Detection of islanding using empirical mode decomposition and support vector machine

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ABSTRACT

Accurate detection of islanding remains to be a challenge for grid connected microgrid system. An effective method to identify the islanding of microgrid has been presented which uses only the voltage at point of common coupling (PCC). Accurate islanding detection is necessary to impose appropriate control for the microgrid operation. Following the islanding of microgrid the intrinsic mode functions (IMF's) of voltage at PCC obtained by empirical mode decomposition (EMD) will be analyzed by support vector machine (SVM) model which identifies the islanding of the microgrid. SVM model learns through the training data set. As many as 150 simulated cases have been used to train the SVM. A practical microgrid system has been simulated for various operating conditions and the data generation has been carried out by series of simulations for various islanding and non-islanding events using MATLAB Simulink. The proposed method gives optimistic results with high accuracy, zero non detection zone (NDZ) and detection time as low as 63.11 ms. Accurate islanding detection leads to smooth transition of microgrid control essential for operators.

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1. INTRODUCTION

The primary objective of the energy sector is sustainability. Limited availability of natural fuel, increase in demand, potential of renewable energy sources, advancement in the technology to integrate generators at load centers are the reasons microgrids and distributed generators are realized and are in use. However, there are issues to be addressed w.r.t grid connected microgrid operation. The islanding occurs when the main power grid fails or undertaken for maintenance, but distributed energy resources (DERs) like solar panels or wind turbines continue supplying electricity [1]–[3]. This may result in safety hazards, equipment damage, and disrupt microgrid operations. To prevent this, it is crucial to detect islanding events quickly and adopting necessary controls and the detection should happen within 2 seconds according to the standards namely IEC 62116, IEEE 1547-2018 and UL 1741. Rapid detection ensures the reliability, safety and smooth operation of the system [4].

Islanding detection methods are categorized into remote and local methods. Remote methods, offer reliability and quick response but they are costly since communication infrastructure is required [5]. The local schemes are classified into passive, active, and hybrid methods. point of common coupling (PCC) variables like frequency, harmonics, impedance, and power. are continuously monitored and it is expected that these variables shifts to a new level based on the active/reactive power fed into/received from the utility during islanding [6]. Researchers have comprehensively studied and evaluated these detection methods to enhance the reliability.

The renewable-based subsystems can be utilized optimally in island mode to meet local demand during emergencies adopting grid-forming capabilities [7]. The increase of distributed generation (DG) is found advantageous reducing transmission and distribution losses and investments for such infrastructures. Grid-connected photovoltaic (PV) generators are preferred due to adequate availability of solar energy, silent operation, and low maintenance. However, such integration is challenging w.r.t islanding issues. Sensitive equipment in the islanded area may be damaged by overcurrent or overvoltage during unsynchronized reclosing. While passive islanding detection methods are simple and cost-effective, they may fail to detect islanding in scenarios with minimum power mismatch within microgrid called as non-detection zone (NDZ). In active methods an intentional disturbance will be injected in controller of DG such a way that these disturbances do not affect the PCC parameter under any of the non-islanding events and importantly they increase the deviation only during islanding, based on which the islanding detection results. The injection of disturbances causes power quality degradation. Hybrid method is a combination of both passive and active methods, the threshold based parameter is continuously observed if it exceeds a minimum threshold but do not reach to the maximum only during such suspicious occasions of islanding disturbance signal is introduced at PCC and its impact is observed for detection, which reduces the possibilities of power quality degradation [8].

Passive methods, based on voltage information at PCC are simple and faster but results in to larger NDZ. Signal decomposition techniques, combined with intelligent classifiers, offer a solution to overcome these limitations. These approaches involve extracting suitable features from the signal to classify the event. Pattern recognition techniques (PRTs) like decision tree (DT), random forest (RF), SVM help classify islanding and non-islanding events accurately, enhancing the reliability and effectiveness of islanding detection methods.

2. LITERATURE REVIEW

Many have tried different methods for islanding detection of microgrid. The studies have been focused on passive, active and hybrid methods of detection, however signal processing and artificial intelligence techniques are investigated recently. The rate of change of power factor angle has been considered as threshold parameter to distinguish the islanding with non-islanding events. Importantly with changing load condition the threshold parameter has been made adaptive which results in improved accuracy. It has been observed that NDZ is reduced compare to methods based on df/dq [1]. Study [2] introduces a technique based on the rate of change of power (ROCOP) using terminal voltage (TV) of the photovoltaic inverter and detection accuracy has been found better than few of the other passive methods, but fails to detect islanding in power matching condition. Detection using rate of change of power angle deviation (ROCOPAD) has been evaluated on MATLAB to demonstrate its effectiveness in terms of detection accuracy and detection time for DG's [3]. Phase angle of positive sequence voltage at PCC has been found to dominate island detection compare to other conventionally used parameters like frequency, voltage, active power, reactive power, power factor and total harmonic distortion (THD) [4]. These passive methods are simple however results in larger NDZ.

The perturbation in the inverter's output current causes voltage variations, which has been observed as an impedance formulated as dv/di. Islanding is detected when impedance surpasses threshold impedance value. The method results in small NDZ with 0.77-0.95 seconds detection time in single-DG systems. However, the detection accuracy drops in multi-inverter systems [5]. The Sandia voltage shift method introduces a positive feedback mechanism to perturb the voltage amplitude at the PCC by injecting reactive power. Under grid connected events minimal impact has been observed on the PCC voltage, but under islanding conditions it is significant for detection [6]. Most of the active methods results in reduced NDZ compare to passive method, but due to injection of disturbance signal causes power quality issues.

