

Multiple distributed generators islanding detection using GBDT-JS techniques

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Abstract. Photovoltaic arrays and wind Distributed Generators (DG) have become integral to our renewable energy landscape. However, when a DG disconnects from the grid, the risk of islanding arises, necessitating detection within the stringent of two-second timeframe mandated by IEEE standards. Machine-level algorithms play a pivotal role in enhancing power system reliability and safety by swiftly identifying and isolating isolated segments, thereby preventing potential hazards and ensuring efficient grid operation. This study introduces an algorithm-based islanding detection approach for distributed generating systems employing both Solar Photo Voltaic (SPV) and wind systems. The GBDT-JS algorithm, a combination of Gradient Boosting Decision Trees and Jelly Fish Techniques, emerges as an intelligent solution. The focus of this technique is based on the Rate of Change in Phase Angle (RCPA) at the target DG position, offering a characterized approach to islanding detection. In addressing the major difficulties and challenges, the GBDT-JS method proves instrumental in categorizing islanding situations and grid disturbances. This classification aids in determining the system's adoptability based on various loading and switching capabilities. The achievements in overcoming these challenges lie in the algorithm's ability to provide a comprehensive solution, ensuring the reliability and safety of distributed generating systems.

Keywords: Photovoltaic arrays, Wind Distributed Generators (DG), Islanding detection, GBDT-JS algorithm and DWT, DWT.

1 Introduction

Over the past few decades, the vital role of renewable, decentralized energy sources in fulfilling the world's energy demands has risen significantly. In typical scenarios, generators often link to a grid but islanding may arise whenever the grid turns off [1]. In addition to causing losses in the system, unintentional islanding harms utility workers who are exposed to shocks [2, 3]. A short-term solution to islanding is required when an electrical system is interrupted [4]. Any frequency and voltage variations must be considered while linking electrical equipment to an islanded section. Island procedures should be separated into different sorts based on the location and communication practices. Local island identification techniques are different from methodologies like passive, active, and hybrid islanding [5–7]. Communication islanding is one of the islanding techniques that are more complicated and more expensive, but it is very reliable [8] and other parameters affecting the Point of Common Coupling (PCC) influence passive islanding [9–11].

The Islanding Detection Technique (IDT) detects fluctuation in the output signal and allows the PCC to allow signals for certain cycles [12–14]. It is more desirable to use the active method for islanding detection than the passive method because it enhances power quality [15–17]. Low-frequency currents are introduced directly into the Neutral Displacement Zone (NDZ) by utilizing a DQ controller [18, 19]. A wide range of common algorithmic strategies, including Decision-Tree models (DTs), Support Vector Machine models (SVMs), and Artificial Neural Networks (ANNs), are utilized to make the distinction between islanding and non-islanding instances [20, 21].

Active methods maintain minimal NDZ despite complex control circuits and real-time processes. The fact is that communication-oriented approaches are far more complicated and costly than alternatives while yet being extremely effective and exhibiting no adverse impacts on a system's power quality. Programmable logic controller circuit (PLCC) and Supervisory Control and Data Acquisition (SCADA) are used in this application. Programmable logic controller (PLC) monitor the utility grid. If this signal is not there, it leads to islanding. To detect islanding, a

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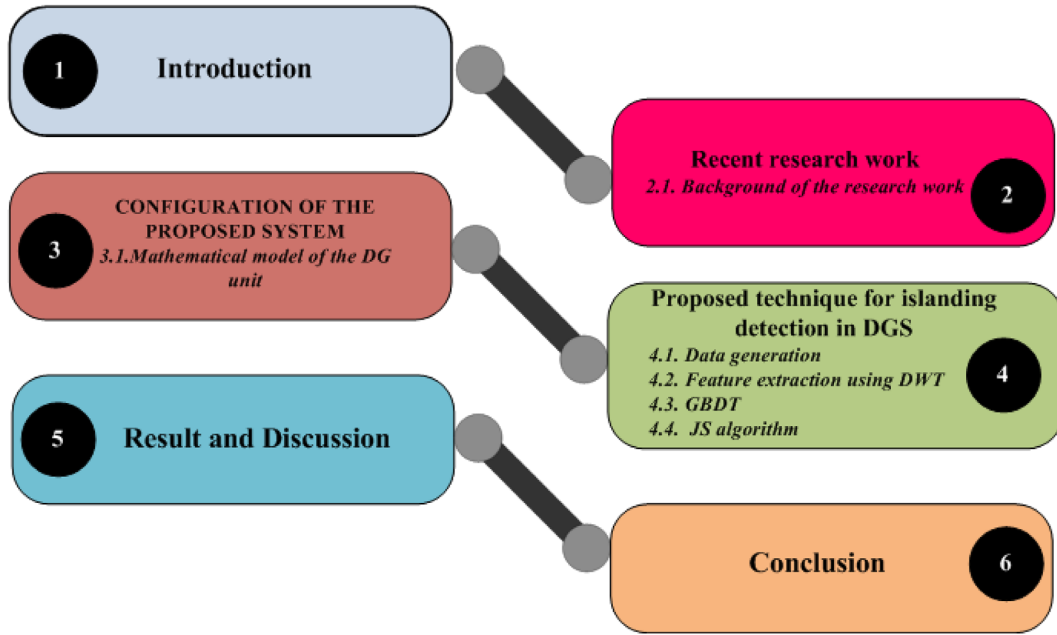


Fig. 1. Organization of the work.

SCADA system relies on the circuit breakers' auxiliary contacts. Here, if the passive method suspects an islanding is taking place, it will be confirmed by the active method. In addition, the low NDZ level affects the system's power quality [24]. The organizational structure of the work is illustrated in Figure 1.

2 Current research work

Over time, further study was conducted implementing various methods and attributes to identify islanding in distributed electricity generation. The following are a few of them:

Taheri Kolli and Ghaffarzadeh [25] employed phaselet algorithms for islanding detection, using efficient half-cycle phaselet multiplication. No disturbances or high-frequency signals were observed during islanding, ensuring reliable results without impacting power quality. Paiva *et al.* [26] introduced real-time execution of wavelet-based hybrid island detection scheme (WB-HIDS), assessing power quality variables to identify islanding conditions or faults.

Özcanlı and Baysal [27] introduced a unique passive Islanding Method (IDM) for inverter-interfaced microgrids (MGs). Microgrids, vital for future energy generation, integrate renewable sources like photovoltaic, wind, and hydropower in islanding or grid-connected modes. Unintentional islanding poses threats to power quality, voltage stability, and security. Simulations on the MATLAB/SIMULINK platform validated the system's efficacy, emphasizing the importance of intelligent IDMs in recognizing islanding instances for ensuring safety in distributed generating systems.

MATLAB/SIMULINK platform was used to conduct simulations. By using intelligent IDMs, the effectiveness

of the introduced system was verified. For the purpose of recognizing islanding instances in the distributed generating systems and assuring the safety of both individuals and machinery, Nayak *et al.* [28] presented a novel islanding detection approach using Empirical Mode Decomposition (EMD). The raw signal was processed into Intrinsic Mode Functions (IMFs) at different frequency scales. In the study, restoration of the signal enabled the use of IMFs based on their correlation coefficients. A hybrid method was implemented to enhance detection speed and accuracy.

Markovic *et al.* [29] introduced Loss of Mains (LoMs) protection as a common interfacing prevention method for Distribution Generation (DG). This technique identifies islanding at the point of connection and disconnects the DG to prevent system damage. Decommissioning synchronous generators and increased DG connections minimize system inertia, resulting in faster changes and larger voltage and frequency fluctuations. The article utilized an analytical approach to determine the NDZ of LoM protection, suggesting the need for inverter performance analysis and comprehensive dynamic simulations to define new operational requirements. Renewable energy sources, driven by advancements in wind turbines, Solar Photo Voltaic (SPV), and fuel cells, are gaining prominence with enhanced power electronics. The increasing demand for electricity necessitates the intermittent activation of distribution generation. To safeguard personnel from power quality issues, a paper emphasized identifying islanding instances during distribution generation. A practical anti-islanding detection mechanism for DG was developed, introducing a Phasor Measurement Unit (PMU)-based system. Substantial results were achieved through simulations using MATLAB/Simulink. Elshrief *et al.* [31] identified an islanding phenomenon and employed passive measures for protection. The focus was on detecting islands

based on time and accuracy using Rates of Change of Power (ROCOF) systems based on Terminal Voltage (TV) of PhotoVoltaic (PV) inverters. This system ensures power supply to the load at the PCC when disconnected from the utility grid. The ROCOF-TV system underwent assessment against various passive sensing relays following synchronization.

Harsito et al. [33] investigate the heat potential within solar panels for thermoelectric generators, utilizing ANSYS software for comprehensive analysis. The research is anticipated to focus on evaluating the thermal efficiency of solar panels and their capability to produce heat for thermoelectric power generation. The choice of ANSYS software implies a sophisticated and widely accepted tool for detailed simulations and engineering analyses, underscoring the research's meticulous approach to unraveling the thermoelectric characteristics of solar panels.

Tahiri et al. [34] focuses on assessing and enhancing hybrid energy solutions (SPV/Batteries/Diesel Generator) in Mobile Service Units (MSU) catering to rural services. Two deployed photovoltaic systems on trucks (2.12 kWp and 3.54 kWp) are evaluated by analyzing solar production, consumption, and battery State of Charge (SOC). The energy conversion chain is modeled and simulated throughout the year, with results compared to on-site measurements. Various PV/battery scenarios are studied to determine optimal combinations considering roof space, battery weight, and lifespan. The proposed solution suggests more efficient PV/storage associations, reducing reliance on the Diesel Generator. Simulation results for different battery capacities show improved performance for a 3540 Wp field compared to a 2120 Wp field, with reduced battery charge/discharge cycles.

