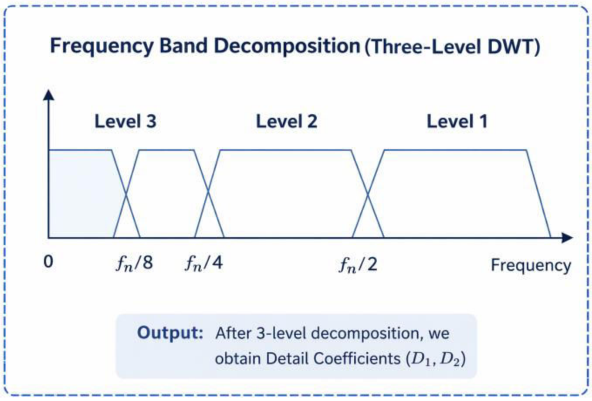


Fig.12 Frequency domain representation of the DWT

F. ANN-Based Controller

Artificial Neural Network (ANN) controllers are widely used in modern power systems due to their ability to handle nonlinearities, uncertainties, and dynamic variations. In the proposed system, an ANN-based controller is employed to enhance system stability and regulate key parameters such as voltage and frequency under varying operating conditions. The ANN controller is designed to learn the relationship between system inputs and desired outputs through a training process. Typically, the inputs to the ANN include system variables such as voltage, current, and frequency deviations, while the output corresponds to the control signal applied to the power electronic converters. The network consists of multiple layers, including an input layer, one or more hidden layers, and an output layer. During training, the ANN adjusts its weights using algorithms such as backpropagation to minimize the error between the actual and desired outputs. In this work, the ANN controller is integrated with the inverter control system to provide adaptive control action. During disturbances such as islanding events, the ANN responds quickly by adjusting control signals to maintain voltage and frequency within acceptable limits. This adaptive behavior improves the dynamic response of the system and reduces oscillations caused by fluctuations in renewable energy sources. Compared to conventional controllers, the ANN-based approach offers faster response, improved accuracy, and better robustness against system uncertainties. As a result, it plays a crucial role in enhancing the overall performance and stability of the proposed hybrid solar–wind distributed generation system.

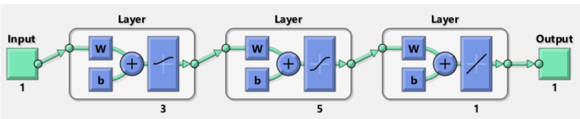
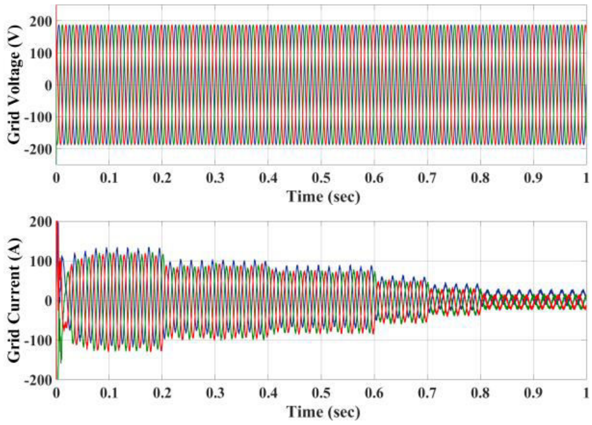


