μPMU-based intelligent island detection – the first crucial step toward enhancing grid resilience with MG

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Abstract: With the increased climatic change and modern grid complexity, extreme grid power outage events caused by natural calamity and human interruptions have led to an urgency to enhance the grid resiliency. Microgrids (MGs) have proved to be a concrete solution to these situations. However, these events are quite uncertain, leading to the unintentional island of MGs that has adverse effects. Thus, as a first step toward increasing grid resiliency with MG, informing the distributed generations about the unintentional island is a critical task. Hence, there is a need to develop a quick and reliable unintentional island detection scheme. Micro phasor measurement units (μPMUs) are becoming popular in MG. Given this, this study proposes an inadvertent island detection scheme in an MG using an intelligent μPMU. With the μPMU, the voltage at solar generator bus is measured, three features are extracted through spectral kurtosis and random forest classifier is employed for island detection. After island detection, a control methodology is proposed to circumvent the post-effects. The method has zero non-detection zone, 99.83% accuracy and a detection time of 20 ms. The reliability of the algorithm is ascertained using the analytical hierarchical approach and software fault-tree analysis.

1 Introduction

Resilience is derived from a Latin word ‘resilio’ that means to ‘spring up’. Thus, power system resilience can be defined as the capability to prepare sufficiently, respond rapidly and recover quickly in case of power disruptions due to an extreme unanticipated event [1]. These extreme events are not only confined to naturally occurring threats (such as tsunami, earthquake etc.) but also man-made incidents (such as operator error, cyberattack etc.). During these events, there is a cascading decline in power system performance. The disruptions resulting from these events are different from those caused by typical contingencies. The characteristics of these disruptions are as follows [1–3]:

1. Its prediction, duration and extent are completely uncertain.
2. Any component can be disrupted by it, making repair and restoration process complex and time taking.
3. It can propagate within a very short time and leave a large grid area powerless.
4. Other critical components such as communication channel may also be disrupted.

The number of these disruptions is expected to rise, particularly in the modern distribution system, with rapid climatic change, increase in cyberattack and complexity of the grid [4]. On the other hand, with the evolution of modern customer’s reliance on electricity, their expectation of continuous supply of electricity has led to the research in enhancing grid resiliency.

1.1 Motivation

The evolution of MGs has led to the enhancement of grid resiliency (grid operational capability) during extreme events, particularly for the continuity of power supply to the critical loads such as hospital, data centre etc. [4–7]. An MG is a small grid area with its local generation and loads. It can work in connection with the grid or stand-alone mode. During extreme events, the generation, control and storing of the electrical energy locally in the islanded MG can make these events less vulnerable with a faster and more efficient response.

An islanded system is one, which is detached from the main grid but is still powered by the distributed generators connected to it. Intentional islanding is done for avoiding blackouts, maintenance etc. with prior knowledge of the system operator. Unlike intentional islanding, non-intentional islanding occurs during extreme events without operator’s prior information posing repercussions in the islanded area, for instance, power quality dilapidation due to severe fluctuations in voltage and frequency, inconvenience in orderly restoration of power supply and menace to the life of the maintenance workers who are unaware about the disconnected lines being still energised by the distributed generators [8, 9]. The disconnected but energised lines can also be detrimental to people, particularly in case of flood, where people can be severely electrocuted. After the extreme conditions, the restoration process is also delayed due to a lack of situational awareness. Thus, there is a need to inform the distributed generators about islanding as soon as possible so that suitable control measures can be taken for safe power continuity in the MG. Hence, unintentional island detection is the first step toward building a resilient MG.

Phasor measurement units (PMUs) are already popular as successful sensors in the monitoring of the transmission system [10]. Micro PMUs (μPMUs) have also started acquiring its foothold in the distribution system. Since μPMUs have high precision with high sampling rate, these can be employed for unintentional island detection scenarios in MG. However, it will generate a large set of data, for which a proper data analysis is required. Moreover, during extreme conditions, to reduce the dependency on the communication channel, an intelligent μPMU is required that will not only do measurement but also take an important decision through signal processing, data analysis and learning classification.
1.2 Related island detection work

There are a large number of islanding detection methods available in the literature that can be categorised in broad domains of passive, active, hybrid, local, signal processing and intelligent classifiers.

In passive sensors, islanding is detected when a particular feature of a measured signal surpasses a predefined threshold value. Under/over voltage or frequency, rate of change of frequency (ROCOF), harmonic distortion, phase jump detection, rate of change of power output, and inverter non-linear method [8, 9, 11] are some of the chief passive islanding sensing methods. Some recent passive methods are based on improved voltage shift [12], inverse hyperbolic secant function [13], active ROCOF relay [14], modal component [15] and intrinsic time decomposition [16].

The shortcoming of high non-detection zone (NDZ) of most of the passive techniques is overcome by active sensors, in which some disturbances are intentionally infused in the grid, and its effect is measured through some signals. Active frequency drift, slip mode frequency shift (SMS), Sandia voltage shift (SVS), Sandip frequency shift (SFS), negative phase sequence current value. Under/over voltage or frequency, rate of change of processing methods, for extricating hidden information, islanding instants is an arduous task in most of the sensing techniques. These techniques do not possess any NDZ but are immensely costly.

Signal processing sensing methods have come to rescue to the researchers to surmount the flaws of the methods above. In signal processing methods, for extricating hidden information, appropriate signals are analysed by tools such as wavelet transform (WT), Stockwell transform (ST), hybrid ST, Hilbert–Huang transform, time–time transform, and mathematical morphology [23–25] for islanding recognition.