The methods described above, including phaselet algorithms, real-time wavelet-based hybrid detection, passive islanding methods, EMD-based detection, LoM protection, and anti-islanding mechanisms, each exhibit specific merits and demerits. While phaselet algorithms and real-time wavelet-based approaches emphasize efficiency and reliability, their performance might be context-dependent. Passive islanding methods, such as IDM, are unique but may have limitations in dynamic scenarios. EMD-based methods offer a novel approach but might face challenges in accuracy. LoM protection ensures disconnection but may lead to rapid changes and fluctuations. Anti-islanding mechanisms are practical but may vary in effectiveness. In contrast, the GBDT-JS machine-level algorithm, not explicitly described, is likely to offer benefits in adaptability and accuracy through its intelligent combination of Gradient Boosting Decision Trees and Jelly Fish Techniques. Its effectiveness may stem from nuanced phase angle analysis and discrete wavelet transformations. However, it may require careful calibration and validation against different scenarios to optimize performance.

3 Configuration of the proposed system

Configuring a system with multiple distributed generation (DG) sources introduces complexities in power flows and voltage variations during islanding events. The diverse

characteristics and control strategies of individual DG resources contribute to this complexity. Dealing effectively with the challenges posed by multiple DG systems requires advanced and comprehensive island detection techniques. Additionally, ensuring proper coordination among DG sources is crucial to avoid issues like imbalanced load and power quality problems during islanding events. By employing sophisticated island detection algorithms like GBDT, and Discrete Wavelet Transform (DWT) techniques which consider the diverse characteristics and control strategies of individual DG resources. This ensures timely and accurate identification of islanding events. Figure 2 illustrates a synchronized system comprising a Phase-Locked Loop (PLL), a synchronized PhotoVoltaic solar energy Distributed Generation (PVDG), and an RLC load ($R = 0.2$, $L = 530$ H, $C = 13,260$ F), connected in parallel with the PVDG and the grid. The proposed system involves a 100 kW solar system linked to a 120 kV main network through a DC-to-DC converter, voltage source inverter, Circuit Breaker (CB), and distribution line. The solar system consists of 330 solar panels connected by 66 threads. Each photovoltaic cell comprises five series-connected strings in the shunt, totaling 100.7 kW (66,5305.2 W). Under 1000 W/m² solar irradiation and 25 °C ambient heat, each panel generates a 5.96 A short circuit current and a 64.2 V voltage in an open circuit. The DC-to-DC boost converter provides a 500-volt output to the inverter, which transforms it into a 260 V AC voltage. The Pulse Width Modulation (PWM) controller generates pulses to control the Voltage Source Converter (VSC) and operate the PVDG in constant Power Quality (PQ) mode. The voltage and current harmonics are resolved through a filtering process. To integrate the voltage into 25 kV and 120 kV feeders, a grid-side transformer boosts the voltage to 120 kV.

The Doubly-Fed Induction Generator (DFIG) wind DG system consists of key elements: a wind turbine, a DFIG generator with its control system, a power converter (rotor-side and grid-side), and a transformer. Wind energy is captured by the turbine, converting it into mechanical energy. The DFIG generator then transforms this mechanical energy into electrical energy with variable frequencies and voltages. For seamless integration into the grid, a power converter aligns the DFIG's output with the grid's voltage and frequency. A transformer adjusts the voltage to match the grid's 120 kV level. Notably, the DFIG wind DG system operates uniquely in the sub-synchronous region, with the rotor speed slightly below the synchronous speed of the grid. This precision is achieved through meticulous control of the rotor current using the converter system. In the scenario of islanding, where the grid disconnects from DGs, the DGs independently bear the load. Significantly, all DG and grid bus bars are interconnected, allowing for power exchange among different sources and the grid. The explanation provides a clear and original overview of the DFIG wind DG system's components and operational intricacies.

$$Q = \frac{3}{2} \text{Im}\{v_s I_s^*\}. \quad (1)$$

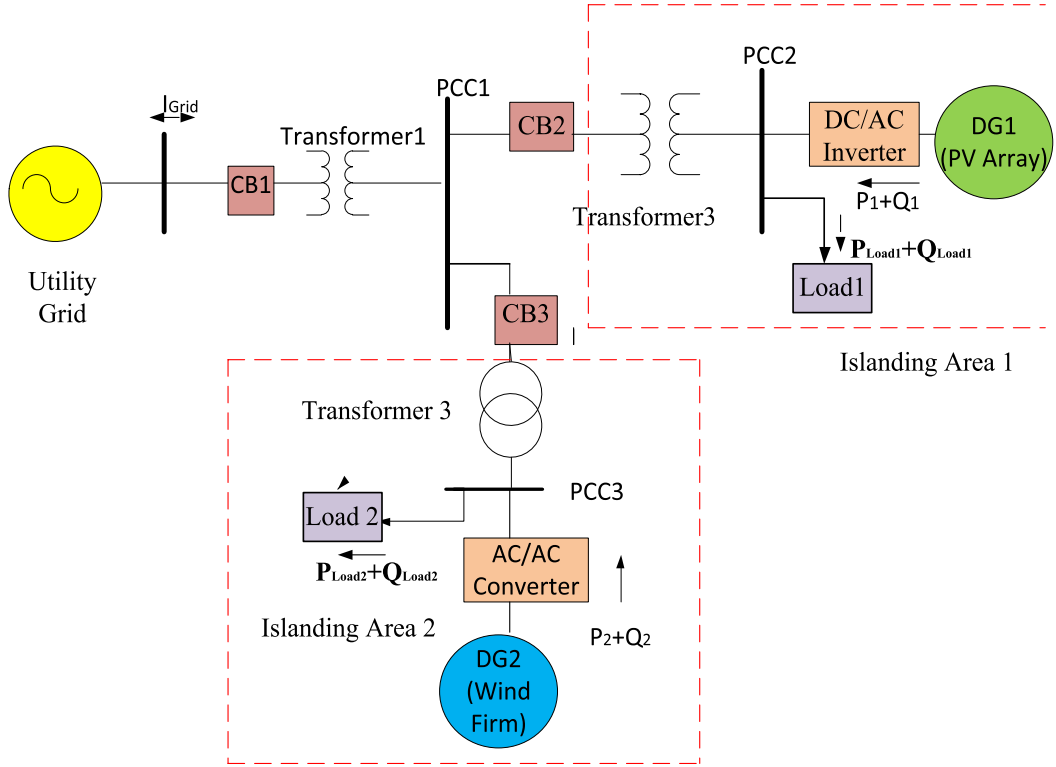


Fig. 2. Proposed grid connected solar PV system.

The Rate of Change in Phase Angle (RCPA) serves to detect islanding at a common PCC as illustrated in Figure 3. The electrical attributes of the Distributed Generation (DG), including RCPA, ROCOV (Rate of Change of Voltage), and ROCOF (Rate of Change of Frequency), are selected as variables in the dataset. After DWT analysis up to level 4, the detailed coefficients dataset is forwarded to the GBDT-JS algorithm. The objective of the GBDT algorithm is to categorize both islanding and non-islanding scenarios within the chosen dataset. Concurrently, the JS algorithm estimates the time required to identify islanding across various scenarios. This approach provides a clear and original explanation of the methodology employed in recognizing islanding events.

4. Proposed (GBDT-JS) approach for islanding detection

4.1. Data generation

The suggested IDT is evaluated for various active power mismatch situations ranging from -20% to $+20\%$ (steps of -40% , -20% , 0% , $+20\%$) while keeping the load power constant. The test system is used to assess the likelihood of islanding events for various loadings [33]. During non-islanding scenarios; capacitor bank switching and inductive load switching are taken into account. The dataset was generated for all case studies.

4.2. Feature extraction using DWT

After the data generation process, the feature extraction method is utilized to gather voltage and signal characteristics that can indicate defects in the DG. In this manner, the suggested approach extracts multiple variables. The variables mentioned above are used to extract features by standard deviation (SD) inside a sliding data window with width T . These attributes are stated in the equations below,

$$\sigma_v = std\{v(\tau), i(\tau); \tau \in [t - \Delta T, t]\} \quad (2)$$

$$\sigma_f = std\{f(\tau); \tau \in [t - \Delta T, t]\} \quad (3)$$

$$\sigma_\delta = std\left\{\delta(\tau), \frac{d\delta(\tau)}{dt}; \tau \in [t - \Delta T, t]\right\} \quad (4)$$

$$\sigma_{PV} = std\left\{\frac{dv(\tau)}{dt}; \tau \in [t - \Delta T, t]\right\} \quad (5)$$

$$\sigma_{Pf} = std\left\{\frac{df(\tau)}{dt}; \tau \in [t - \Delta T, t]\right\}. \quad (6)$$

Thus, a feature vector is assessed below,

$$x = [\sigma_v \sigma_f \sigma_\delta \sigma_{PV} \sigma_{Pf}]^T \quad (7)$$

where T represents the transpose operator.

A wavelet transform, which comprises the location and dimension of two fundamental components, is the ideal