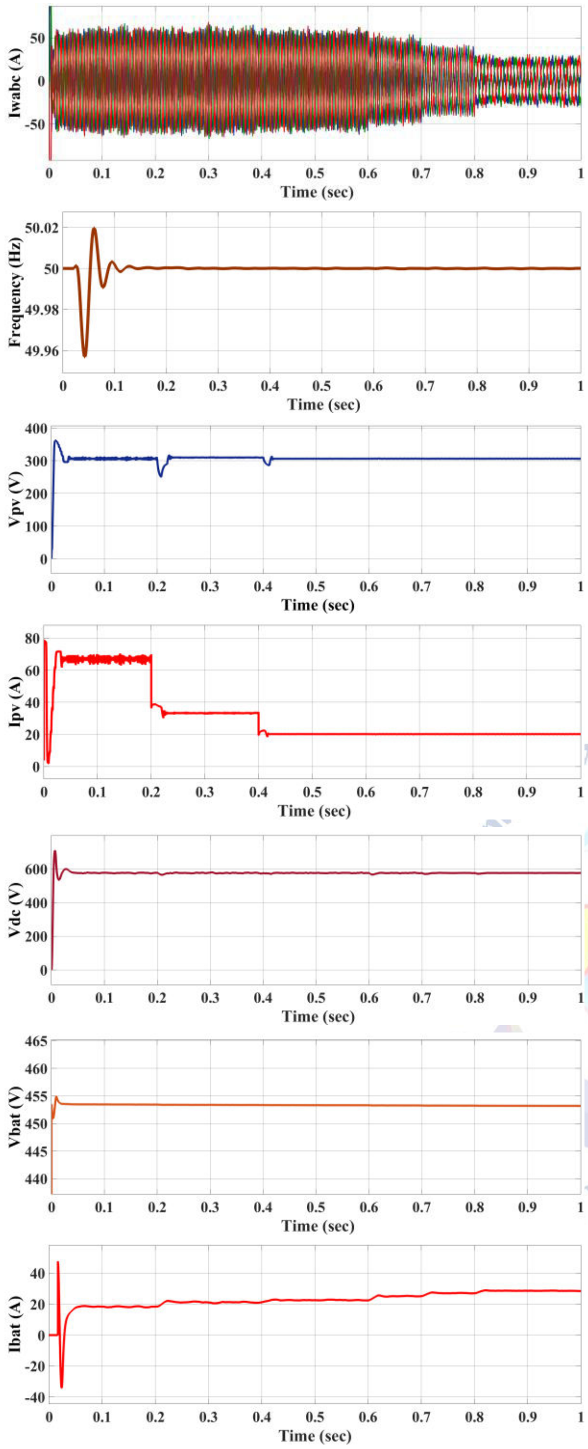
Figure 7: Structure of Neural Network

V. SIMULATION RESULTS AND DISCUSSION

A. Power Sharing Analysis of Solar–Wind–Battery System

The performance of the proposed hybrid ROCOF–DWT based islanding detection method is evaluated through simulation by analyzing the power variations of different components in the system. The figure shows the dynamic response of grid power, wind power, PV power, battery energy storage system (BESS), and AC load over time. At the initial stage (0–0.2 s), the system operates under grid-connected conditions. The wind power remains relatively high and stable, while the PV power gradually increases and stabilizes. The battery initially absorbs or supplies power to maintain system balance, and the grid power is negative, indicating power import from the grid to support the load demand. During the interval from approximately 0.2 s to 0.6 s, the system reaches a quasi-steady state where power sharing among wind, PV, and battery is balanced with the load demand. The grid contribution reduces, indicating improved utilization of renewable sources. The AC load remains relatively constant, ensuring stable system operation. At around 0.6 s, a disturbance occurs, which can be interpreted as an islanding event or change in operating condition. Following this event, significant variations are observed in the power profiles. The grid power starts to increase toward zero, indicating disconnection from the grid. Simultaneously, the wind and PV power outputs adjust to meet the local load demand. The battery plays a crucial role during this transient period by compensating for the power mismatch and stabilizing the system. After 0.7 s, the system transitions into islanded mode. The grid power becomes nearly zero, confirming successful isolation from the utility grid. The wind and PV sources, along with the battery, supply the required load power. The battery continues to smooth out fluctuations, reducing oscillations and improving dynamic stability. The simulation results demonstrate that the proposed system effectively maintains power balance during both grid-connected and islanded conditions. The integration of renewable energy sources with battery storage ensures reliable operation, while the hybrid detection method enables fast and accurate identification of islanding events. The system exhibits reduced oscillations, improved stability, and efficient power sharing, validating the effectiveness of the proposed approach.