Hybrid islanding detection method for grid-connected photovoltaic systems has been discussed in reference [7]. In the first step it detects a potential islanding event when the absolute deviation of the PCC voltage exceeds a threshold and in second step after a defined delay a transient disturbance is injected into the inverter's d-axis reference current which reduces the active power output causing the PCC voltage to drop only during islanding. Study [8] proposes a method for inverter-based DGs. Bidirectional reactive power variation is triggered only when voltage unbalance (VU)/THD suspects islanding, this method has negligible effects on power factor. A hybrid technique with fuzzy system has been proposed aiming zero NDZ [9]. Reactive power injection as a disturbance will be done for island detection, the THD due to injection remains below IEEE standards under normal condition. In hybrid methods the introduction of perturbation only during suspicious conditions reduces power quality impacts compare to active methods, keeping the advantage of reduced NDZ.

Artificial neurological network (ANN) method of DT characteristics has been used for islanding detection, an accuracy of 99.1% has been observed, but results in more computation time [10]. In the paper [11] it is proposed a method for island detection based on genetic programing named as advanced islanding detection multi-gene genetic programming, it shows the performance better than ANN based methods, however the data set used is not uniform and dominance of non-islanding data is observed. The reference [12] proposes a method based on deep convolutional neural networks where in the signals are converted to 2D images using constant Q transform followed by hierarchical features extraction from the images for PV integrated microgrids.

The intrinsic mode functions (IMF's) of the voltage obtained by empirical mode decomposition (EMD) have been used for detection and the method is tested for microgrids with inverter and direct fed types of distributed generations [13]. Sliding window discrete Fourier transform and EMD techniques are used to decompose current and voltage signal into IMFs, which have been used for event identification. High classification accuracy of 98.4%, detection time of 66.94 ms and reduced NDZ has been claimed in the paper [14]. The voltage signal at PCC has been decomposed by variational mode decomposition (VMD) to obtain the IMF's. It has been shown that the variation in energy of IMF_2 is very low for non-islanding compare to islanding events, and therefore used as a threshold parameter. The NDZ has resulted in less than 1%, but only active power matching conditions have been considered [15]. An island detection method for photovoltaic systems where VMD processes voltage and power signal has been proposed, ensemble bagged-trees method detects islanding events effectively during power mismatch events with detection time of 4.8 milliseconds and results in a NDZ of less than 4% [16].

The study carried out in [17] proposes an islanding detection approach based on discrete Fourier transform and DT which has been tested on a microgrid equipped with synchronous generator. The detection results within three cycles of the signal. Islanding detection in multiple DG microgrid using discrete wavelet transform for extracting unbalanced voltage characteristics has been discussed. RF approach is used for classification, importantly diverse operating conditions are considered for performance testing and found effective [18]. A method based on RF approach with effective utilization of histogram of oriented gradients (HOG) features for pattern recognition is proposed in [19] and an accuracy of 98.75% has been claimed with 192 ms of detection time. Fast discrete S-transform (FDST) and bidirectional extreme learning machine (BELM) has been used on negative sequence voltage and current signals at the DG end for detection. The features such as energy, standard deviation of the signal has been selected for classification. The accuracy has been found to be 91.5% with noise of 20 dB, however training data set has been found biased [20]. The features of voltage, current and frequency at PCC have been extracted using wavelet transform for analysis and have been used with machine learning (ML), an accuracy of 97.9% on trained data has been observed with training time of 16.9 seconds [21]. The study focuses on detecting unintentional islanding using machine learning for a grid-connected PV system. The use of phasor measurement units (PMU) for recording big data has been useful for islanding detection [22]. The discussion of pre-processing steps in artificial neural networks for classification related to islanding such as loading data from a CSV file, handling missing values, feature scaling, and encoding categorical features, description of the modeling process using the RF, including dataset splitting, and DT construction. has been done [23]. RF approach for islanding detection in DC microgrid has been proposed in [24]. Extracting indexes, like current, voltage, output power, and their first-order backward difference to effectively distinguish islanding from non-islanding conditions by processing large datasets.

Standardized test procedures and guidelines for evaluating island detection methods would enhance the comparability and reliability of future studies in this area [25]. The standard test procedure for island detection is different for various countries, however in most of the approaches to have generosity R-L-C parallel combination has been considered as load since island detection is challenging under such conditions. The potential integration of ML, artificial intelligence (AI) technologies has also been underlined [26]. Study [27] summarizes islanding detection standards in various countries.

Researchers have investigated passive, active and hybrid methods of detection and finds the scope for improvement. The literature review carried out underlines the possibilities of enhancement using advance signal processing techniques and various AI methods. The paper is organized in the following manner Section 3 briefs motivation and problem definition, section 4 details the proposed method with sub sections covering the data generation, signal decomposition, feature extraction, and event detection by SVM. Section 5 deals with for results in terms of accuracy, prediction time and NDZ. Section 6 concludes the paper.

3. MOTIVATION AND PROBLEM DEFINATION

Most of the grid connected microgrid/DG systems are underutilized due to the need of imposing P-Q control in grid connected mode and f-V control in islanded mode. The primary requirement for assigning these controls is accurate detection of islanding *i.e.* the resulted event is a non-islanding event like internal faults or islanding *i.e.* the separation of the microgrid from the main grid. The operating conditions of microgrid for which the existing methods fail to detect the islanding called as NDZ or false identification of the event happens. If islanding event is wrongly identified as non-islanding and if P-Q control is assigned then issues like voltage drift, unstable frequency, power imbalance, load sharing issues and system collapse as well may result, on the other hand if f-V control is applied during grid connected mode it may result in to destabilization of PCC, inappropriate P-Q injection, overloading, under loading or even system failure due to frequency conflict. Ultimately to ensure safe, stable and economic operation of grid connected microgrid precise detection of the islanding and non-islanding events and associated controls are necessary. The study undertaken addresses accurate detection of the islanding and non-islanding events which is the primary and crucial requirement of the microgrid control operation.