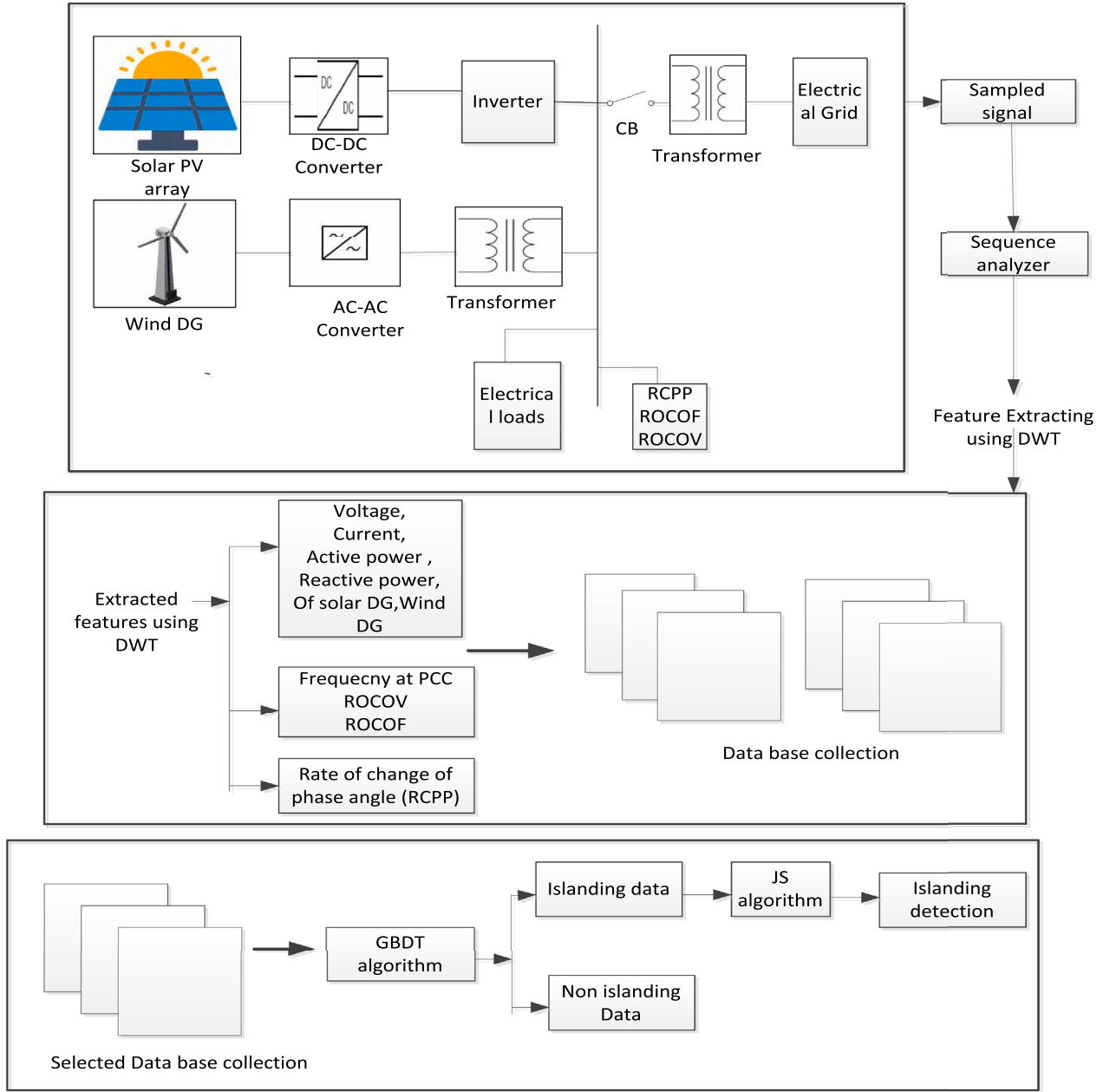


Fig. 3. Block diagram for presenting the process of proposed system.

choice for signal processing [34, 35]. The wavelet transform is made up of a series of wavelet functions of different dimensions. Lower-resolution components are generated using the High Pass Filter (HPF) and Low Pass Filter (LPF). The decomposition process is repeated until the final components. The objective signal (S) is sent via the HPF and LPF. Wavelet transform is classified into two types such as continuous (CWT) and discrete (DWT).

A CWT signal expressed as

$$(v, x, y) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} v(t) \psi^* \left(\frac{t-y}{x} \right) dt \quad (8)$$

where x indicates the scale (dilation) constant, y denotes the translation (time shift) constant and the mother wavelet is denoted by ψ^* .

A DWT signal denoted as

$$(v, x, y) = \frac{1}{\sqrt{x_0^m}} \sum_k v(k) \psi^* \left(\frac{n - kx_0}{x_0^m} \right) \quad (9)$$

x and y terms in equation (9) are replaced by using integer variables x_0^m . The HPF preserves the wavelet function's signal qualities, whereas the LPF demonstrates the approximation signal's coarser information. DWT analysis is done up to level 4.

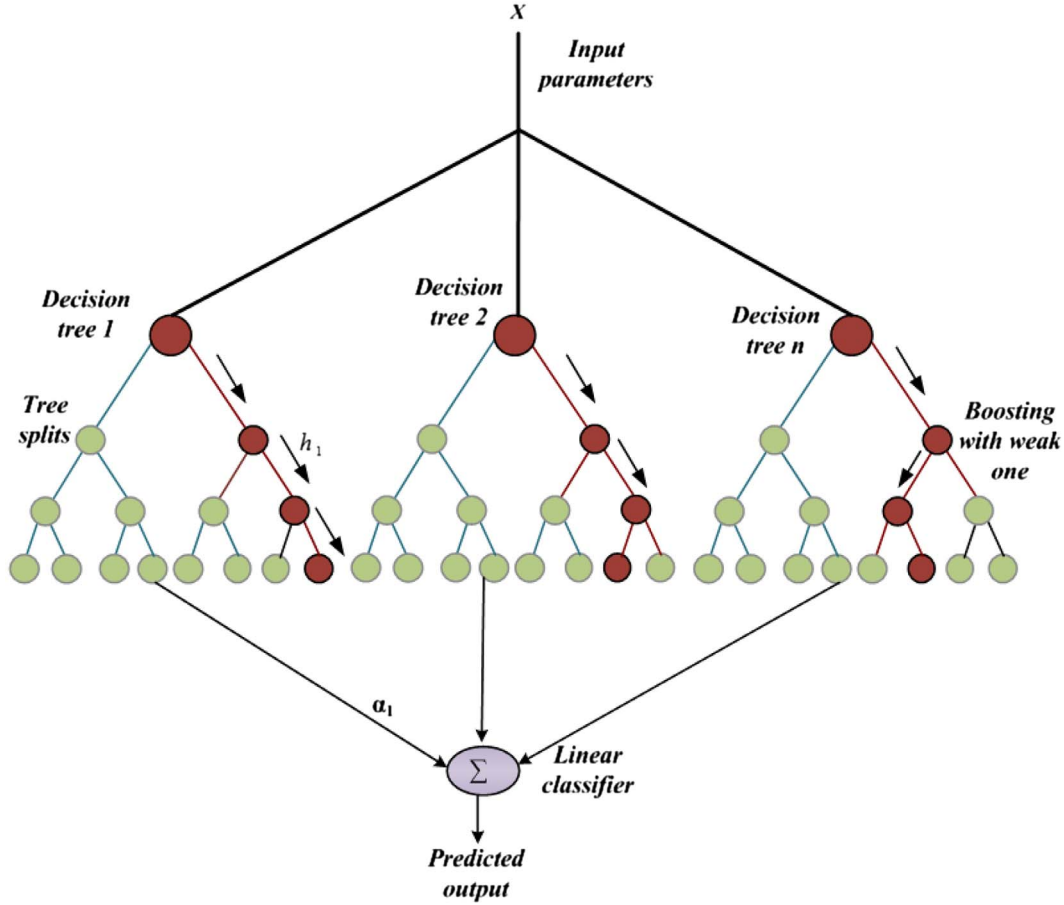


Fig. 4. Inspiration diagram of the GBDT approach.

4.3 Gradient boosting decision tree (GBDT)

The GBDT technique used a stage-by-stage approach in model construction, allowing the optimization function and model to be extended [36]. The decision tree with the constant size is used as the base learner in a gradient-boosting system. The main task of the GBDT is to improve the weak base classifiers obtained in the robust classifier. It can also be utilized to accelerate the algorithm's global convergence. The inspiration diagram of the GBDT approach is portrayed in Figure 4.

4.3.1 Algorithm steps

For sample test signals up to level 4, a DWT is applied in Part 1. A set of coefficients representing signals at various frequency bands or resolutions is produced by the DWT if applied to a signal. The signal was decomposed into 4 levels of approximation and detail coefficients

Part 1:
Begin

1. Importing the data matrix with all key elements such as time, R, Y, and B phase voltages, currents in R, Y, and B circuits, active power, reactive power, ROCOF,

RCP, ROCOV, load, target, and so on. DWT is used to decompose the time series.

2. In the data set's respective load, X indicates the influence factor of the first 12 columns, and Y denotes the island formation instant. $X = \text{data}(11:12)$, $Y = \text{data}(13:14)$
3. Choose X as a desired data set and set some parameters for islanding detection and the maximum level of bands
4. Use `pyt.Dwt discrete-level transforms` function to decompose the signal up to level 4 and save the results.

Before training the model in Part 2, several hyperparameters must be set up using the GBDT. These hyperparameters govern the complexity of a model, and their effects on performance can be significant.

Following the determination of the hyperparameters, the data is generally separated into training and test sets. During training, a test set is utilized to evaluate the model's performance. During training, the GBDT iteratively constructs a series of decision trees, with each new tree seeking to correct the faults of previous trees. Several hyperparameters in GBDT, such as loss function, random variables, maximum features, and so on, might impact model performance.

Hyperparameters, such as `n_estimators`, `learning_rate`, `random_state`, and `max_features`, play a crucial role in optimizing the GBDT algorithm's performance on a specific dataset. After training the model with parameters set at `n_estimators=500`, `learning_rate=0.05`, `random_state=100`, and `max_features=5`, its evaluation involves metrics like accuracy, specificity, recall, precision, RMSE, MBE, MAPE, and consumption time. These metrics collectively assess the model's effectiveness, helping identify strengths and areas for improvement without borrowing from existing content.

Part 2:

Train the GBDT model with the training set

1. Import ensemble and metric modules using the sklearn function
2. Divide the decomposed results into training data ($X_{\text{train}}, Y_{\text{train}}$) set and testing data set ($X_{\text{test}}, Y_{\text{test}}$).
3. Set the number of regression trees `n`, learning rate, loss function, random state, and max features.
4. Params={`n`, learning rate, 'loss'}
5. the training set to fit the GBDT model
6. Clf=ensemble. Gradient boost Regressor (**params)
7. Use the fit function to test training data
8. Clf.fit($X_{\text{train}}, Y_{\text{train}}$)

In Part 3, the Jellyfish Search algorithm (JS) and a swarm intelligence-driven optimization algorithm that mimics jellyfish movements to find food are applied. The algorithm takes into account the current from the ocean and uses a time delay mechanism to move within the swarm.

Jellyfish have been known to travel into areas with ample food availability when they are looking for food. This behavior is used by the JS algorithm to determine which solution would be most effective for an optimization problem. Use the fitness function, which guides the algorithm's movements, to represent the amount of food available at each location.

The algorithm consists of a swarm of jellyfish, each representing a potential solution to the problem. The jellyfish navigate around the search space based on their fitness value and the location of other jellyfish in the swarm.