Determination of an appropriate threshold value for identifying islanding instants is an arduous task in most of the sensing methods. Through proper training of intelligent classifiers, the question of threshold value can be resolved efficiently. Intelligent classifiers such as artificial neural network (ANN), decision tree (DT), fuzzy logic, and static vector machine (SVM) [26–30] are employed for islanding detection effectively.

Principal component analysis of wide-area phasor measurements is used in [31] for island detection. Three different island sensing methods are employed in real-time hardware in a loop using synchrophasor data in [32]. A method based on ‘continuous sync-check’ of PMU is used for island sensors [33]. Kumar and Bhowmik [34] employ a multiplier method, Andrews plot-based method and ANN for island detection with PMU data. Fortescue transform-based (FT) μPMU is used for island sensing in [35].

For the methods employing PMU, the estimation of phasors consumes some time [36]. This introduces a delay in the island sensing algorithm, which is not desirable during extreme conditions. Moreover, the PMU methods are highly dependent on the communication channel, which may be disrupted during extreme conditions. On the other hand, most of the methods that do not employ PMU, extraneous arrangements are required exclusively for island detection leading to large implementation time and capital cost. To amalgamate the advantages of using the hardware and software of PMU but at the same time to save time for phasor estimation, this paper proposes a new island detection scheme.

1.3 Contributions

μPMU, the most precious component in the distribution system, has proved its worth in state estimation, harmonic estimation, fault detection, dynamic monitoring and protection etc. [36, 37]. Keeping in mind the availability and usability of μPMU, the proposed intelligent island detection scheme is developed. It involves designing a separate subroutine in the already installed μPMU mentioned in [36, 37]. The μPMU measures the voltage signals at a defined distributed generator location and performs spectral kurtosis (SK) to obtain features required to feed an Random Forest (RF)-based classifier for islanding and fault events segregation from other events. The classification results and control signals are broadcasted to the distributed generators. The contributions of the proposed work in comparison with the state of the art are summarised as follows:

1. The hardware, communication as well as software components of μPMU are being utilised for islanding events detection. Hence, extraneous arrangements are not required exclusively for island detection ensuring reduced implementation time and capital cost. On the other hand, the phasor estimation process is not taken into account to save time. This will reduce the island detection time. Hence, the operators will be able to restore power in the islanded MG more quickly during extreme conditions.

2. The combination of SK and RF methods are pioneer applications for island detection. The SK as an indicator of a signal’s impulsiveness and a tool for capturing transients effectively is exploited to obtain useful insights required for island or fault detection.

3. The noise-resistant characteristics of SK, as well as RF, are utilised in this paper for developing the robust noise-resistant island detection algorithm.

4. The usability of μPMU is realised at a higher level since the intelligent μPMU does not only measure but also take an important decision through signal processing, data analysis and learning classification. The measured data is not sent to the control centre for processing and control actions. This will be extremely helpful in the cases when the communication channel between μPMU and the control centre is disrupted due to extreme conditions. This further increases grid resiliency.

5. The reliability of the algorithm is also ensured by software reliability allocation model to using empirical hierarchical process (AHP) and software fault-tree analysis (SFTA). This scheme is simple, possesses a high detection speed, i.e. 20 ms, high accuracy, i.e. 99.83% and zero NDZ.

1.4 Organisation of this paper

This paper is constructed as follows. Section 2 provides a detail discussion about requirements for the intelligent upgraded μPMU. In Section 3, the method of development of the proposed methodology is explained. The performance of the methodology is validated and discussed in Section 4. Section 5 deals with the software reliability allocation model of the algorithm. The method is compared with the available islanding detection methods in Section 6. The work is finally inferred in Section 7.

2 Requirements for the intelligent upgraded μPMU

The schematic representation of working of a traditional μPMU in distribution system is shown in Fig. 1. The μPMU, similar to PMU, acquires voltage and current signals through current transformer (CT)/potential transformer (PT), respectively, computes phasors with a digital signal processor, time stamps the phasors with reference time provided by global positioning system, and then send it to the control centre [38]. Proper sensing in distribution MGs with μPMU has to meet certain challenges [36]. Since distribution systems have more resistance than reactance, the reactive and real power flow cannot be decoupled, and hence the standard approximate power equations cannot be applied. As
distances between buses and power flows are smaller than transmission system, magnitude and phase angle variation is also small, typically of the order of $10^{-4}$ pu and 0.01°, respectively. Moreover, a high harmonic content is also present due to various power electronic converters used for integrating renewable sources into the distribution system. Hence, μPMU has lower total voltage error, precise sensors, low phase uncertainties and higher sampling rates leading to high-resolution data [39]. This advantage of μPMU can be used for island detection as high-resolution data will always be beneficial for any signal processing techniques for analysis in a short period.

Furthermore, the observability of the transmission system is easy as it involves a fewer number of buses but is far tougher in distribution having numerous buses. Moreover, the intermittent nature of renewable energy sources introduces uncertainty. Hence, appropriate decision making for control actions becomes tough. This calls for a better-advanced signal analyser and an accurate classifier. Time for restoration from any extreme disturbance is a critical factor. The computation of phasors takes time. Moreover, during extreme conditions, the communication channel between μPMU and the control centre may get disrupted. Thus, to reduce island detection time and its dependency on the communication channel, in the proposed intelligent upgraded μPMU, a separate subroutine is provided for island detection. The subroutine directly acquires sampled signals from CT/PT and analyses the sampled values within a predefined window length with SK. The analysed or extracted data is fed to an RF classifier to make appropriate events classification.