4. PROPOSED METHOD

Simplicity of passive methods, the advanced signal processing tools, AI-ML techniques, IC technology with better computation possibilities encourages to carry out the research studies for the enhancement of passive methods. The 3-phase voltage signal extracted from the PCC experiences variations during islanding, faults, and load switching. Signal decomposition further details even the minute variations and ML being the best tool to differentiate these variations, it has been used to classify the events.

The high inertia offered by synchronous generator of the microgrid causes minimal variations in the threshold parameters referred for islanding detection resulting in to NDZ. Therefore, it is important to consider a microgrid consists of synchronous generator along with PV generator for the study, so that the proficiency of the detection method can be underlined. The system under study consists of 10 MVA, 33 kV grid, synchronous generator of 0.750 MW, PV generator of 0.250 MW and loads, the single line diagram is shown in Figure 1 and specifications in Table 1. The system is simulated on MATLAB R2024a platform for diverse dataset generation.

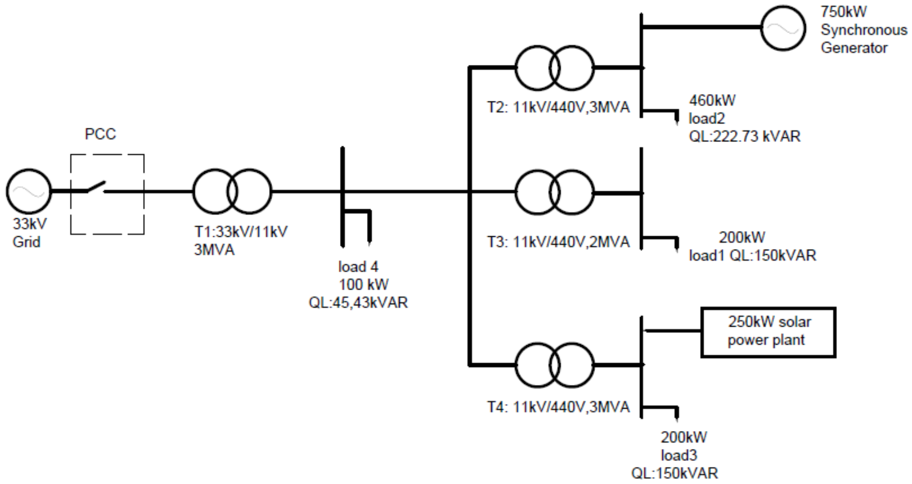


Figure 1. System under study

Table 1. Specifications for the System under study

Equipment	Specifications
Grid	33 kV, 50 Hz, 10 MVA
Transformer	T1: 3 MVA, T2: 3 MVA, T3: 2 MVA, T4: 3 MVA, T1:33/11 kv, T2–T4:11kV/0.44 kV
Line impedance	Positive sequence impedance = 0.0127 + j0.2933 Ω/km, zero sequence impedance= 0.38+ j1.29 Ω/km
Variable Load	L1: 0.2 MW+j0.115 MVAR, L2: 0.5 MW + j0.215 MVAR, L3:0.2 MW+j0.115 MVAR, L4: 0.100 MW+j0.04843 MVAR
Synchronous Generator	DG1: 0.75 MW (at distance of 1 km from PCC)
P-V Plant	DG3: 0.25 MW (at distance of 1 km from PCC)

Threshold based passive methods though simple they are found not to be consistent for precise detection [1], [2]. Frequency variations of the PCC voltage are found similar for islanding and non-islanding events and are not always sufficient enough to distinguish them. Also, it is expected that it remains crossing the threshold at least for 40 ms for detection. Figure 2 shows frequency variations during islanding and Figure 3 shows frequency variations for L-G fault at the microgrid load.

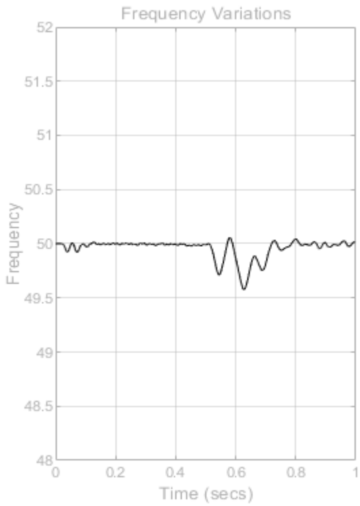


Figure 2. Change in frequency of PCC voltage during islanding

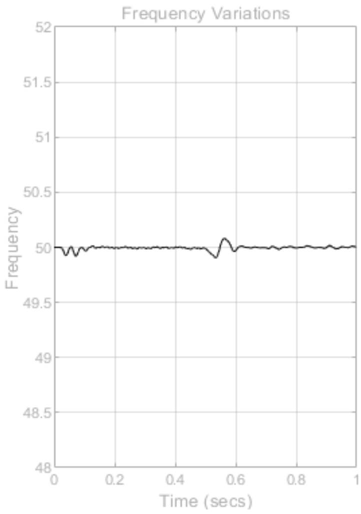


Figure 3. Change in frequency of PCC voltage during fault (non-islanding)

4.1. Data generation

The phase voltages namely V_A, V_B, and V_C at PCC is the primary data set generated and recorded as time series data for various events under diverse operating conditions. The system under study has been simulated for islanding at different active and reactive power situations within microgrid and for non-islanding events under different fault conditions at various locations and fault impedance. The 3-phase voltages at PCC as shown in Figure 4 have been recorded by conducting simulations with active power variations ranging from 100% to 70% matching condition, by opening the main circuit breaker at 50^{th} millisecond to realize islanding events. The voltage signal data extracted for the timeframe such a way that it accommodates the transition i.e. switching from grid connected to islanded mode. The non-islanding events namely Line-to-line (LL), Line-to-ground (LG), and Line-to-line-to-line-to-ground (LLLG) faults in microgrid are introduced at 50^{th} millisecond keeping circuit breaker closed. Fault resistance was varied across a wide range as mention in Table 2. The data set has been generated for in total 500 events, comprises of 250 islanding and 250 non-islanding events.