To control the movement of the jellyfish, the algorithm uses a time control mechanism. When the algorithm finds an optimal solution, it slows the jellyfish's movement and helps to minimize overshooting. The time control mechanism of the JS algorithm is shown in Figure 5. In general, JS algorithm is an effective optimization method that may be used in a variety of applications, such as island discovery in distributed power systems to find the best answer to difficult optimization problems, an algorithm capable of reproducing jellyfish mobility in pursuit of food can be used.

An algorithm for jellyfish is created using the three key rules listed below and illustrated in the JS algorithm flow-chart in Figure 6.

1. The jellyfish traverses in tandem with the swarm's timing mechanism while taking the ocean current into account.

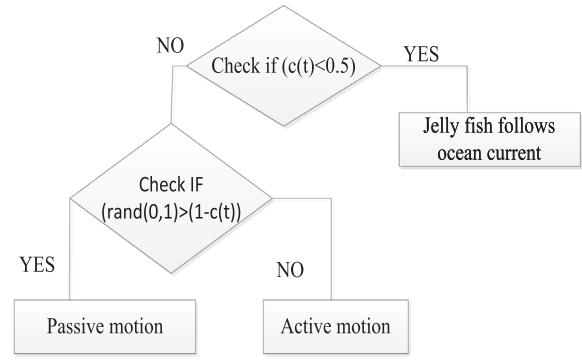


Fig. 5. Time control mechanism of Jelly Fish (JS) algorithm

2. When a jellyfish is in quest of food, it floats through the water and draws itself to locations where it finds plenty of food.
3. The amount of food used in conjunction with location and its equivalent function.

Part 3:

Begin

Choose map coefficient `self.eta=4.0`, distribution coefficient `self.beta= 3.0`, motion coefficient `self.gamma=0.2`

Build the class of parameter

Self. Class(params)

Initialize chaotic mapping to generate random variable `r1`

Calculate the mean location of all jellyfish 'u' using `np.mean` function

Determine ocean current 'TREND'

Trend=best_agent.position-self.beta×r1×u

Calculate Type A and Type B motion using random variable `r1`, mean location of jellyfishes

In type A the jellyfish are available at their location represented

$$x_i(t+1) = x_i(t) + \gamma \times \text{Rand}(0,1) \times (u_b - l_b). \quad (10)$$

Here γ represents the motion coefficient and u_b and l_b represent upper and lower boundaries of search space basespace.

$$\vec{STEP} = \vec{RAND}(0,1) \times \vec{DIRECTION}. \quad (11)$$

In type B motion

$$x_i(t+1) = x_i(t) + \vec{STEP} \quad (12)$$

For $i = 1$

$$\vec{Direction} = \begin{cases} x_j(t) - x_i(t) & \text{if } f(x_i) \geq f(x_j) \\ x_i(t) - x_j(t) & \text{if } f(x_i) \leq f(x_j) \end{cases}. \quad (13)$$

Calculate the time control function $c(t)$

$$C(t) = \left| \left(I - \frac{t}{\max_{\text{iter}}} \right) \times (2 \times \text{Rand}(0,1) - 1) \right|. \quad (14)$$

Here t represents the time-identified iteration number and a maximal number of iterations is represented as $\max_{\text{iter}}$ which is an initialized parameter.

```

If c(t) ≥ 0.5
  Jellyfish follows ocean current i.e. predicted output
  follows normal data set
Else
  Jellyfish moves inside the swarm i.e. predict output
  follows new data set
  If rand(0, 1) > (1 - c(t));
    Jellyfish exhibits TYPE A motion i.e. exhibits Islanding
    events
  Else
    Jellyfish exhibits TYPE B motion i.e. exhibits non-
    Islanding events
  End if
End if
End for
Evaluation of the above model is done to calculate
various parameters like Accuracy, MSE, etc
Ypredict = clf.predict (XTest);
Accuracy = accuracy_score (YTest, Ypredict);
MSE = mean_squared_error (YTest, Ypredict);

Precision =  $\frac{TP}{TP + FP}$ ;
Sensitivity =  $\frac{TN}{TP + FN}$ ;
recall =  $\frac{TP}{TP + FN}$ ;
F1-score =  $\frac{2 \times \text{precision} \times \text{recall}}{\text{Precision} + \text{recall}}$ ;
Specificity =  $\frac{TN}{TN + FP}$ ;
End

```

5 Result and discussion

Under identical conditions, the GBDT-JS method is employed for the same test system depicted in Figure. For step-by-step analysis, both decreased loading and balanced loading are initially evaluated, and final results for various loading circumstances are provided.

Case 1: Conditions of reduced loading

Figure 7 depicts estimated and detailed Daubechies wavelet family coefficients up to level 4 under 70% loading circumstances. During islanding the phase angle between the voltage and current signals will start to diverge slightly from the expected value due to reduced load burden. The PLL-based IDT monitors the phase angle continuously and detects islanding within nearly 15 ms.

Figures 8a–8d and 9a–9d show the approximation and detail coefficients up to level 4 for decreased loading. This decomposition approach allows for accurate identification and separation of the most important frequency components. At level 1, the approximation components represent the signal's slowly fluctuating frequency information. From Figures 8a–8d, it is noted that the magnitudes

of approximation signal coefficients grew steadily from level 1 to level 4, indicating that low-level frequency components became more prominent owing to noise level reduction. Similarly, the detailed coefficients shown in Figures 9a–9d show that the magnitudes of the detail coefficients are lowered, indicating a reduction in high-frequency noise or tiny scale changes in the signal. When compared to detail coefficients, these detail coefficients contain more significant fluctuations in the signal, allowing the GBDT-JS algorithm to predict islanding detection more correctly.

Case 2: Conditions of balanced loading

During balanced load conditions, RCPP technique detects islanding within 13.8 ms as shown in Figure 10. DWT evaluation during balanced loading involves splitting voltage and current signals into smaller bands and assessing their behavior during islanding and non-islanding circumstances.

The phase angle deviations at the PCC caused by islanding are also taken into consideration. The RCPP waveform obtained from the DWT analysis as shown in Figures 11a–11d and 12a–12d can provide useful information for detecting islanding. The characteristics of the sub-bands and the threshold values for detecting islanding may vary depending on the loading conditions.

Case 3: Normal loading conditions

During normal circumstances, RCPP detects islanding condition at 15 ms as shown in Figure 13. The RCPP approach can identify alterations in frequency and phase angle at the PCC. The DWT analysis can extract sub-band signals from the RCPP waveform and analyze their frequency and amplitude changes under normal loading conditions. These changes can then be used to identify the presence of islanding and trigger appropriate control measures to ensure system stability.

Case 4: Conditions of overloading

The voltage and current signals may deviate more from their normal values due to the increased current flow and voltage drops across the system components. So RCPP detection technique detects islanding within 13.3 ms much faster than the balanced loading situation as shown in Figure 14. The approximation and detail coefficients of the Daubechies wavelet family up to level 4 for overloading situations with a load capacity of 120% of its DG capacity.

Case 5: Switching conditions for inductive loads (50 HP) (non-islanding)

When an inductive load connected to the common bus bar is switched on or off, it can cause transient changes in the voltage and current waveforms which can temporarily affect the phase relationship between voltage and current. However, these deviations are very small compared to islanding situations so the RCPP technique is unable to detect islanding as these deviations will not exceed the threshold value (2000 °/ms) as shown in Figure 15.

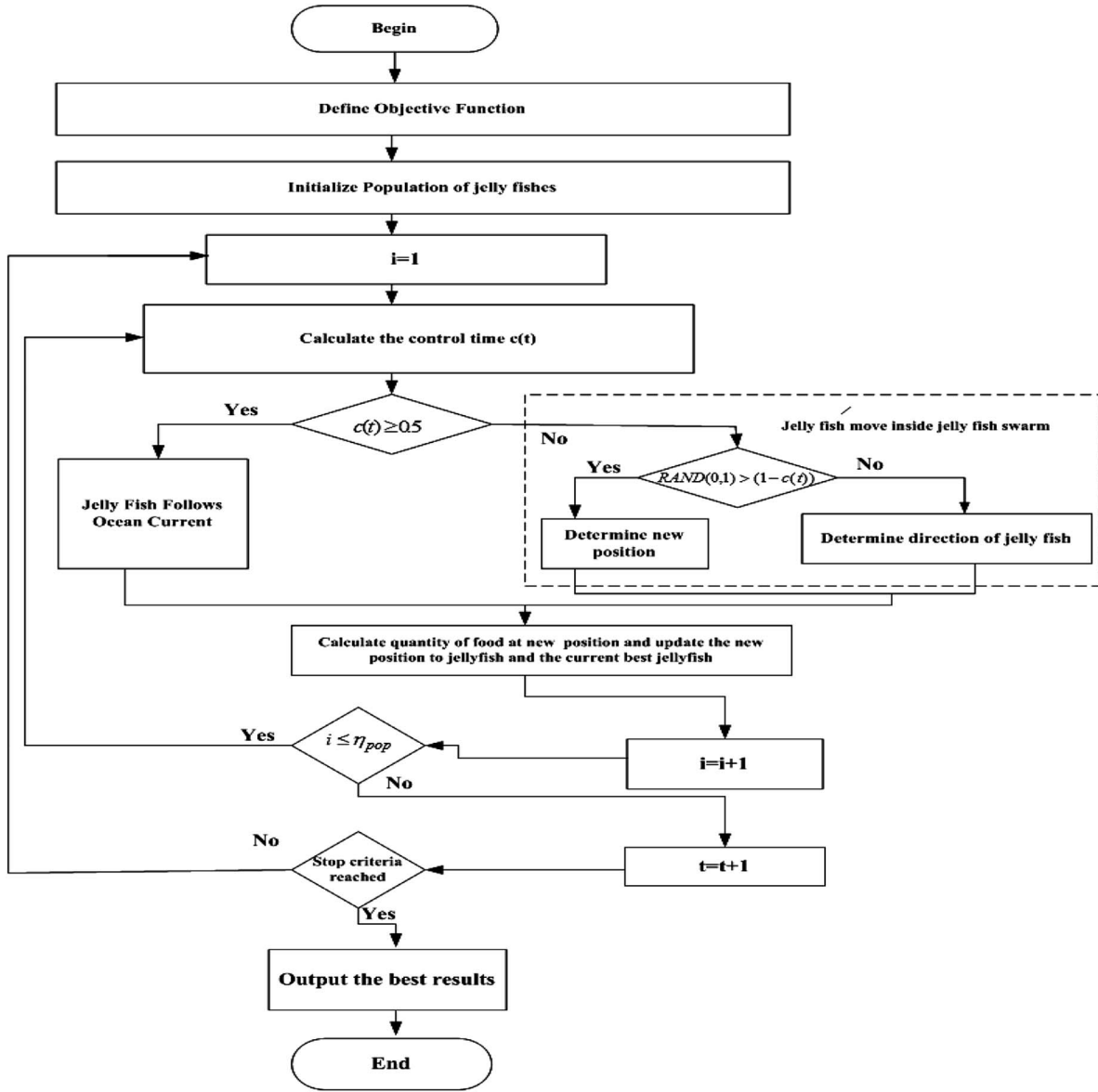


Fig. 6. Flow chart of Jelly Fish (JS) algorithm.