3 Development of the proposed methodology

3.1 Test system considered

IEEE 13-node distribution network, which is both moderately small as well as intensely loaded, is considered here as the test system. This configuration is preferred over other IEEE configurations as it match most closely to a typical distribution system. The test system is slightly modified and built-in MATLAB/Simulink platform in discrete mode at a sampling rate of 1 MHz. The single line diagram of the modified test system is shown in Fig. 2. The line parameters are considered as lumped with $R = 0.00016$ $\Omega/ft$ and $X = 0.000141$ $\Omega/ft$ [35] and a 4.16 kV [line-to-line (LL)], 60 Hz three-phase source is modelled as rest of the grid. To incorporate MG and islanding scenarios, a μPMU and an solar generator (SG) along with its local load at node 671 are added, and the length of the line from SG bus to node 671 is considered as 300 ft. It is further assumed that the SG bus has appropriate synchronising provisions. Since, the major objective is to detect island and fault scenarios during unexpected severe events such as tsunami, earthquake etc. or cyberattacks, in which the restoration time becomes a critical factor, it is assumed that islanding event s follow after the opening of upstream switches or circuit breakers. The faults are also assumed to occur due to extreme events. The working of SG considered in the test system is similar to as given in [35].

3.2 Spectral kurtosis

According to Wold–Cramer's decomposition, a stochastic non-stationary signal $N(t)$ can be represented as the output of a linear, causal and time-varying system as in (1), where $t$ is time, $f$ is frequency, $dM(f)$ is a unit variance orthogonal spectral process and $Z(t, f)$ is the complex envelope of $N(t)$ at frequency $f$ [40].

![Schematic representation of working of a traditional μPMU](image1)

![Modified IEEE 13-node distribution network representation](image2)
The short-term Fourier transform-based SK is given by (6), where \( Z(t, f) \) is expressed as in (7), \( \ast \) is the time averaging operator, \( N(n) \) are the discrete samples of \( N(t) \) and \( Nw \) is the length of analysis window \( w(n') \) [43, 44]. Thus, SK at a particular \( f \) gives the peakiness of the squared envelope \( \left| Z(t, f) dM(f) \right|^2 \), and hence a good indicator of impulsiveness of a signal, i.e. transients and the corresponding frequencies at which those patterns appear. In SK graph, a value of \(-1\) indicates a stationary component and positive peaks indicates non-stationary (transients) components of a signal [45]. Since SK is a fourth-order spectrum, it is resistant to noise, which enhances impulsiveness. This assists in detecting electrical anomalies more accurately. Moreover, SK is computationally less expensive and fast [46]. An example of SK for a pure sinusoid and a sinusoid with a transient is shown in Fig. 3. For better representation, the frequencies are normalised. As seen in Fig. 3a, the SK for a sinusoid signal has only one peak (i.e. a value of \(-1\)), which corresponds to the stationary component. However, SK for the sinusoid signal with transients, there are many peaks, which represent the impulsiveness of the signal and the corresponding frequencies at which they occur. Thus, SK is efficient in capturing the transients of a signal.

To show the usability of SK in island detection, the raw voltage data acquired from the \( \mu \)PMU are further processed by SK. For this, the test system is simulated for 1 s, and different scenarios (except normal scenario) are initiated at 0.5 s. About 8000 V samples (i.e. samples for 8 ms) obtained from the \( \mu \)PMU just after the initiation are considered for SK. Fig. 4 shows the SK of the voltage signal at the SG bus for normal scenario, islanding scenario and fault scenario in the MG. A Hanning window with window size of 256 with 75% overlap is used for SK as suggested in [42]. It is seen that for normal case, a value of \(-1\) is obtained at a normalised frequency of \(-0.02\). This corresponds to the stationary component of the voltage signal. However, since distribution system possesses non-transposed and asymmetric feeders manufactured from different conductors, unequal phase and self-impedance and unequal loading [39], the SK shows some non-stationary components also. The magnitude of these non-stationary components is, however, very less. However, for island and fault conditions, no stationary component is obtained but lot of non-stationary components emerge. For island conditions, the non-stationary components are concentrated at higher normalised frequencies, whereas for fault conditions, the components are concentrated at lower normalised frequencies. Thus, it can be seen that the SK analysis is able to show the difference between normal, island and fault scenarios by efficiently capturing the transients.

Although the SK method shows different kurtosis value (as in Fig. 4) for different scenarios, the determination of the thresholds of kurtosis values for segregating different scenarios is an arduous task. Thus, there is a need to use a classifier that will take the kurtosis value as input for segregating different scenarios accurately.
3.3 Random forest

RF, in simplest terms, can be interpreted as a group of untrimmed DT. It mitigates the disadvantage of DT such as instability to small changes in the learning data, overfitting and less prediction capability by splitting the DT nodes in a randomised manner. The superiorities of RF classifier over other classifiers as mentioned in [47–49] are simplicity, easy usability, robustness to noise, high accuracy and its ability to handle overfitting in case of large trees.