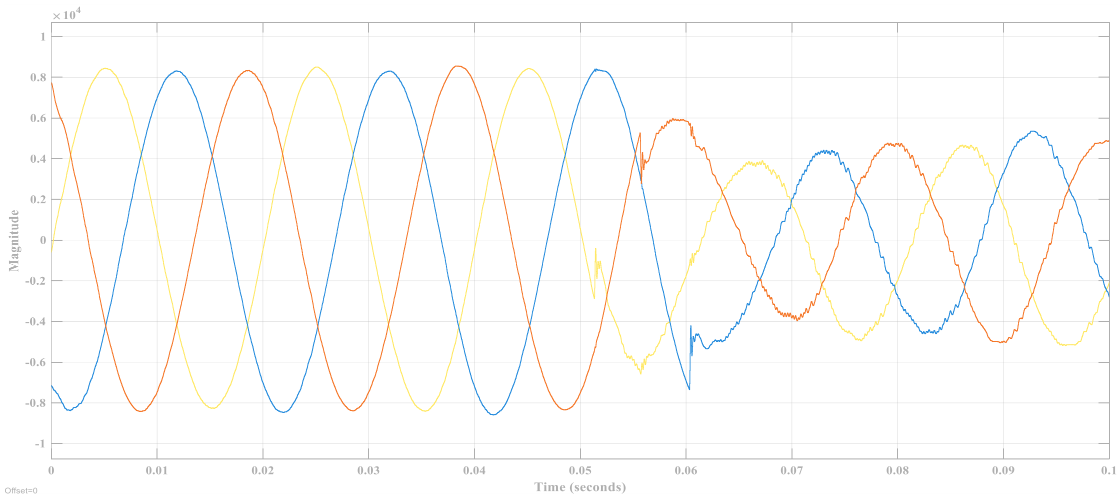


Figure 4. Three phase voltages at PCC

Table 2. Non-islanding events

Event	Dynamics/Specifications	Category	Number of cases
L-G Fault	($R_f \rightarrow 1$ to 5Ω)	Non-Islanding	92
LLL-G Fault	($R_f \rightarrow 1$ to 5Ω)	Non-Islanding	66
LL Fault	($R_f \rightarrow 1$ to 5Ω)	Non-Islanding	92
PCC CB Open	P_g, Q_g, P_L, Q_L (70% to 100% Matching)	Islanding	250

The choice of a 100ms time frame with event introduction at 50^{th} ms has been significant for several reasons, particularly in the context of analyzing power system dynamics during events like islanding or faults.

a. Capturing pre-event conditions (0–50 ms): The first 50ms of the simulation represents the system operating under normal conditions. This allows the system to learn and identify steady state behavior. This enables algorithms to learn normal behavior, improving detection accuracy.
b. Capturing event transition (50–100 ms): This part captures the system's dynamic response to the events *i.e.* the variations in instantaneous values of 3-phase voltage. The 3-phase voltage is a key parameter that reflects the system's operational state. During islanding, voltage magnitude variations occur due to the loss of grid support, while internal faults cause voltage drops and phase imbalances. Both islanding and faults exhibit transient behaviors.

The simulation has been carried out on a system with Intel(R) Core (TM) i5-3230M processor @ 2.60 GHz, 64-bit operating system and 8.00 GB RAM.

a. Non-stationary behavior of voltage signal: During islanding, the local energy resources cause voltage signal to behave non-stationary due to load-generation imbalance, with sudden deviations in voltage, frequency and power. Also, the internal fault event causes non-stationary behavior with sharp spikes and high-frequency components. Basically, a non-stationary signal is one whose statistical properties like mean, variance, and frequency. changes over time, therefore the study has been carried out considering such features. Tools like wavelet transforms, short-time Fourier transforms, Hilbert-Huang transforms are better platforms to analyze non-stationary signals and extract meaningful features for classification.
b. Sampling frequency: To capture the most possible details of a continuous signal, the sampling frequency must be high enough. In the work carried out 5000 samples are captured for 100 ms length of the signal which represents 5 cycles of 50 Hz signal. Time per sample given (T_s) and Sampling frequency (f_s) are mentioned in (1) and (2) respectively.

$$T_s = \frac{Time}{Number\ of\ samples} = \frac{100ms}{5000} = 20\ \mu s/sample \tag{1}$$

$$f_s = \frac{1}{Ts} = \frac{1}{20\mu s} = 50\ kHz \tag{2}$$

4.2. Signal decomposition

The voltage signal at PCC during islanding and faults behaves non-linear and non-stationary. The decomposition of such a signal using Fourier transform (FT) assumes the signal stationary, Wavelet transforms dose fairly good job but has fixed scale. EMD decompose the signal into a set of IMFs corresponding to different frequency bands, allowing the separation of high-frequency from low-frequency trends containing information suitable for event identification. EMD can uncover hidden periodic and transient behaviors which might not be readable from the original signal. Dynamic frequency tracking is the feature of EMD which provides a time-frequency representation of the signal, *i.e.* changing frequency content of non-stationary signals. EMD helps identify irregular voltage fluctuations or transients in electrical signals. The EMD flow chart is shown in Figure 5 and the algorithm has been described below further.