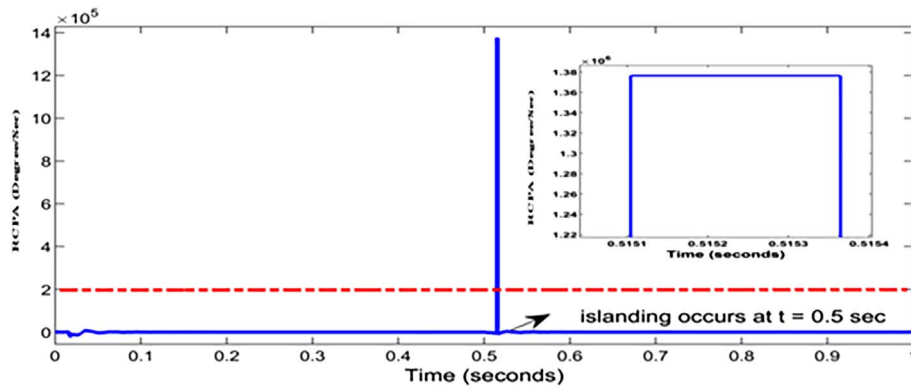


Fig. 7. RCPP islanding detection during reduced loading.

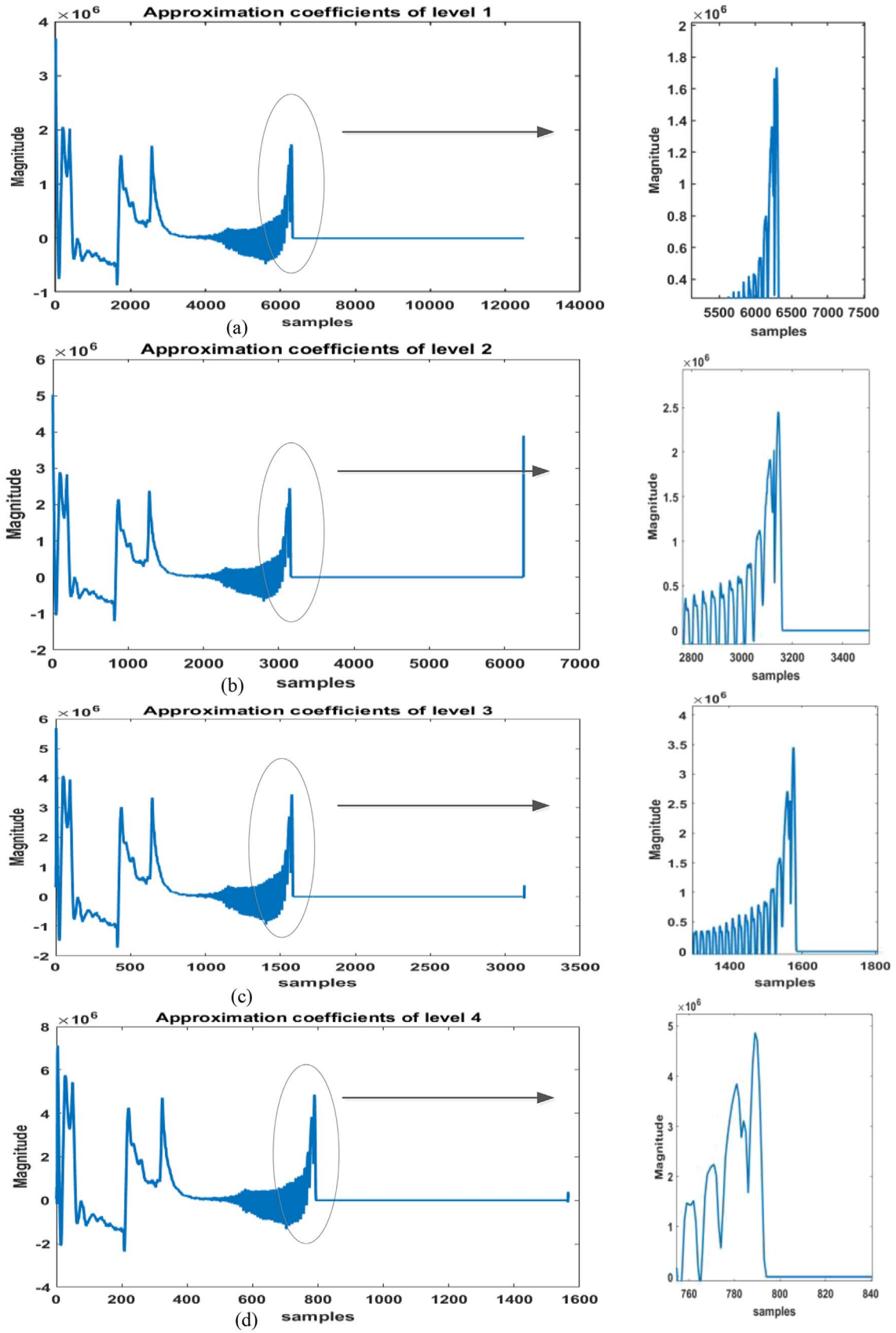


Fig. 8. (a)–(d) Approximation coefficients up to level 4 during 60% loading.

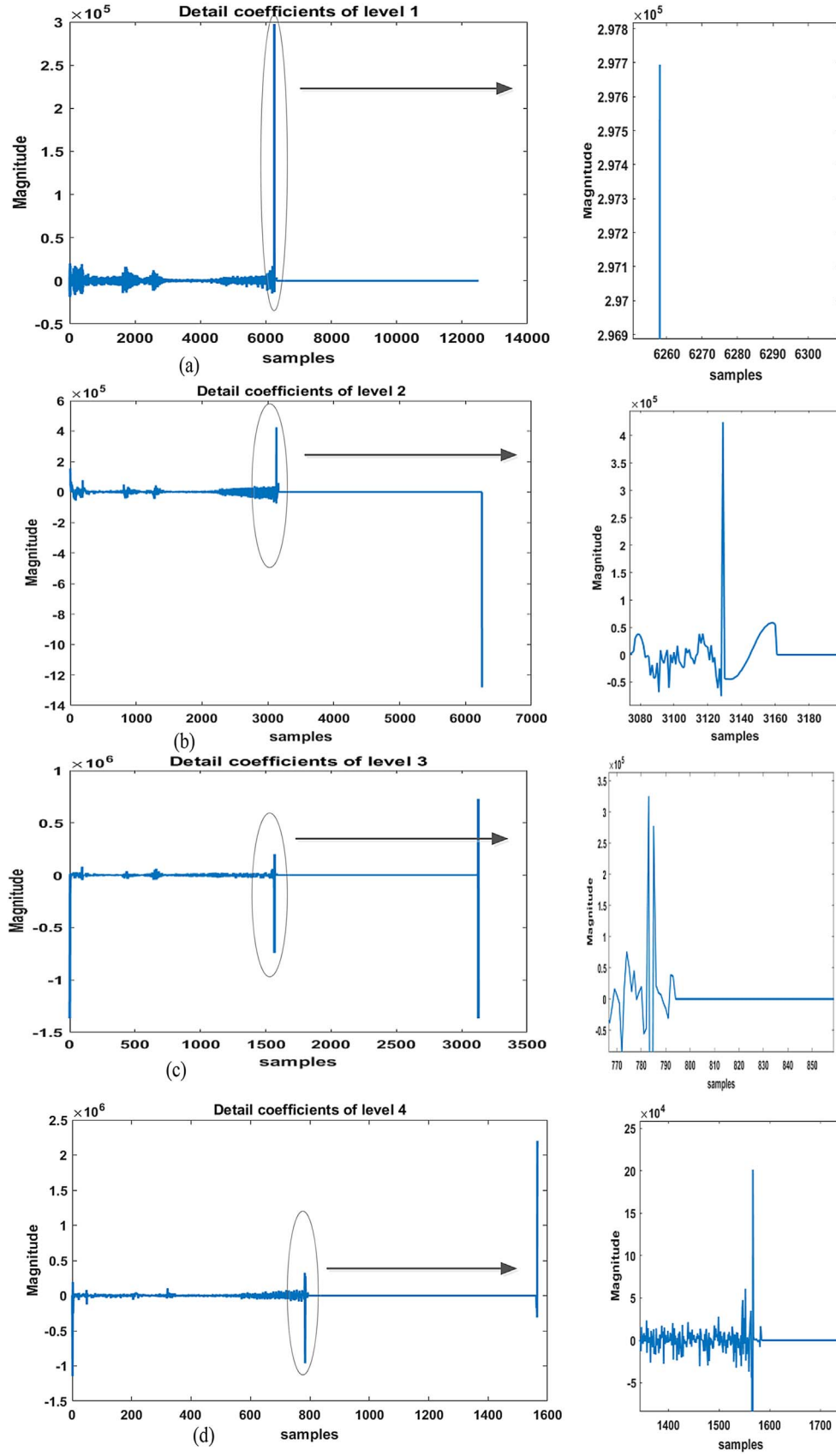


Fig. 9. (a)–(d) Detail coefficients up to level 4 during 60% loading.