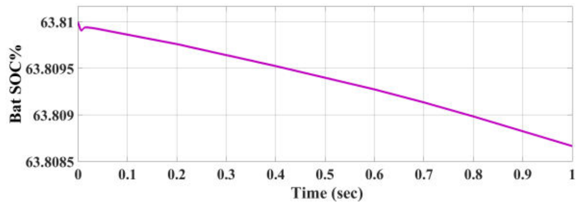


Fig.13 Simulation Results and Performance Analysis of Power Flow in Hybrid System

B. Islanding Detection Using Discrete Wavelet Transform (DWT)

The performance of the proposed islanding detection method is evaluated using the waveforms of three-phase voltages, instantaneous frequency, ROCOF, and DWT detail coefficients. Under normal operating conditions (prior to 0.5 s), the three-phase voltages Va, Vb, and Vc are balanced and exhibit sinusoidal behavior, indicating stable grid-connected operation. The system frequency remains constant, while the ROCOF and DWT coefficients are close to zero, confirming steady-state conditions. At approximately 0.5 s, an islanding event occurs, which introduces noticeable disturbances in the system. The voltage waveforms exhibit transient oscillations and slight distortions, indicating a sudden change in operating conditions. Although the voltage variations are not highly pronounced, they reflect the impact of grid disconnection. The instantaneous frequency shows a sudden deviation at the time of islanding due to the imbalance between generation and load. This deviation is further highlighted in the ROCOF waveform, which exhibits a sharp spike corresponding to the rapid change in frequency. The ROCOF method provides a fast response; however, its sensitivity may be limited in near power-balanced conditions.

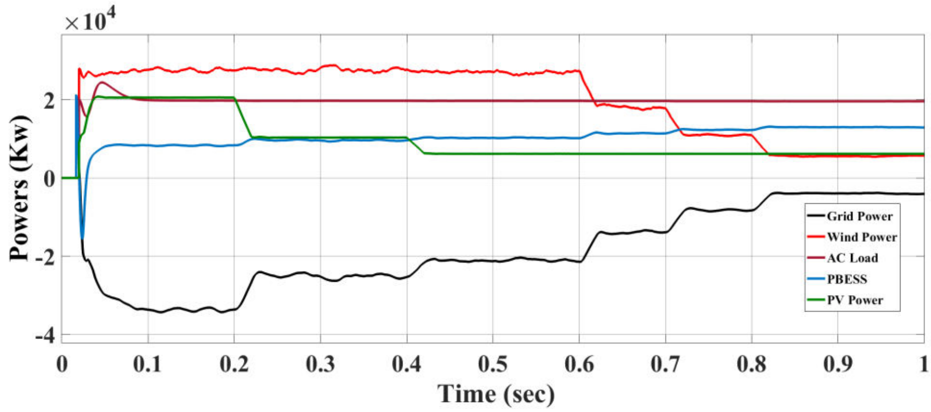


Fig.14 Power Variation Analysis during Grid-Connected and Islanded Operation

To enhance detection accuracy, the DWT detail coefficient (D5) is analyzed. At the instant of islanding, the DWT coefficient exhibits a significant spike due to the presence of high-frequency transient components. This response clearly distinguishes islanding events from normal operating conditions. The DWT technique provides superior time–frequency localization, enabling the detection of subtle transient features that may not be captured by conventional methods. After approximately 0.6 s, the system transitions to a stable islanded mode. The voltage waveforms regain a near-sinusoidal shape, and the frequency stabilizes. Correspondingly, the ROCOF and DWT coefficients return to near-zero values, indicating system stabilization. The results demonstrate that the combined use of ROCOF and DWT enables fast and accurate islanding detection. While ROCOF provides rapid identification of frequency changes, the DWT enhances sensitivity by capturing transient disturbances. Therefore, the proposed method effectively reduces detection time and improves reliability under various operating conditions.