IMF_1 represents the highest frequency content in the signal which indicates sudden changes, transients and sometimes high frequency noise. High frequency components are prone during islanding, whereas IMF_2 reflects relatively lower frequency and sustained changes in voltage which may result due to faults at far end from PCC. Therefore, the information obtained from both IMF's is useful, however IMF_1 has been used in the work carried out. The IMF's plot for one of the events has been shown in Figure 6.

Algorithm 1. EMD algorithm
Step 1: The sampled time series data of all phases is treated as signal $x(t)$.
Step 2: Determine all the local maxima and minima of $x(t)$.
Step 3: Interpolate maxima and minima to form upper and lower envelopes $e_{max(t)}$ and $e_{\min(t)}$ and compute the mean, $m(t) = (e_{max(t)} + e_{\min(t)})/2$.
Step 4: Subtract $m(t)$ from the original signal: $h(t) = x(t) - m(t)$. If $h(t)$ satisfies the conditions *i.e.* it is mean value is close to zero then $h(t)$ is considered as IMF_1. Else, repeat steps 1-4 considering $h(t)$ as x(t).

Step 5: Once an IMF_i is identified, subtract it from the signal: $r(t) = x(t) - IMF_i$

Step 6: If $r(t)$ is monotone then end the process, else treat $r(t)$ as $x(t)$ and process it again until $r(t)$ results in monotone.

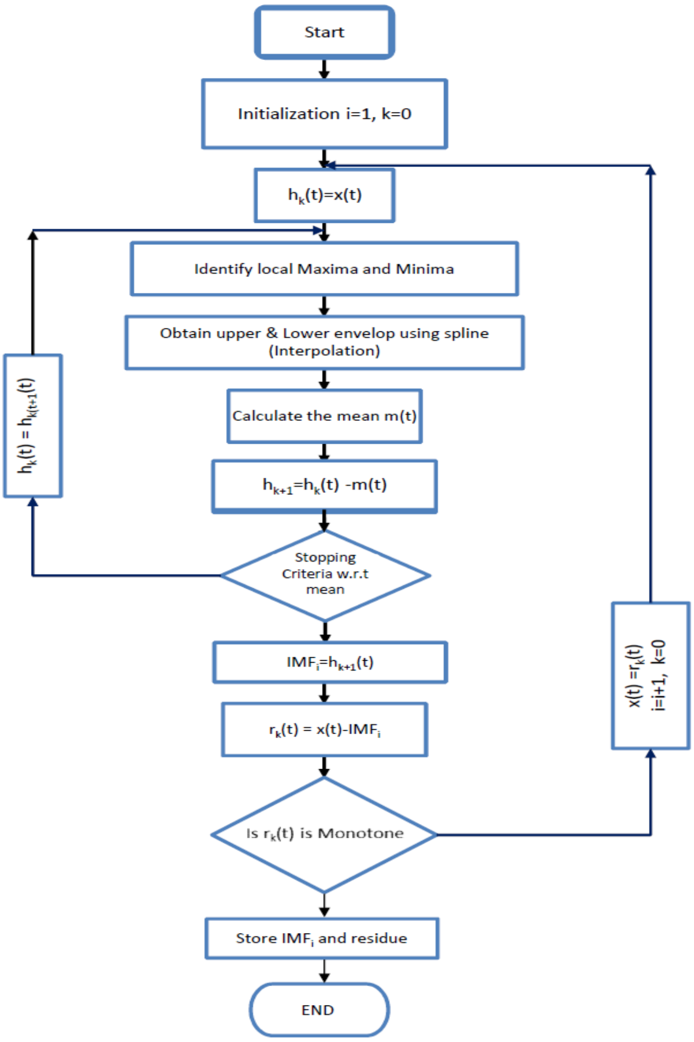
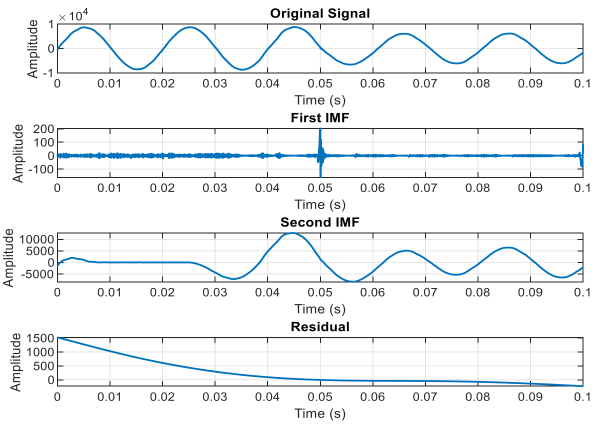


Figure 5. EMD flow chart



Number of cycles in IMF_1: 690
Frequency of IMF_1: 13871.3146 Hz
Number of cycles in IMF_2: 39
Frequency of IMF_2: 853.1041 Hz
Max Time taken to extract IMF_1: 0.061871 seconds (varies from 30 to 61.87 ms)

Figure 6. Resulting IMF’s using EMD

4.3. Feature selection

Appropriate statistical feature selection in classification problem is important. In the work carried out nine prominent features applicable for time series data have been considered and discussed below.

- Mean (M) is one of the basic features which is computed as the average value of a signal $x(t)$ formulated as given in (3). It reduces data complexity keeping important information of the signal useful for classification.

$$M = \frac{1}{n}\sum_{t=1}^{n} x(t) \tag{3}$$

where n is the number of data points in the dataset.