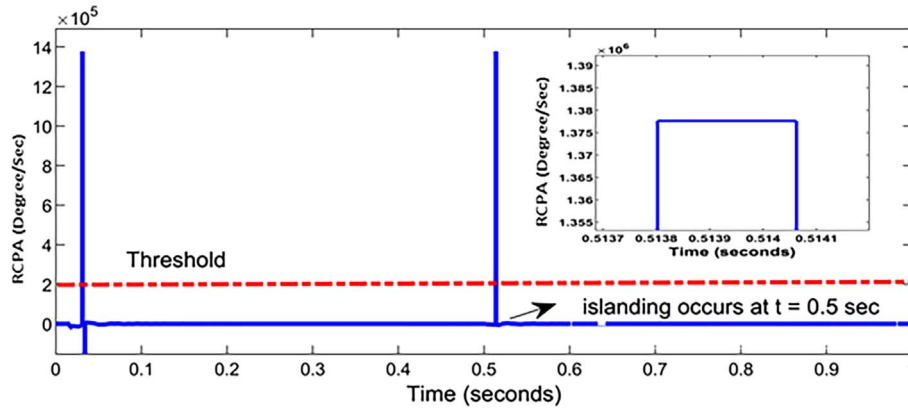


Fig. 10. RCPP detection during balanced loading conditions.

The DWT analysis may be utilized to extract the high-frequency components of the RCPP waveforms and investigate their variations to detect any abnormal system behavior during inductive load switching. The changes in the wavelet coefficients can be used to identify any sudden changes in the power factor or reactive power demand, which can cause voltage fluctuations and affect the system's stability. This information can be used by the control system to take corrective actions, such as adjusting the voltage or reactive power control, to maintain system stability.

Case 5: Switching condition of a capacitor (10 KVA) (non-islanding)

A rapid change in voltage and current may occur when a capacitive load connected to the common bus bar is turned on or off. The current-voltage phase connection may be momentarily interrupted. However, the RCPP approach is unable to detect islanding because these deviations are so small compared to the island conditions since they do not meet the threshold value of $2000^\circ/\text{ms}$, as shown in Figure 16.

Capacitor switching can change reactive power abruptly, causing voltage and current waveform distortions. High-frequency components of the RCPP waveform capture this distortion. The DWT can be used to analyze these high-frequency components and detect any sudden changes during islanding. This technique can ensure system stability during capacitor-switching events.

5.1 ANN modeling and its performance comparison with GBDT algorithms

The ANN algorithm is used to differentiate between islanding and non-islanding events to predict islanding events. The ANN model is used to extract voltage, current, and active and reactive power features of both DG systems, RCPP, and % loading.

The classifier algorithm is tested in two ways:

1. 80% Training data and 20% Testing data.
2. 70% Training data and 30% Testing data.

Various parameters of the different classifiers are explained below during the data classification process. Based on the islanding accuracy, the random states, loss function, and learning rate are chosen in the algorithm. During ANN modeling 80% of Training data and 20% of Testing data have shown better performance which is shown in Figure 13.

Level 4 signals are more susceptible to rapid changes or disturbances in the system than level 1 signals. As a result, during islanding events, level 4 coefficients can be employed to provide more exact and thorough information about the system's dynamics. As a result, islanding detection times can be more accurately predicted. A good epoch selection results in increased accuracy during testing and training. Different case studies have variable levels of accuracy based on the number of epochs and time approximation samples employed.

Data testing becomes more accurate as epochs increase, whereas islanding identification becomes more accurate as epochs decrease. Epochs will be chosen as part of the islanding prediction model based on accuracy, precision, and recall levels.

The suggested method predicts islanding with an accuracy of 94–99% for varied loads with different islanding detection durations, whereas the accuracy for balanced islanding occurrences is around 87%. The suggested DWT-ANN approach showed increased accuracy, precision, sensitivity, recall, and score for level 4 coefficients during islanding prediction.

The GBDT-JS algorithm classifier's performance is evaluated on the test system depicted in Figure 17, and it is validated using both the ANN classifier and the light Gradient boost classifier (GBDT algorithm). As mentioned in Section 4, the data is classified into two. Initially, the GBDT-JS algorithm is tested under low-load conditions. The performance indicators of this classifier are compared to those of ANN and GBDT classifiers. Following that, the final outcomes of various loadings are discussed. The confusion matrices of all three classifiers under lower loading circumstances are shown in Tables 1 and 2.

5.1.1 Discrete wavelet and ANN

The number of neurons in the input, hidden, and output layers, Activation function, learning rate, Batch size, and

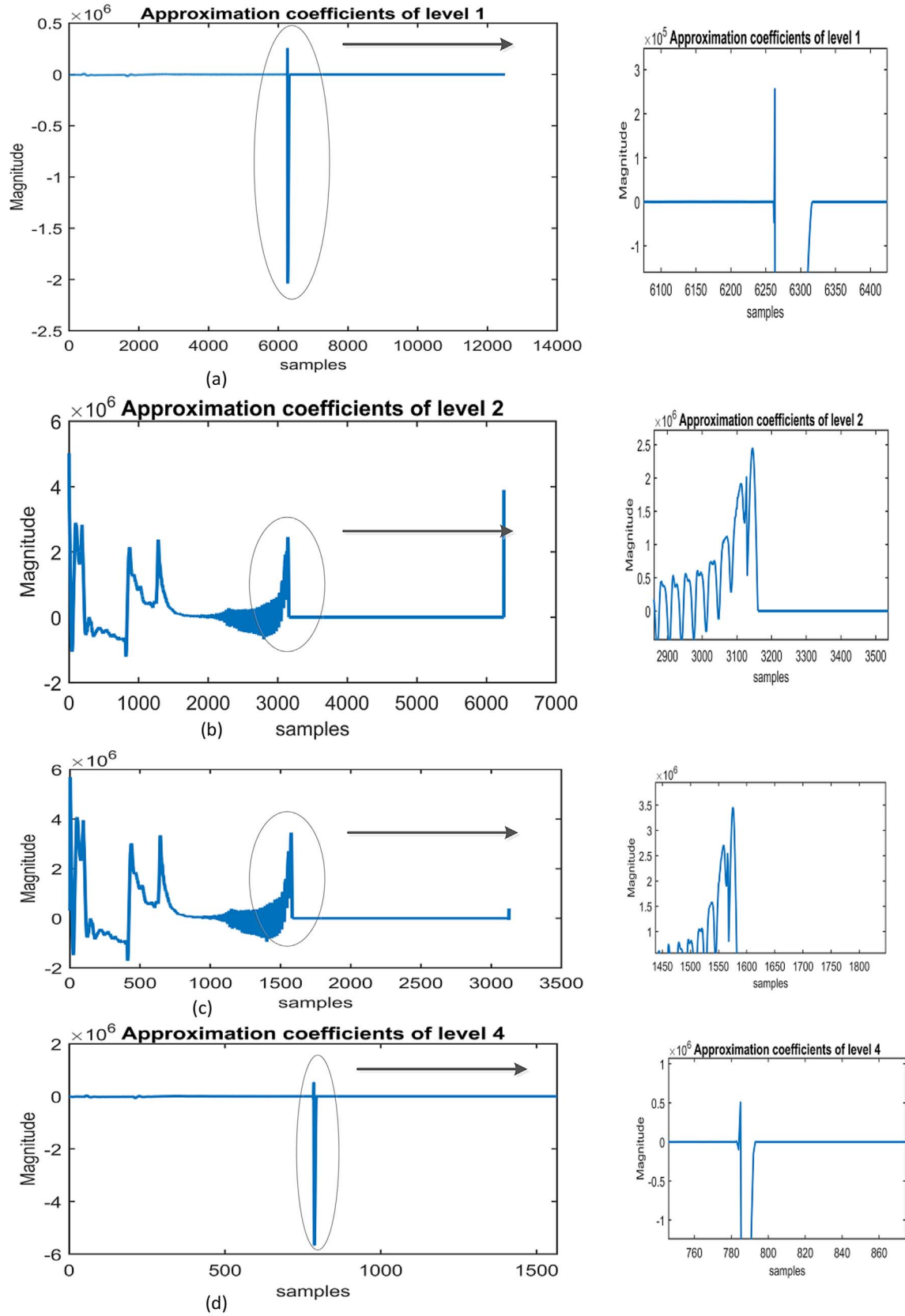


Fig. 11. (a)–(d): Approximation coefficients up to level 4 during 100% loading.