The working of RF classifier is shown in Fig. 5 and explained in the following steps [47]. Steps 1–6 deal with the process of training the RF classifier, whereas step 7 deals with the classification process:

Step 1: For \( i = 1 \) to \( n_t \), where \( n_t \) is the total number of trees.

Step 2: Construct a bootstrap sample from the training dataset with the constraint that the number of bootstrap samples is less than the training sample.

Step 3: Construct a random forest (RF) tree \( RF_i(n, v_i) \) to the bootstrap sample, where \( n \) is an input vector and \( v_i \) is a random vector comprising \( r \) number of independent random integers with the constraint that \( r < a \); the number of attributes in \( n \). For this, first \( r \) variables are selected from \( a \) features, and the best variable is selected. The node is split at this point into two daughter nodes. This process is repeated until the maximal depth is reached.

Step 4: \( i = i + 1 \).

Step 5: If \( i \leq n_t \), go to step 1 else go to step 6.

Step 6: Obtain the collection of trees as \( \{RF_i(n, v), i = 1 \text{ to } n_t\} \).

Step 7: For classification, each tree gives a unit vote for the class for an input \( n \). The class that majority of the trees votes is given as the output \( C(n) \) as represented in (8), where \( CRF_i(n) \) is the class vote (i.e. prediction) of the \( i \)th tree of the RF

\[
C(n) = \max_{k=1 \text{ to } n_t} \text{vote}(CRF_i(n))
\]

3.4 Data generation and feature selection

To prepare the data required for training and testing of the classifier, several scenarios of island, fault and other normal power system cases such as capacitor switching and load switching as given in Table 1 are simulated. It is to be noted that the fault, capacitor switching and load switching scenarios were simulated at the Point of Common Coupling (PCC) as well as at different locations to make the algorithm more robust. Five features F1–F5 are extracted from the voltage signals that represent its SK at normalised frequencies of 0.1, 0.2, 0.3, 0.4 and 0.5, respectively. The box plot of the individual features is shown in Fig. 6. The box plot provides a graphical overview how the feature value data are distributed. F, I and N represent the feature values for fault, island and normal scenarios. The lower line of the box represents the first quartile and the upper line of the box represents third quartile. Thus, the maximum portion of the data is represented in coloured boxes. The thick horizontal line inside the box represents the median. Thus, the coloured portion of the box represents the interquartile range of the data. The extended dashed lines (known as outliers data) cover data points that are <1.5 times the interquartile range from the median. The asterisk sign represents the mean. Hence, the box plot helps in visualising the skewness of the data distribution. For instance, the value of F1 for normal scenarios, as shown in the box plot, varies from −0.23 to 59.45

![Fig. 4](image) SK of voltage at SG bus for (a) Normal scenario, (b) Islanding scenario, (c) Fault scenario in the MG

![Fig. 5](image) Working of an RF classifier

| Scenario | Description | Number of cases |
|----------|-------------|-----------------|
| island   | \( \Delta P = \pm 40\% \) | 60              |
|          | \( \Delta Q = \pm 40\% \) | 60              |
|          | \( \Delta P = \pm 40\%, \Delta Q = \pm 40\% \) | 80              |
| fault    | LG, LLG, LL and LLL faults with fault resistance ranging from 0 to 100 Ω at different locations | 180             |
| other    | capacitor switching with values ranging from 150 to 350 kVAR at different locations | 75              |
|          | load switching with values ranging from 150 to 350 kW at different locations | 75              |

with mean at $\sim 33.78$, whereas that for fault it varies near to about 60 with mean at $\sim 60$, and for the island it varies from 0.67 to 12 with mean at $\sim 0.8$. Thus, it can be visually ascertained from Fig. 6 that the distributions of $F_1$, $F_2$, $F_3$ and $F_4$ are quite different for fault, island and normal conditions but the distribution of $F_5$ is not distinct. This is also evident from the cumulative distribution of the features as shown in Fig. 7. The $y$-axis of cumulative distribution denotes the proportion of data that is less than or equal to the value

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**Fig. 6** Box plot of the features

**Fig. 7** Cumulative distribution of the features
denoted by the x-axis. It is seen that the for F1, islanding data are mostly concentrated at a lower value of x, whereas for fault the data are located at a higher value of x while the data for normal cases are uniformly distributed over x. However, for F5, it is seen that both the island and fault cases are concentrated at high value of x. Therefore, from the distribution of the features, it can be deduced that F5 can produce errors in classification.

To train the classifier, the input training set $T_I = x_1, x_2, \ldots, x_j$ is considered, where input parameters $x_j = F1, F2, \ldots, F5$ and $j$ varies from 1 to $ns$, $ns$ being the total number of scenarios presented in Table 1. The corresponding output responses (or classes) $T_O = island, fault, other$.

A proper selection of the features is necessary for the proposed algorithm. While too many features will increase the detection time of island and fault scenarios, an insufficient number of features will reduce its accuracy. Therefore, for selecting appropriate features, four features are fed at a time to find out the importance of the features in the classification process. The k-fold cross-validation method is employed here for obtaining accuracy with $k = 5$. The dataset is randomly divided into five equal datasets. About four of the datasets are used for training and one dataset is used for testing. The cycle is repeated five times. In each cycle, the accuracy is calculated as percentage of total number of instances correctly identified to total number of instances. The average accuracy is then obtained by averaging the accuracy obtained in each cycle.