- Standard deviation (σ) represented in (4) is considered as second feature. A low value σ for voltage at PCC indicates stable grid operation, whereas higher values are indicative of events like islanding or faults.

$$\sigma = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x(t) - M)^2} \tag{4}$$

- Skewness (*S*) is a measure to quantify the degree of asymmetry in the signal, formulated as given in (5). Positive *S* indicates imbalances or transients whereas negative *S* reflects variations like voltage sags.

$$S = \frac{n}{(n-1)(n-2)}\sum_{t=1}^{n}(\frac{(x(t)-M)}{\sigma})^3 \tag{5}$$

- Kurtosis (*K*) reflects the outliers, such data may be found useful for detecting switching events like islanding and faults, and it is expressed in (6).

$$K = \frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum_{t=1}^{n}(\ (x(t) - M/\sigma)^4 - 3(n-1)^2/(n-2)(n-3)) \tag{6}$$

- Harmonic distortions are measured by total harmonic distortion (THD) given in (7), THD gets influenced largely during islanding and fault events.

$$THD = \frac{\sqrt{H2^2+H3^2+H4^2+\cdots+Hn^2}}{H1} \tag{7}$$

$H1$: Amplitude of the fundamental frequency, $H2, H3, \dots, Hn$: Amplitudes of the higher order harmonics.

Sudden variations in signal energy (E) reflects uncommon patterns in voltage signal indicates happening of the events. It is formulated as given in (8).

$$E = \sum_{n=0}^{N-1} x(n)^2 \tag{8}$$

The peak-to-peak value of the signal given in (9), represents the range of variations. The power quality events impact on such variations.

$$V(P-P) = \max\{x(t)\} - \min\{x(t)\}, t \in T \tag{9}$$

Where *T*: 20 ms time window is considered.

Root mean square (RMS) value of voltage signal is another measure of the magnitude variation and found useful for electrical system behavior analysis [28]. RMS is given in (10).

$$RMS = \sqrt{\frac{1}{N}\sum_{t=1}^{N} x(t)^2} \tag{10}$$

Mean absolute deviation (MAD) assess the variability of the voltage signal helpful for event detection. MAD is formulated in (11).

$$MAD = \frac{1}{N}\sum_{t=1}^{N} |x(t) - M| \tag{11}$$

4.4. Classification by support vector machine

Support vector machine (SVM) is a powerful machine learning model used for classification. SVM works by finding the optimal hyperplane that best separates data into different classes. To reduce the need of large data sets SVM has been preferred over ANN and DL, reduced computation time and clearly visible decision boundaries are the added advantages of SVM.

In the context of islanding detection, SVM is trained on features extracted from voltage data. The weights (w) of each feature contribute in determining the decision boundaries which are learned by machine during training to maximize distance between the hyperplane and support vectors. The bias (b) positions the hyperplane optimally, in case data is not centered on origin. The decision function is defined as in (12) where 'x' is the feature value.

$$f(x) = dot(w, x) + b \tag{12}$$

The SVM classifies the events as islanding if $f(x) \geq 0$ and as non islanding if $f(x) < 0$.

Following are the steps involved in SVM algorithm.

Step 1: Feature vector initialization $x_i = [x_1, x_2, \ldots, x_N]$ and Labels $y_i = [y_1, y_2]$ have been set as 1 and -1 indicating the class, suffix 'i' refers to sample number. The hyperplane is formulated as in (13).

$$w^T x + b = 0 \tag{13}$$

Step 2: Margin maximization is achieved by (14), margin $i.e.$ the distance between the two class boundaries is defined in (15)

$$y_i\,(\mathrm{w}^T \mathrm{x}_i + b) \geq 1 \tag{14}$$

$$\text{Margin} = \frac{2}{||\mathrm{w}||} \tag{15}$$

Step 3: Optimal values of w and b are obtained in such a way that $||w||$ results in to minimum as described in (16), this ensures maximum margin satisfying (14) and (15).

$$\min_{w,b} \frac{1}{2} \| w \|^2 \tag{16}$$

Step 4: It is now treated as dual objective problem namely for maximum margin and unbiased hyper plane referring to Lagrangian described in (17).

$$L(w, b, \alpha) = \frac{1}{2}||W||^2 - \sum_{i=1}^{N} \alpha_i [y_i(\mathrm{w}^T \mathrm{X}_i + b) - 1] \tag{17}$$

Partial derivatives of Lagrangian w.r.t w gives optimal weights which is linear combination of the training samples vector and equating it to zero determines weight values for each feature described in (18). The expression (19) leads to an unbiased hyperplane for the two classes.

$$\frac{\partial L}{\partial \mathrm{w}} = 0 \Rightarrow \mathrm{w} = \sum_{i=1}^{N} \alpha_i y_i x_i \tag{18}$$

$$\frac{\partial L}{\partial \mathrm{b}} = 0 \Rightarrow \sum_{i=1}^{N} \alpha_i y_i = 0 \tag{19}$$

Substituting into the Lagrangian the dual optimization problem is formulated as in (20) and (21).

$$\max_{\alpha} = \sum^{n}{}_{i=1} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j \mathrm{X}_i^{\mathrm{T}} \mathrm{X}_j \tag{20}$$

$$\alpha_i \geq 0, \sum_{i=1}^{N} \alpha_i y_i = 0 \tag{21}$$

Step 5: Obtaining α_i using quadratic programming solvers and identifying support vectors (SV). Computation of weights (w) is described in (22) and that of bias (b) for support vector x_k is formulated in (23).

$$w = \sum_{i \in SV} \alpha_i y_i x_i \tag{21}$$

$$b = y_k - w^T X_k \tag{22}$$

Step 6: Function in (24) is used for classification, as islanding (+1) if $f(x) \geq 0$ and non-islanding (-1) if $f(x) < 0$.

$$f(x) = w^T x + b \tag{24}$$

5. RESULTS AND DISCUSSION

The detection accuracy and prediction time are the parameters of primary interest in this study. Obtained data sets has been used in 7 different approaches named as Method-1 to Method-7. All these methods are described in the following paragraphs. Table 3 details the detection accuracy and prediction time for Method-1 to Method-7 and Figure 7 gives detection accuracy comparison.