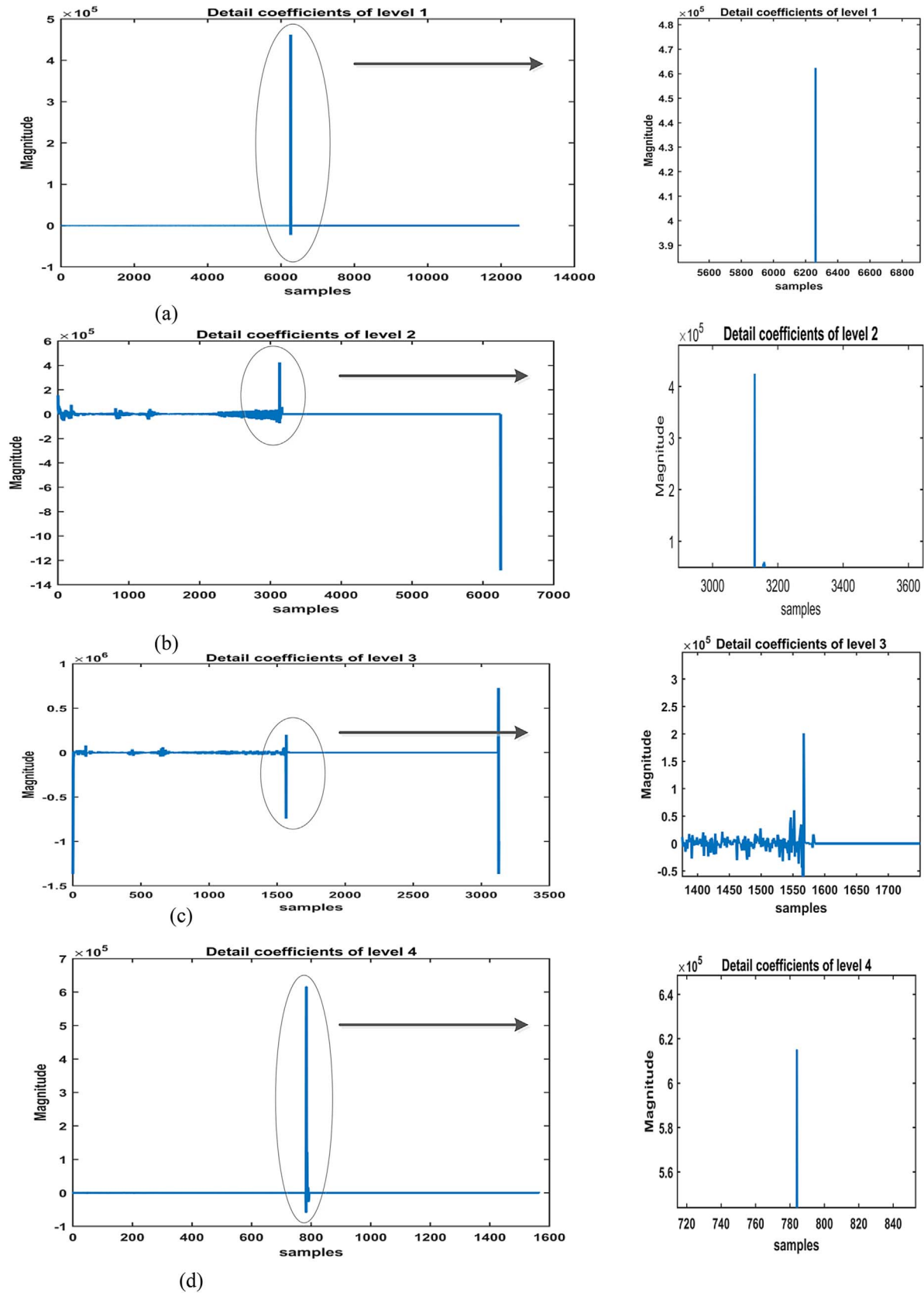


Fig. 12. (a)–(d): Detail coefficients up to level 4 during 100% loading.

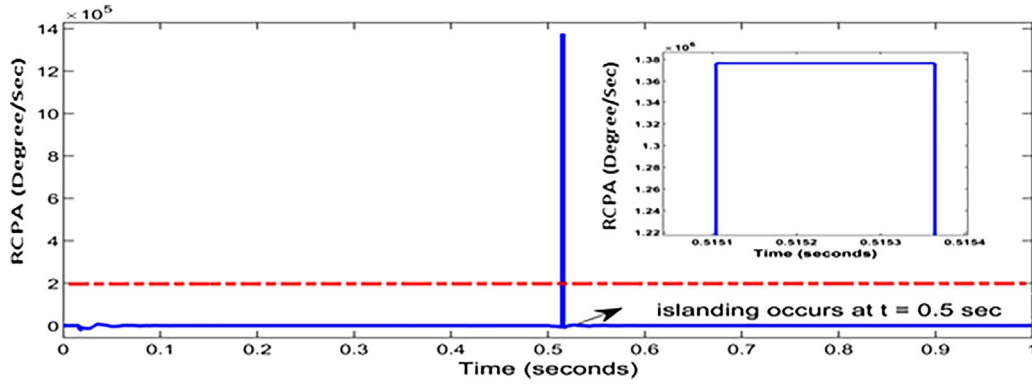


Fig. 13. RCPP detection during normal loading conditions.

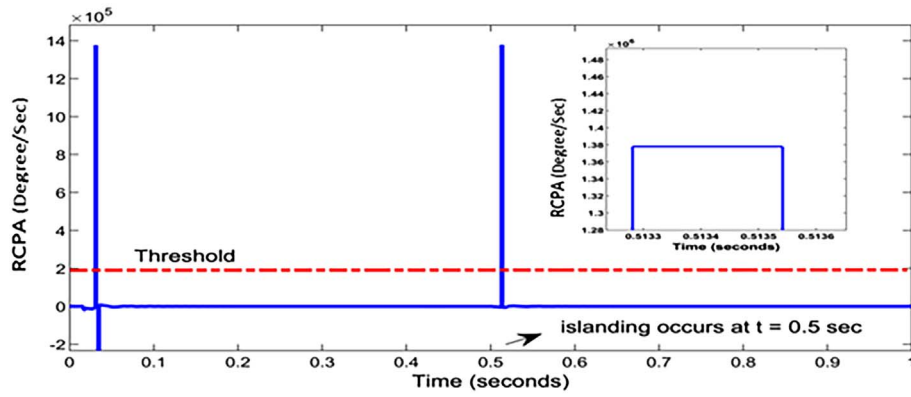


Fig. 14. RCPP detection during overloading conditions.

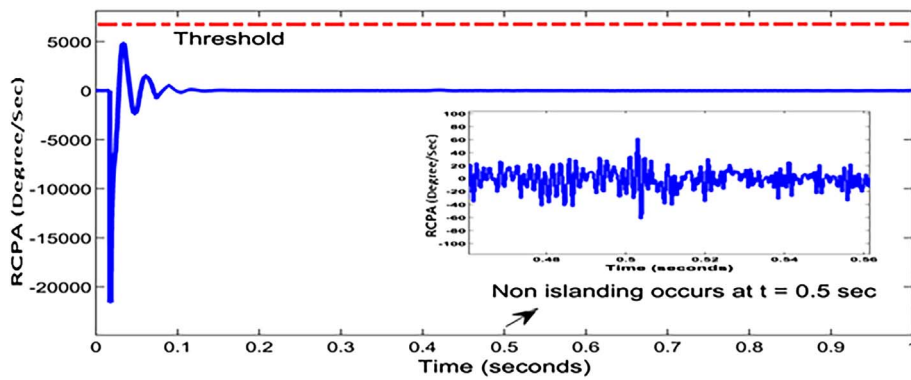


Fig. 15. RCPP detection during inductive load switching.

Number of epoch selections are important factors in neural network classification. The neural network classifier achieved a high accuracy of 87.53% for 80% training data and 20% testing data respectively. The classifier also achieved a low Mean Squared Error (MSE) of 0.1045. In

addition, the classifier achieved high precision, recall, F1-score, specificity, and sensitivity, with respective ranges of 0.806, 0.988, 0.92387, 0.4567, and 0.9887 for 80% of training data and 20% of testing data. Similarly, the classifier achieved accuracy (84.09%), MSE (0.0476), precision

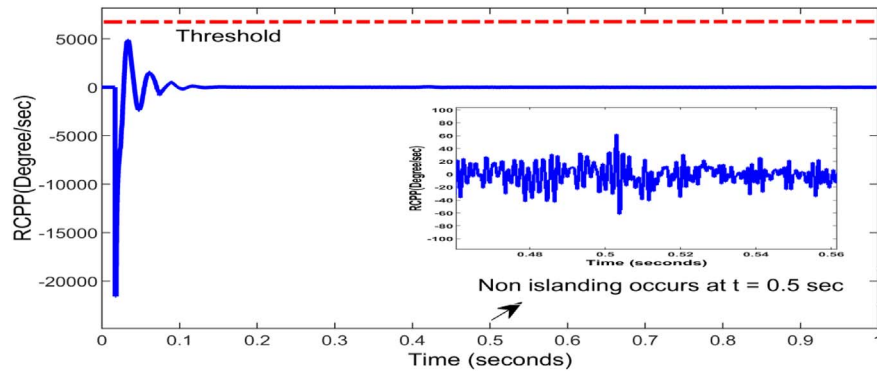


Fig. 16. RCPP detection during capacitive load switching.



Fig. 17. ANN classifier performance under various wavelet coefficient levels.

Table 1. Confusion matrices for 80% training data and 20% testing data.

S.No	Detail coefficients	Confusion matrix of testing data			Confusion matrix of training data		
		ANN	GBDT	GBDT-JS	ANN	GBDT	GBDT-JS
1	Level 1	$\begin{bmatrix} 758 & 120 \\ 201 & 1422 \end{bmatrix}$	$\begin{bmatrix} 796 & 110 \\ 230 & 1365 \end{bmatrix}$	$\begin{bmatrix} 800 & 78 \\ 217 & 1406 \end{bmatrix}$	$\begin{bmatrix} 4420 & 0 \\ 8081 & 0 \end{bmatrix}$	$\begin{bmatrix} 3887 & 533 \\ 1125 & 6956 \end{bmatrix}$	$\begin{bmatrix} 4064 & 356 \\ 1182 & 6899 \end{bmatrix}$
2	Level 2	$\begin{bmatrix} 250 & 48 \\ 85 & 868 \end{bmatrix}$	$\begin{bmatrix} 295 & 43 \\ 78 & 835 \end{bmatrix}$	$\begin{bmatrix} 256 & 42 \\ 87 & 866 \end{bmatrix}$	$\begin{bmatrix} 1563 & 0 \\ 4688 & 0 \end{bmatrix}$	$\begin{bmatrix} 1398 & 165 \\ 418 & 4270 \end{bmatrix}$	$\begin{bmatrix} 1356 & 207 \\ 365 & 4323 \end{bmatrix}$
3	Level 3	$\begin{bmatrix} 66 & 46 \\ 21 & 493 \end{bmatrix}$	$\begin{bmatrix} 109 & 22 \\ 40 & 455 \end{bmatrix}$	$\begin{bmatrix} 97 & 20 \\ 38 & 470 \end{bmatrix}$	$\begin{bmatrix} 553 & 0 \\ 2573 & 0 \end{bmatrix}$	$\begin{bmatrix} 483 & 70 \\ 191 & 2382 \end{bmatrix}$	$\begin{bmatrix} 482 & 71 \\ 188 & 2385 \end{bmatrix}$
4	Level 4	$\begin{bmatrix} 25 & 15 \\ 7 & 263 \end{bmatrix}$	$\begin{bmatrix} 22 & 14 \\ 42 & 73 \end{bmatrix}$	$\begin{bmatrix} 30 & 13 \\ 8 & 262 \end{bmatrix}$	$\begin{bmatrix} 195 & 0 \\ 1368 & 0 \end{bmatrix}$	$\begin{bmatrix} 143 & 52 \\ 43 & 1326 \end{bmatrix}$	$\begin{bmatrix} 156 & 39 \\ 57 & 1311 \end{bmatrix}$

Table 2. Confusion matrices for 70% training data and 30% testing data.