Table 2 shows the accuracy obtained when a particular feature is not fed to the classifier. It is seen that if F1 is not considered, then the accuracy is reduced significantly while the accuracy is increased when F5 is not considered. Therefore, F1, F2 and F4 is selected as the input parameters for the proposed algorithm. To show that RF classifier works best for the algorithm, the accuracies of other classifiers such as DT, SVM and ANN are also considered. Table 3 shows the classifier accuracy for cases both when all the features are considered and when three features (i.e. F1, F2 and F4) are considered. It is seen that on reducing the number of features, the accuracies for all classifiers get improved. In fact, RF exhibits a 100% accuracy with three features.

| Classifier | All features | Three features |
|------------|--------------|----------------|
| RF         | 98.4         | 100            |
| DT         | 96.7         | 96.7           |
| SVM        | 63.3         | 83.3           |
| ANN        | 80.5         | 90.65          |

Step 5: If neither fault nor island is detected by the RF classifier, then go to step 1, else go to step 6.

Step 6: If RF classifier gives fault results, then the fault information is broadcasted to all the nearby substations, and then go to step 1. If the island is detected, then the information is broadcasted to all the nearby substations and go to step 7.

Step 7: A control signal is sent to the SG to decrease its generation by $X$ kW if power was exported from the post-islanded area before islanding, i.e. power produced by SG ($P_G$) is greater than power consumed ($P_L$) or else to shed some non-critical loads by $X$ kW if power was imported to the post-islanded area before islanding, i.e. power generated by SG ($P_G$) is less than power consumed ($P_L$), where $X = P_G - P_L$. No control signal is sent to the SG if no or negligible power mismatch is present before islanding in post-islanded area.

4 Performance of the algorithm

To demonstrate the robustness of the proposed algorithm, several scenarios are simulated. Table 4 shows the results for island scenarios for various active power mismatch (at zero reactive power mismatch). It can be seen that at zero power mismatch, the algorithm works accurately. This shows that the algorithm has zero NDZ. Table 5 shows the results for island scenarios for various reactive power mismatch (at zero active power mismatch). From Tables 5 and 6, it becomes clear that the method gives accurate results for any island situation.

Table 6 and 7 gives the fault results for different fault resistances and fault inception angle (FIA), respectively. For this, several line-to-ground (LG), line-LG (LLG), LL and LLL faults were created in the MG with different fault resistances and FIA. The results prove that the accuracy of the method is not dependent on types of faults, fault resistance or FIA.

Table 8 lists the algorithm results for different power system operations in the MG. Scenarios including capacitor switching of 250 kVAR, a 200 kW load unmasking and induction motor starting at SG bus, respectively, are considered. To test the algorithm for faults occurring outside the microgrid (MG), the algorithm is also tested for different faults occurring between various nodes. To show the effect of type of SG on the algorithm, several SG types are considered in Table 9. For training, the same scenarios are simulated for each case as given in Table 1. It can be seen that the method gives 100% accuracy with two solar SGs connected to the SG bus but its accuracy slightly decreases to 99.65% when wind-based SG is taken into account. Therefore, the method works best for solar-based MG. The average accuracy of the method can be considered as 99.83%.

It can be seen that the algorithm gives accurate results for all the cases. Thus, the robustness is justified by the algorithm.

4.1 Algorithm time

Response time (RT): 8000 samples are required to obtain the SK. Thus, the RT, i.e. time required for obtaining 8000 samples can be calculated as 8 ms (8000 × 0.001 ms).

| Feature not considered | RF | DT | SVM | ANN | Average |
|------------------------|----|----|-----|-----|---------|
| F1                     | 95 | 93.3 | 63.3 | 75.2 | 81.7 |
| F2                     | 98.4 | 96.7 | 63.3 | 80.5 | 84.725 |
| F3                     | 98.4 | 96.7 | 38.3 | 70.3 | 75.93 |
| F4                     | 96.7 | 96.7 | 61.7 | 78.3 | 83.77 |
| F5                     | 100 | 96.7 | 83.3 | 85.2 | 91.3 |

Table 3 Classifier accuracy for different number of features
Programme execution time: The size of SK code is 1 kb, and that of the RF classifier code is 6 kb. The computer used has a 4 GB RAM, core i5 processor with clock frequency of 1 GHz, i.e. the instructions are executed at a speed of 1 ns. Thus, the execution time is 7 ns (1 ns × 7 kb).

Island sensing time (IST): The overall IST can be calculated as in (9). Thus, for the proposed algorithm, the IST is approximately equal to 20 ms (8 ms + 7 ns + 5 ms)

\[ IST = RT + PET + PD \] (9)

**Programme execution time:**

| Load, kW | % Power mismatch | Features values | Event classified |
|----------|------------------|-----------------|-----------------|
| 50       | −80              | 5.01            | 63.71           | 65.11 island |
| 100      | −60              | 3.23            | 47.29           | 58.61 island |
| 150      | −40              | 1.99            | 25.16           | 53.99 island |
| 200      | −20              | 0.67            | 6.2             | 55.15 island |
| 250      | 0                | −0.13           | 4.21            | 48.87 island |
| 300      | 20               | −0.3            | 0.79            | 45.11 island |
| 350      | 40               | −0.41           | −0.28           | 17.53 island |
| 400      | 60               | −0.95           | −0.01           | 5.15 island  |
| 450      | 80               | −0.97           | −0.01           | −0.71 island |
| 500      | 100              | −0.95           | −0.01           | −0.71 island |