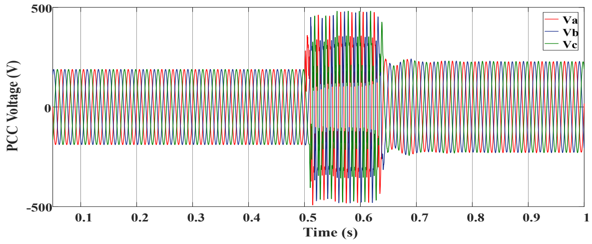


Fig. 15. Three-phase PCC voltage response during islanding event

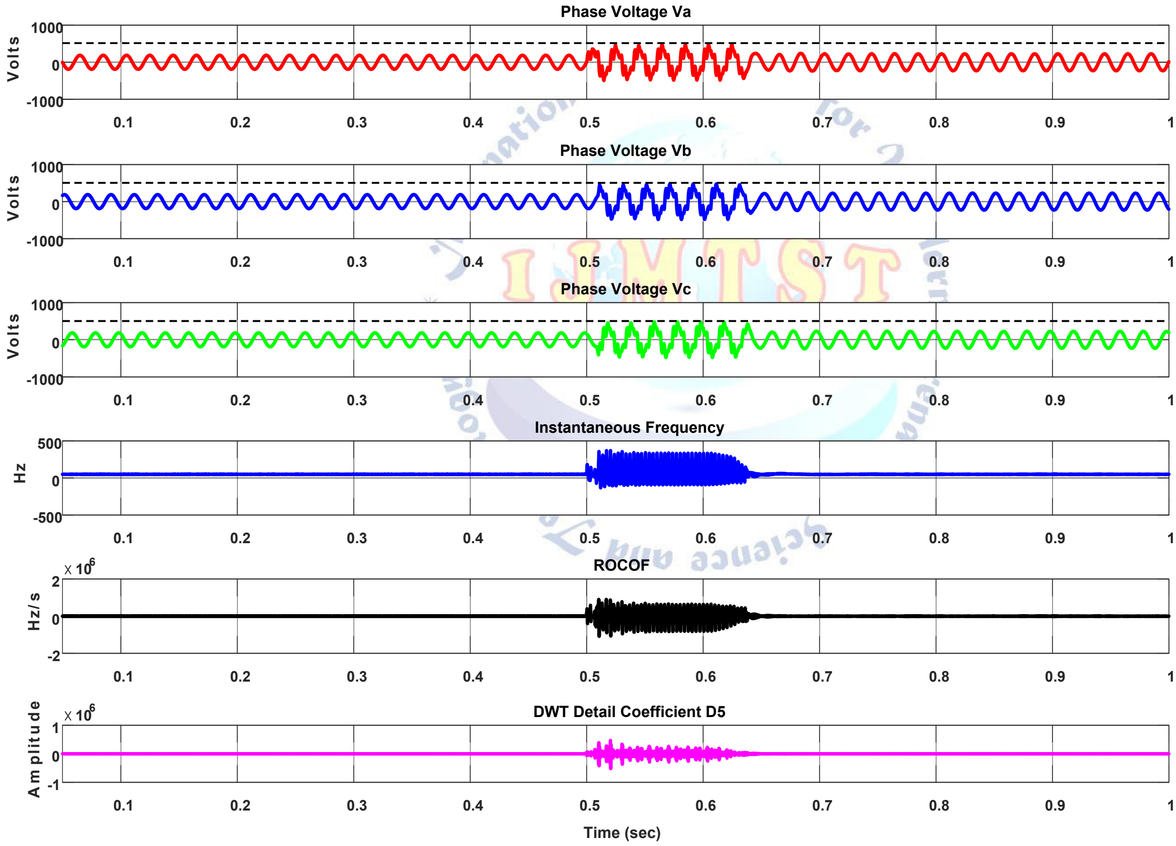


Fig. 16 Dynamic response of voltage, frequency, ROCOF, and DWT during islanding event

VI. CONCLUSION

This paper presented an adaptive hybrid islanding detection method for solar–wind grid-connected distributed generation systems by integrating ROCOF and Discrete Wavelet Transform (DWT) techniques with an Artificial Neural Network (ANN)-based controller. The proposed approach effectively combines the fast response capability of ROCOF with the superior time–frequency analysis of DWT to achieve accurate and reliable islanding detection. The simulation results demonstrate that the proposed method significantly improves detection performance by reducing the non-detection zone and minimizing false tripping. The system is capable of detecting zero power-balanced islanding conditions within 200 ms and unbalanced conditions within 100 ms, which is well within the limits specified by IEEE 1547 standards. Furthermore, the incorporation of the ANN controller enhances system stability by regulating voltage and frequency under dynamic operating conditions, thereby reducing oscillations caused by renewable energy fluctuations. Overall, the proposed hybrid method provides a robust, fast, and efficient solution for islanding detection in modern renewable energy-based DG systems. It ensures reliable operation under varying load and generation scenarios, making it suitable for practical implementation in smart grid environments.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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