S.No	Detail coefficients	Confusion matrix of testing data			Confusion matrix of training data		
		ANN	GBDT	GBDT-JS	ANN	GBDT	GBDT-JS
1	Level 1	$\begin{bmatrix} 1067 & 228 \\ 253 & 2203 \end{bmatrix}$	$\begin{bmatrix} 1258 & 86 \\ 409 & 1996 \end{bmatrix}$	$\begin{bmatrix} 1193 & 102 \\ 343 & 2113 \end{bmatrix}$	$\begin{bmatrix} 4420 & 0 \\ 8081 & 0 \end{bmatrix}$	$\begin{bmatrix} 4185 & 235 \\ 1263 & 6818 \end{bmatrix}$	$\begin{bmatrix} 4130 & 290 \\ 1213 & 6808 \end{bmatrix}$
2	Level 2	$\begin{bmatrix} 389 & 76 \\ 118 & 1293 \end{bmatrix}$	$\begin{bmatrix} 429 & 67 \\ 127 & 125 \end{bmatrix}$	$\begin{bmatrix} 399 & 66 \\ 123 & 1288 \end{bmatrix}$	$\begin{bmatrix} 1563 & 0 \\ 4688 & 0 \end{bmatrix}$	$\begin{bmatrix} 1390 & 173 \\ 411 & 4277 \end{bmatrix}$	$\begin{bmatrix} 1356 & 207 \\ 365 & 4323 \end{bmatrix}$
3	Level 3	$\begin{bmatrix} 113 & 57 \\ 27 & 741 \end{bmatrix}$	$\begin{bmatrix} 154 & 33 \\ 47 & 704 \end{bmatrix}$	$\begin{bmatrix} 135 & 35 \\ 50 & 718 \end{bmatrix}$	$\begin{bmatrix} 553 & 0 \\ 2573 & 0 \end{bmatrix}$	$\begin{bmatrix} 468 & 85 \\ 157 & 2416 \end{bmatrix}$	$\begin{bmatrix} 466 & 87 \\ 170 & 2403 \end{bmatrix}$
4	Level 4	$\begin{bmatrix} 32 & 29 \\ 8 & 400 \end{bmatrix}$	$\begin{bmatrix} 31 & 18 \\ 6 & 414 \end{bmatrix}$	$\begin{bmatrix} 43 & 18 \\ 14 & 394 \end{bmatrix}$	$\begin{bmatrix} 195 & 0 \\ 1368 & 0 \end{bmatrix}$	$\begin{bmatrix} 143 & 52 \\ 42 & 1326 \end{bmatrix}$	$\begin{bmatrix} 154 & 41 \\ 55 & 1313 \end{bmatrix}$

(0.8754), recall (0.99975), F1-score (0.9302), specificity (0.1693), and sensitivity (0.9974) of 70% of training data and 30% of testing data. Overall, these results suggest that the neural network classifier with appropriate activation function and hidden layer selection can achieve high precision, accuracy, and efficiency in classification tasks.

5.1.2 Light gradient boost classifier

This classifier uses random_states (42), max_depth (5), Learning_rate (0.09), n_estimators (100) are used to estimate islanding detection time. The classifier achieved high accuracy (96.16%), low MSE (0.0383), high precision (0.9923), high recall (0.9629), high F1-score (0.9774), high specificity (0.9534), and high sensitivity (0.9629) when evaluated using 80% training data and 20% testing data. Similarly, the classifier achieved an accuracy (94.66%), MSE (0.0534), precision (0.97528), recall (0.9657), F1-score (0.9692), specificity (0.8196), and sensitivity (0.9656) of 70% of training data and 30% of testing data.

5.1.3 Gradient boost classifier and jellyfish algorithm

The DWT is utilized up to level 4 to extract intrinsic features during islanding and grid disturbances. The extracted features are then classified using the GBDT-JS algorithm. The results show that the GBDT-JS algorithm achieved high accuracy (98.3%), low MSE (0.0251), high precision (0.9892), high recall (0.9866), high F1-score (0.9885), high specificity (0.9649), and high sensitivity (0.9867) when evaluated using 80% training data and 20% testing data. Similarly, the classifier achieved an accuracy (95.8%), MSE (0.0123), precision (0.9673), recall (0.9841), F1-score (0.9766), specificity (0.9552), and sensitivity (0.9798) of 70% of training data and 30% of testing data. The Gradient Boost-Jellyfish search algorithm demonstrated better performance in optimizing the hyperparameters of the model.

The Gradient Boost Classifier with Jellyfish Algorithm showcases superior performance across various metrics. It consistently achieves the highest accuracy rates in both training and testing datasets. Additionally, it boasts the

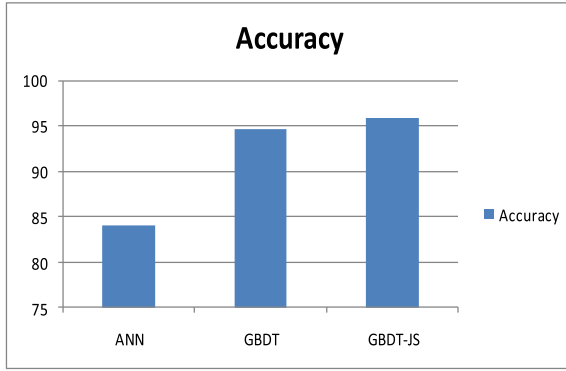


Fig. 18. Accuracy comparison of different classifiers for 70% of Training data and 30% of Testing data.

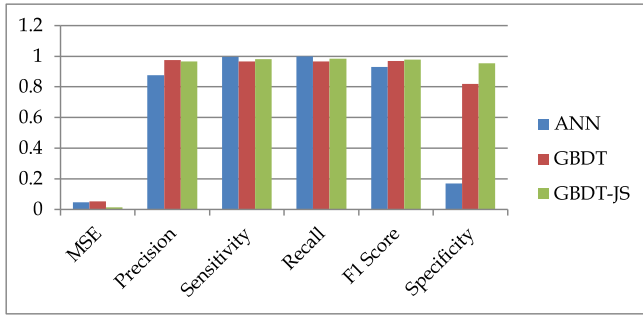


Fig. 19. Performance parameters of the Test system model for 70% of Training data and 30% of Testing data.

lowest MSE, signifying enhanced predictive capabilities. Furthermore, its precision, recall, F1-score, specificity, and sensitivity values remain consistently high, indicating a robust and well-balanced classification performance. The incorporation of the Jellyfish algorithm for hyperparameter optimization evidently contributes to its superior performance. While the Light Gradient Boost Classifier also delivers commendable results, the Gradient Boost Classifier with Jellyfish Algorithm demonstrates a more refined and optimized approach, notably reflected in its higher accuracy and lower MSE. Overall, these results are shown in [Figures 18–21](#) and [Tables 3–5](#) which indicate that the combination of DWT feature extraction and the GBDT-JS algorithm with optimized hyperparameters is an effective approach for detecting islanding and grid disturbances with high accuracy and classification performance.

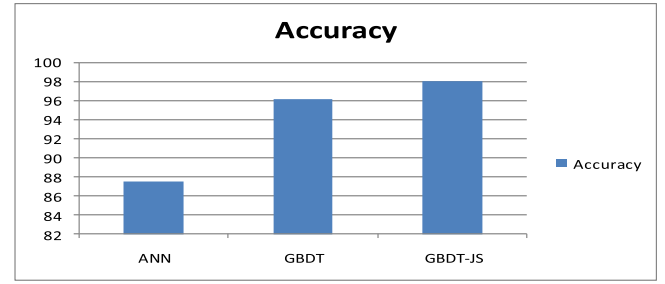


Fig. 20. Accuracy comparison of different classifiers for 80% of Training data and 20% of Testing data.

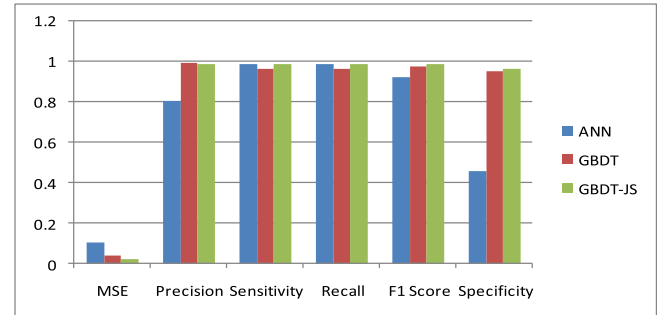


Fig. 21. Performance parameters of the Test system model for 80% of Training data and 20% of Testing data.

6 Conclusion

This chapter introduces RCPP, a new parameter for passive recognition, for wind and solar DG systems connected to a shared grid. Various islanding and non-islanding scenarios are investigated. The balanced islanding detection time is 15 ms, which is slightly faster than a single DG system. With a threshold of 2000 °/ms, this approach effectively distinguishes between islanding and non-islanding conditions. This system is subjected to an ANN-DWT analysis, and its performance is compared with intelligent algorithms such as Light GBDT and the GBDT-JS algorithm under balanced circumstances, revealing that the GBDT-JS algorithm predicts islanding with a high accuracy of almost 98.3%. Advanced approaches such as multiple regressions, recurrent neural networks, and others can be used to implement the recommended approach for detecting islands without sacrificing accuracy in the future.

Table 3. Detection time comparison under balanced loading.

S.No	Islanding detection method	Predicted islanding detection time (ms)	Accuracy (%)
1	Artificial Neural Network & Discrete Wavelet Transform (ANN & DWT)	70	85.96
2	Light Gradient Boost Classifier	65	96.16
3	Gradient Boost-Jelly fish search	52	98.30

Table 4. Proposed strategy on existing techniques.

Methodology	Islanding estimation (ms)
Rate of change of frequency [11]	500
Positive sequence voltage and current [31]	100
Active ROCOF [9]	200
Regulator voltage in excess of reactive power [23]	300
Proposed system	<60

Table 5. Detection results of proposed technique.

S.No	Case studies	Classification rate (%)
1	5.1 MW load	98.5
	7.1 MW Load	97.4
2	9.1 MW load	98.65
3	11.1 MW load	99.43
4	Inductive load switching	97.65
5	Capacitor switching	98.46
		98.3%

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