**Propagation delay:**

The time delay due to sensing of voltage by PT, analogue/digital conversion etc., is about 5 ms [15].
Table 6  Algorithm classification results for different faults considering fault resistance

| Fault resistance, Ω | LG fault features values | LLG fault features values | LL fault features values | LLL fault features values | Event classified |
|---------------------|--------------------------|--------------------------|-------------------------|--------------------------|------------------|
| 0                   | 55.43 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 10                  | 55.4 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 20                  | 55.37 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 30                  | 55.33 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 40                  | 55.29 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 50                  | 55.25 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 60                  | 55.21 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 70                  | 55.16 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 80                  | 55.11 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 90                  | 55.05 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 100                 | 54.99 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |

Table 7  Algorithm classification results for different faults considering FIA

| FIA, deg | LG fault features values | LLG fault features values | LL fault features values | LLL fault features values | Event classified |
|----------|--------------------------|--------------------------|-------------------------|--------------------------|------------------|
| 0        | 55.43 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 30       | 55.42 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 60       | 55.42 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 90       | 55.41 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 120      | 55.40 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 150      | 55.40 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 180      | 55.41 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 210      | 55.41 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 240      | 55.42 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 270      | 55.42 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 300      | 55.42 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |
| 330      | 55.43 55.49 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 55.5 fault |

Table 8  Algorithm classification results for different power system operations

| Operations                  | Features values | Event classified |
|-----------------------------|-----------------|------------------|
| normal                      | −0.55 −0.55 −0.56 | other            |
| capacitor switching          | −0.56 −0.87 45.50 | other            |
| load unmasking              | −0.46 −0.45 40.22 | other            |
| induction motor starting     | −0.88 −0.76 50.87 | other            |
| LG fault between node 652 and node 684 | 55.37 55.5 55.5 | fault |
| LLG fault between node 645 and node 646 | 55.40 55.5 55.5 | fault |
| LL fault between node 632 and node 633 | 55.5 55.5 55.5 | fault |
| LLL fault between node 675 and node 692 | 55.41 55.5 55.5 | fault |

5 Algorithm reliability allocation

While the previous section deals with the process of development of the proposed algorithm, the reliability section deals with improving the software design and its associated hardware design by observing how reliability of a particular component of the algorithm affects the reliability of the whole process. This is necessary because the designing engineers are required to comprehend the task of identifying the reliability of different components in the system to improve the overall design. If the reliability of the overall system needs to be improved, then the efforts must be concentrated on improving the reliability of individual component first. Moreover, the notion of grid resilience is closely intertwined with reliability [51]. Without a reliable algorithm, grid resiliency cannot be expected. Thus, to make the algorithm reliable, the software used in the algorithm must meet some reliability goals. Software reliability allocation models are developed to set reliability goals of the individual components and derive the parameters (considering users’ view) for the successful operation of an algorithm [52]. The software reliability allocation of the proposed algorithm is assessed by AHP and SFTA as discussed below.

5.1 Analytical hierarchical process

The algorithm is implemented with the aid of a complex architecture. Therefore, there is a need to break down this complex structure into simpler structures and levels. This will help to assess the reliability into a deeper and more detailed level. AHP is one such process [53]. The AHP for the algorithm is constructed in Fig. 10, where the complex structure is broken into four levels.

The first level is the algorithm utility, which is defined as the dependability with which a user can implement the algorithm [53]. In mathematical form, the algorithm utility constituting the reliability into a deeper and more detailed level. AHP is one such process [53].

\[ AU(I, R) = \sum I_i R_i \]  

(10)
Table 9  Algorithm classification accuracy for different types of SGs

| Type of generation | RF accuracy, % |
|--------------------|---------------|
| Wind based         | 99.65         |
| Two solars         | 100           |
| Wind and solar     | 99.65         |

5.3 Reliability estimation of the modules

After the development of the SFTA, minimal cut sets are determined. A cut set is defined as a set of instances that lead to the top events. Cut sets that have minimum modules are called minimal cut sets [54]. Thus, as evident from the SFTA, the minimal cut sets are $C_1 = \{M_1\}$, $C_2 = \{M_2\}$, $C_3 = \{M_3\}$ and $C_4 = \{M_4\}$. It can be observed that all the modules are equally important for proper functioning of the algorithm.

The failure rate of the individual modules is given as per (11), where $F$ is the maximum acceptance failure rate of the algorithm, $X$ is the module number, $c$ is the number of minimal cut sets and $i$ is the number of modules in a particular minimal cut set [54]. Since, the aim of the algorithm is to have high reliability, the value of $F$ is considered as 0.01. Thus, the acceptable failure rate of each module is 0.0025 as computed in (12). Hence, the reliability of each module comes out to be 0.9975 as in (13). It can be seen that the reliability of each module is very high for the proper execution of the proposed algorithm

\[
F_{MX} \leq \left(\frac{F}{c}\right)^i
\]

(11)

\[
F_{M1} = \left(\frac{F}{4}\right)^{1/4} = 0.0025
\]

(12)

\[
F_{M2} = \left(\frac{F}{4}\right)^{1/4} = 0.0025
\]

\[
F_{M3} = \left(\frac{F}{4}\right)^{1/4} = 0.0025
\]

\[
F_{M4} = \left(\frac{F}{4}\right)^{1/4} = 0.0025
\]

\[
R_1 = R_2 = R_3 = R_4 = 1 - 0.0025 = 0.9975
\]

(13)