Table 3. Classification results

Method	Data and features used for classification	ML Technique	Accuracy	Detection time	Detection Time with IMF_1 extraction time
Method 1	Phase voltages (V_A, V_B, V_C)	Decision Tree	70.41%	1.9 ms	63.77 ms
Method 2		Random Forest	71.46%	88.71 ms	150.58 ms
Method 3	IMF_1 of phase A (4 features)	SVM model	84.60%	3.31 ms	65.18 ms
Method 4	IMF_1 of all 3 phases (4 features)	SVM model	94.80%	3.50 ms	65.37 ms
Method 5	IMF_1 of phase A (9 features)	SVM model	97.60%	1.31 ms	63.18 ms
Method 6	Average of IMF_1 of 3 phase voltages	SVM model	99.8%	1.24 msec	63.11 ms
Method 7	IMF_1 of all 3 phases (27 features)	SVM model	99.4%	1.42 msec	63.29 ms

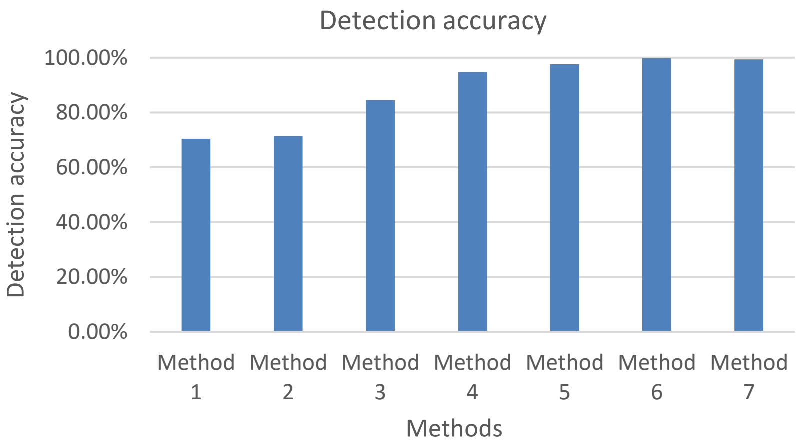


Figure 7. Detection accuracy comparison of different methods

In Method-1 and Method-2, phase voltages namely V_A, V_B, and V_C in the form of time series data has been used for classification, the original form of the signal is used without any decomposition. DT and RF ML techniques are used for classifying the events and it is found that detection accuracy is as low as 70.41% which is not satisfactory. To examine the significance of signal decomposition, in Method-3 the IMF_1 of phase voltage V_A generated by EMD has been used. Here four features namely Mean, SD, Energy and THD of IMF_1 of V_A has been considered for classification using SVM technique, though only one phase data is used accuracy has increased to 84.60% which is significant compare to Method-1and Method-2.

Consideration of only one phase data cannot be generalized since resulting events impacts all three phases. Therefore, in Method-4 above mentioned features of IMF_1 of all 3-phase voltages namely V_A, V_B, and V_C are used and classification is observed using SVM. Accuracy in this case has increased almost by 10% compare to Method-3 *i.e.* 474 events are correctly detected resulting in an accuracy of 94.80%.

To check the impact of additional statical features Method-5 uses nine features for IMF_1 of only V_A namely Mean, SD, Skewness, Kurtosis, Energy, THD, RMS, peak to peak value and MAD. Method-7 considers all these features for IMF_1 of V_A, V_B, and V_C making a large data set of 27 features. Importantly the accuracy has been found to be better than the previous attempts.

Under normal operating condition the average of 3-phase voltage instantaneous value supposed to be minimum and considerable during the events. Therefore, the average of IMF_1 of all three phases is used in Method-6, above mentioned nine features are applied to this data. It may be observed that with no loss of the data, number of features are reduced from 27 to 9. This method is found to be the best among all practiced in terms of accuracy and detection time. The total detection time resulted for this approach is 63.11 ms, which is quite promising. The maximum time for IMF extraction is found to be 61.87ms.

The NDZ is plotted for Method-4 as shown in Figure 8, fourteen islanding events out of 250 cases have been wrongly detected and it includes operating conditions with active power mismatch (Δp/p) of 21% and reactive power mismatch (Δq/p) of more than 10%, which is not good. However, when the same data set is used in Method-6 all these cases have been detected correctly resulting in no NDZ *i.e.* all 250 islanding events have been detected correctly, however one non islanding case has been detected as islanding. The simulation time for classification has resulted in the range of 0.16 to 0.61 sec for methods using IMF time series data, whereas for the Method-1 and Method-2 where the data in its original form is used it is around 3 minutes.

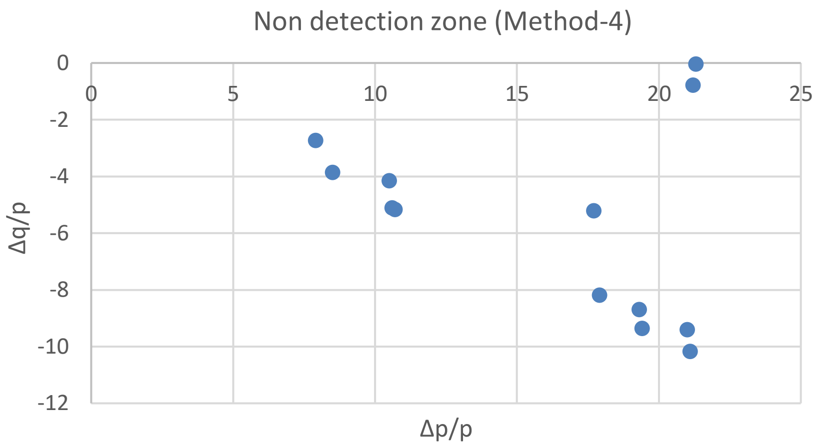


Figure 8. NDZ for Method-4

Further study of Method-6 is carried out to optimize the selection of features using correlation matrix shown in Figure 9. It has been observed that the same accuracy is retained selecting loosely correlated 5 features namely Energy, THD, Kurtosis, Skewness and MAD. The weight values of the features and bias value are mentioned in Table 4. It can be clearly observed that MAD dominates in islanding, whereas other features for non-islanding. The decision function $f(x)$ defined in (12) is resulting in clear segregation with $f(x) \geq 0$ for islanding and $f(x) < 0$ for non-islanding. The overall approach gives customized solution for identified system and therefore any updates incorporated in the system, new data set is to be generated for training to set the reference. Results have been compared with other references in Table 5.