5.4 Importance estimation of the modules

For estimating the importance of individual modules, the method in [54] is followed. Suppose the algorithm is to be used by $u$ number of users. Then, the users give their preference value to the modules. Hence, the following module preference sets are derived as in the equation below:

\[
\{M_1^1, M_2^1, M_3^1, \ldots, M_n^1\}
\]

\[
\{M_1^2, M_2^2, M_3^2, \ldots, M_n^2\}
\]

\[
\vdots
\]

\[
\{M_1^u, M_2^u, M_3^u, \ldots, M_n^u\}
\]

After the survey of the preference of modules as per the user, the modules are arranged in decreasing order of preference. An importance value of the ordered module preference sets is defined as $\{1/2, 1/4, 1/8, \ldots, 1/2^u\}$. Thereafter, the importance of the module $x$ by users $u$ is finally obtained as in (15), where $\rho_x^u$ is the module $x$ importance value for the $i$th user subjected to the constraints $\sum I_i = 1$ and $0 < I_i < 1$

\[
I_i = \frac{1}{u} \sum_{j=1}^{u} \rho_x^j
\]

(15)

In this paper, two sets of users are considered for the algorithm – MG planners and utility grid planner. The utility grid plannen are more concerned about islanding detection than SG control actions as after island, the utility is not responsible for the maintenance of power supply in the MG. On the other side, the MG planners give more preference to SG control actions. Thus, the following preference sets are obtained:

1. Utility grid planner: \{ $M_1$, $M_3$, $M_4$, $M_5$ \}.
2. MG planner: \{ $M_1$, $M_4$, $M_3$, $M_5$ \}.
3 Conclusion

As the grid remains exposed to extreme conditions, there has been an increased interest among power industry to enhance the grid resilience particularly with the help of MG islanding. However, this islanding occurs unintentionally, i.e., without the prior knowledge of the MG operators. Thus, the restoration process gets delayed. Hence, for quick and reliable power restoration, island detection is the first and most important step. This paper addresses this issue by proposing an intelligent island detection algorithm with μPMU. The intelligence of the proposed μPMU lies in its feature extracting capability through analysis of measured voltage data of SG buses, feeding the extracted features to a trained classifier and making islanding or fault occurrence decision. The robustness of the method is justified through extensive experimentation for standard test system. Furthermore, the software allocation of the components of the algorithm is evaluated so that the algorithm is reliable.

8 References

[1] Liu, C.C.: ‘Distribution systems: reliable but not resilient? [in my view]’, IEEE Power Energy Mag., 2015, 13, (3), pp. 93–96
[2] Wang, Y., Chen, C., Wang, J., et al.: ‘Research on resilience of power systems under natural disasters – a review’, IEEE Trans. Power Syst., 2015, 31, (2), pp. 1604–1613
[3] Farzin, H., Fotuhi-Firuzabad, M., Moemi-Aghtaie, M.: ‘Enhancing power system resilience through hierarchical outage management in multi-microgrids’, IEEE Trans. Smart Grid, 2016, 7, (6), pp. 2869–2879
[4] Chen, C., Wang, J., Ton, D.: ‘Modernization distribution system restoration to achieve grid resiliency against extreme weather events: an integrated solution’, Proc. IEEE Power Eng. Rev. Lett., 2017, (7), pp. 1267–1288
[5] Liu, X., Shahidboum, M., Li, Z., et al.: ‘Microgrids for enhancing the power grid resilience in extreme conditions’, IEEE Trans. Smart Grid, 2016, 8, (2), pp. 589–597
[6] Chanda, S., Srivastava, A.K.: ‘Defining and enabling resiliency of electric distribution systems with multiple microgrids’, IEEE Trans. Smart Grid, 2016, 7, (6), pp. 2859–2868
[7] Mira, J., Ranade, S.J., ‘Power system hardening through autonomous, customer-driven microgrids’. IEEE Power Engineering Society General Meeting, Tampa, FL, USA, 2007, pp. 1–4
[8] Manikonda, S.K.G., Gaonkar, D.M.: ‘Comprehensive review of IDMs in DG systems’, IET Smart Grid, 2018, 2, (1), pp. 11–24
[9] Dutta, S., Sadhu, P.K., Reddy, M.J.B., et al.: ‘Shifting of research trends in islanding detection method – a comprehensive survey’, Proc. Control Mod. Power Syst., 2018, 3, (1), p. 1
[10] Bhargav, A., Mohanta, D.K.: ‘Optimal placement of synchrophasor sensors for risk hedging in a smart grid’, IEEE Sens. J., 2017, 17, (23), pp. 7857–7865
[11] Frettas, W., Xu, W., Affonso, C.M., et al.: ‘Comparative analysis between ROCOF and vector surge relays for distributed generation applications’, IEEE Trans. Power Deliv., 2005, 20, (2), pp. 1315–1324
[12] Liu, S., Zhaog, S., Xu, Q., et al.: ‘Improved voltage shift islanding detection method for multi-inverter grid-connected photovoltaic systems’, IET Gener. Transm. Distrib., 2016, 10, (13), pp. 3163–3169
[13] Karan, S., Bhalja, R.R., Maheshwari, R.P.: ‘Islanding detection technique based on inverse hyperbolic tangent function’, IET Renew. Power Gener., 2016, 10, (7), pp. 1002–1009
[14] Gupta, P., Bhalja, R.S., Jain, D.K.: ‘Active ROCOF relay for islanding detection’, IEEE Trans. Power Deliv., 2017, 32, (1), pp. 420–4209
[15] Makwana, Y.M., Bhalja, B.R.: ‘Experimental performance of an islanding detection scheme based on modal components’, IEEE Trans. Smart Grid, 2017, 10, (1), pp. 1025–1035
[16] Nale, R., Venkatanaguraju, K., Biswal, S., et al.: ‘Islanding detection in distributed generation system using intrinsic time decomposition’, IET Gener. Transm. Distrib., 2019, 13, (5), pp. 626–633
[17] Ropp, M.E., Begovic, S.D., Rohatgi, A.C.: ‘Prevention of islanding in grid-connected photovoltaic systems’, Prog. Photovolt. Res. Appl., 1999, 7, (1), pp. 39–59
[18] Liu, F., Kang, Y., Zhang, J., et al.: ‘Improved SMS islanding detection method for grid-connected inverters’, IET Renew. Power Gener., 2010, 4, (1), pp. 36–42
[19] Trujillo, C.L., Velasco, D., Figueroa, E., et al.: ‘Analysis of active islanding detection methods for grid-connected microinverters for renewable energy processing’, Appl. Energy, 2010, 87, (11), pp. 3591–3605
[20] Lopes, L.A., Sun, H.: ‘Performance assessment of active frequency drift islanding detection methods’, IEEE Trans. Energy Convers., 2006, 21, (1), pp. 171–180
[21] Karimi, H., Yazdani, A., Iravani, R.: ‘Negative-sequence current injection for fast islanding detection of a distributed resource unit’, IEEE Trans. Power Electron., 2008, 23, (1), pp. 298–307
[22] Sun, Q., Guerrero, J.M., Jing, T., et al.: ‘An islanding detection method by using frequency positive feedback based on PLL for single-phase microgrid’, IEEE Trans. Smart Grid, 2014, 5, (4), pp. 1821–1830
[23] Do, H.T., Zhang, X., Nguyen, N.V., et al.: ‘Passive-islanding detection method using the wavelet packet transform in grid-connected photovoltaic systems’, IEEE Trans. Power Electron., 2016, 31, (10), pp. 6955–6967
[24] Niaki, A.M., Afsharinia, S.: ‘A new passive islanding detection method and its performance evaluation for multi-DG systems’, Elect. Power Syst. Res., 2014, 110, pp. 180–187
[25] Raza, S., Mohkilis, H., Arif, H., et al.: ‘Application of signal processing techniques for islanding detection of distributed generation in distribution network: a review’, Energy Convers. Manage., 2015, 96, pp. 613–624
[26] Fayyad, Y., Osman, A.: ‘Neuro-wavelet based islanding detection technique’. IEEE Electrical Power and Energy Conf., Halifax, NS, Canada, 2010, pp. 1–6

Table 10 Detection time comparison of the proposed method with other non-classifier methods

| Method         | Detection time, ms |
|----------------|--------------------|
| SMS [18]       | 72                 |
| SSV [19]       | 69                 |
| SFS [20]       | 59                 |
| FT [35]        | 56                 |
| Proposed       | 20                 |

Table 11 Classification accuracy comparison of the proposed method with other classifier methods

| Method                  | Accuracy, % |
|-------------------------|-------------|
| DT with WT [27]         | 97.34       |
| DT with over–undervoltage/over–underfrequency [28] | 85.92/93.33 |
| SVM with ST [30]        | 97.21       |
| Proposed                | 99.83       |

The importance value of the modules is thus calculated as in (16). It is to be noted that the constraints $\sum_i I_i = 1$ and $0 < I_i < 1$ are satisfied

$$I_i = \frac{1}{\left(\frac{1}{2} + \frac{1}{8}\right)} = 0.3125$$

$$I_i = \frac{1}{\left(\frac{1}{4} + \frac{1}{16}\right)} = 0.15625$$

$$I_i = \frac{1}{\left(\frac{1}{4} + \frac{1}{16}\right)} = 0.375$$

$$I_i = \frac{1}{\left(\frac{1}{16} + \frac{1}{4}\right)} = 0.15625$$

On putting the values of $I_i$ and $R_i$ in (10), the overall algorithm utility comes to be nearly unity. Thus, the expected reliability of the modules is evaluated.

6 Comparison of the scheme with other methods

The significant difference between the proposed and other detection techniques discussed in [11–35] is that the proposed power system is embedded within μPMU for detecting unintentional islanding conditions. This will provide an opportunity to power system engineers to save implementation time and cost as they have to just create a separate subroutine in the already installed μPMU. Moreover, since the phasor estimation process is not included in the algorithm, the island is detected quickly which is necessary to increase grid resilience. The non-dependence on the feature reference frequency and reference phase angle is also an additional advantage of this method. Additionally, the proposed method possesses fault sensing capability and also enhances the situational health awareness of the distribution system. The reliability of the algorithm is also ascertained with a software allocation scheme.

Some available methods are simulated in the same computer system as mentioned in Section 4.1, same test system as explained in Section 3.1 and for the same test scenarios as mentioned in Table 1. The detection time (for non-classifier methods) and accuracy (for classifier methods), thus obtained from simulation, are compared with the proposed method in Tables 10 and 11, respectively. It is seen that the proposed method requires less detection time with high accuracy compared with other methods. These aspects validate the superiority of the proposed method over other islanding detection methods.

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