The conventional methods have limitations in terms of detection time, NDZ, impact on power quality. Therefore, the study has been carried out in the context of enhancing the detection accuracy, minimizing NDZ and reducing detection time using signal decomposition and ML. The decomposition of the signal gives hidden insights of the signal. The use of statistical features for classification using SVM leads to more robust detection.

The findings of the study are as follows.

a. Average values of IMF_1 of three phase voltages are found to be the best dataset among other datasets used in the study.
b. The statistical feature MAD obtained for average values of IMF_1 of three phase voltages is prone towards islanding, whereas Energy, THD, Kurtosis and Skewness are inclined towards non islanding events, Table 4 may be referred for weight values.
c. SVM classifier using the above-mentioned features gives an accuracy of 99.8%. Importantly the overall detection time is only 63.11 ms.

The outcome of the study is that it provides a framework for integrating signal decomposition and ML for accurate islanding detection for grid connected microgrids.

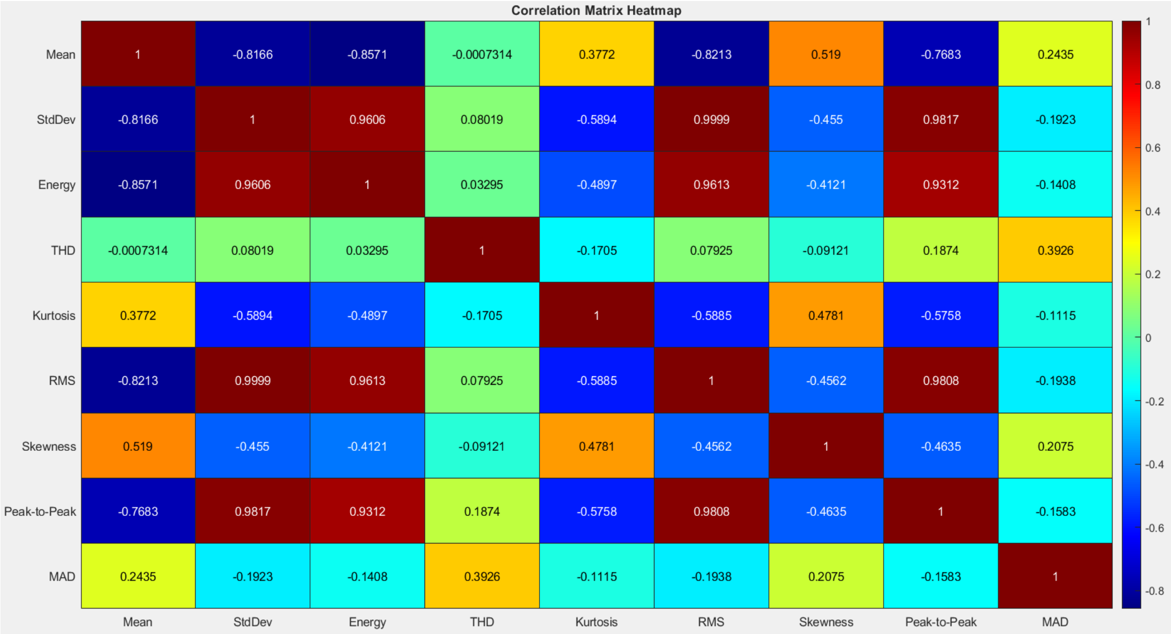


Figure 9. Correlation matrix for Method-6

Table 4. Weight values of the features and bias value

Parameter	Weight (W)/Bias(b)	Values
Energy	W_1	-0.5582
THD	W_2	-0.1305
Kurtosis	W_3	-0.1528
Skewness	W_4	-0.6122
MAD	W_5	1.4956
Bias	b	-0.1724

Table 5. Comparison with other approaches

Method	Detection time	Accuracy	NDZ	DG types
Ref [10]	-	99.10%	Small	PV
Ref [19]	192 ms	98.75%	Small	PV
Ref [15]	110 ms	-	Small	PV, Wind, Synchronous
Ref [4]	100 ms	-	Zero	Synchronous
Proposed	63.11 ms	99.80%	Zero	PV, Synchronous

6. CONCLUSION

Passive methods for islanding detection are prone to larger NDZ *i.e.* they fail to detect islanding during power matching conditions; active and hybrid method causes power quality issues and communication-based methods are costly. The study carried out emphasizes that using advanced signal processing tools like EMD for signal decomposition and ML platform, the island detection of microgrids happens in minimum time and results in zero NDZ. The fast variations of the signal are visible through IMF_1 obtained by EMD and are found valuable for distinguishing the islanding with other events, also the ability of SVM to optimize the selection of hyperplane, maximizing the margin has given promising results in terms of accuracy of 99.8%, zero NDZ and detection time as low as 63.11 ms for diverse operating conditions of the microgrid. Precise detection of the events leads to steady operation of the microgrids allowing smooth transition of the control modes, contributing in to safety, reliability, optimal usage of the resources and financial benefits for the microgrid owners.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review and **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, BP, upon reasonable request.

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