Islanding detection using total variation-based signal decomposition technique

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Abstract: This study presents a passive islanding detection technique based on the approach of total variation filtering (TVF) for inverter-based distributed generation under noisy environment. Contamination of noise in the signal makes the islanding detection threshold less reliable. Therefore, the modal voltage signal is analysed through TVF-based decomposition procedure and several statistical features are obtained from its output. For decision making, the features are compared with the pre-specified threshold. To tackle the challenge of islanding detection in the presence of the high-quality factor load, phase angle of the positive sequence voltage is considered as the second level of detection criterion. The proposed scheme is validated on IEEE 34-bus standard distribution system. The scheme is tested under islanding as well as all possible non-islanding network disturbances. Hardware-in-loop results are also presented in support of the theory. A comparative analysis of the proposed algorithm with the well-established S-transform is presented. The proposed scheme is found to be working effectively and can detect islanding condition within three cycles of its inception.

1 Introduction

Distributed generation (DG) is a promising approach for supplying electricity in the heart of power system. There is a substantial increase in the installation of DGs near utility distribution system over the past decade [1]. For the safe and reliable operation of DG in the distribution system, the DG must be equipped with anti-islanding protection. Islanding is the condition, in which one or more DG along with some load get disconnected from the utility and start operating independently. This imports adverse effects such as safety issues to the working personnel, out-of-phase reclosing, power quality problems, reduced life of appliances, interference with protection devices etc. Therefore, the IEEE Std. 2003 requires disconnection of DG from the utility within 2 s of islanding inception [2].

The methods used to detect islanding condition are of three categories: passive method, active method and communication-based method. Passive methods depend on the measurement parameters obtained locally to check whether the DG is connected to the grid or not. Hence, it is cost-effective with fast detection speed and does not interfere with the normal operation of the system. Therefore, it is easy to implement [3]. In active islanding detection technique, the system is subjected to an intentional disturbance to exaggerate the disturbance in parameters after utility cut-off to detect the islanded area power system. This scheme is able to achieve accurate and fast detection with negligible non-detection zone (NDZ). However, it degrades the system’s power quality and imports instability to the system with additional complexity [4]. In communication-based method, the detection algorithm depends on the communication links between the DG and the utility and is able to overcome the demerits of both passive and active methods. On the other hand, it is quite costly to implement in microgrid protection [5]. In [6], Menon and Nehrir have proposed hybrid detection scheme, which combines both active and passive methods and is also able to overcome their drawbacks. However, it imports additional complexity to the system. Passive method is the simplest one to implement among all the methods; however, the appropriate selection of powerful monitoring parameter and its threshold under various network disturbances are the main challenges behind passive methods.

Meanwhile, to eradicate the large NDZ of passive methods, many signal processing tools are being applied on the test signal. Versatility, stability, cost effectiveness and ease of modification properties of the signal processing technique are powerful weapons to extract the hidden characteristics of the measured signals for islanding detection [7]. These techniques include fast Fourier transform (FFT), Hilbert–Huang transform, t-t transform, Kalman filtering, wavelet transform (WT) and S-transform (ST). FFT is efficient for feature extraction of stationary signal at specified frequencies; however, it lacks the ability to detect time distribution of various frequencies as well as incapable of finding any momentary fluctuations [8]. WT provides the signal decomposition into components as a function of time and frequency along with the information of precise time location of transients [9, 10]. However, it only extracts the low-frequency band, thereby ignoring some useful properties of the high-frequency band. Hence, it loses some substantial information in high-frequency band, which have significant contribution to reveal islanding condition [11]. Moreover, it requires additional filtering if signal contains noise [12]. Wavelet packet transform overcomes the drawbacks of WT by dividing the whole time–frequency plane, instead of the low-frequency band only during signal decomposition [11]. The variable window property of Short-time Fourier transform (STFT) and expansion property of WT are merged to form the ST, which provides frequency-dependent resolution. It can provide significant improvement in the detection and localisation of disturbances due to islanding even under noisy conditions [12, 13]. However, its performance reduces under transients, and the computational burden of ST is quite high [14, 15, 16]. In empirical mode decomposition, the signal recursively breaks down into different unknown components known as intrinsic mode functions in time domain, which further approximates instantaneous amplitude, phase and frequency of individual modes using Hilbert transform [17, 18]. However, it is sensitive to noise and has the problem of end effect and mode mixing [8]. Recently, some newly developed passive detection methods have been reported in the literature. In [19], a combined detection approach using both the transient index value and the positive sequence superimposed current angle at point of common coupling (PCC) is proposed. Although this scheme has some merits over the existing rate of change of phase angle difference, rate of change of positive/negative sequence component of current signals, it has not considered the presence of noise in the signal. The detection of islanding based on the derived factor from the modal transformation of voltage is...
Overall, the black box nature of the classification techniques inherent to these models. These methods require large datasets and based features and ROCOPSA enable the scheme for successful oscillations in the signal are small. In such cases, no significant signal between the signal values. In this work, the modal voltage and reliable islanding detection. robust and reliable islanding detection scheme, the rate of change in variations are noted in the TVF output. Hence, to provide a highly noisy environment. It is an effective tool to capture the changes in process. As a result, this paper presents the application of the total variation filtering (TVF) scheme for islanding detection under noisy environment. It is an effective tool to capture the changes in signal between the signal values. In this work, the modal voltage component of the PCC voltage is computed and passed through the TVF. The output of TVF is used for extraction of features for effective and reliable islanding detection. On the other hand, for change in R/L ratio [i.e. under varying load quality factors (Q_L)], the oscillations in the signal are small. In such cases, no significant variations are noted in the TVF output. Hence, to provide a highly robust and reliable islanding detection scheme, the rate of change of positive sequence voltage phase angle (ROCOPSA) is included in the detection algorithm. The combined monitoring by TVF-based features and ROCOPSA enable the scheme for successful and reliable islanding detection.

Researchers have developed different classification techniques for islanding detection such as pattern recognition, decision tree and neural network [23, 24]. However, there are many issues inherent to these models. These methods require large dataset and rigorous training procedure, thus missing of data creates large concern [25]. Also, it demands exorbitant amount of time and provide dissatisfaction results in case of unknown datasets. The detailed shortcomings of their training algorithms are presented in [26]. Overall, the black box nature of the classification techniques prohibits easy interpretation of the relationships between the actual behaviour and the predicted value [27]. In view of the above facts, the careful selection of threshold considering possible network disturbances can result to a potent solution for decision making. Therefore, in this paper, threshold-based detection of islanding is carried out.

This paper is organised as follows. Section 2 describes the test system study under noisy environment. Section 3 provides a brief detail of TVF. In Section 4, the challenge behind the detection of islanding under high-quality factor load is described. In Section 5, the proposed detection scheme is discussed. The simulation study and results under simple test system and IEEE 34-bus system are analysed in Sections 6 and 7, respectively. The performance of the TVF algorithm on hardware-in-loop (HIL) is presented in Section 8. A comparative analysis with ST is given in Section 9. Conclusions are provided in Section 10.

2 System study under noisy environment

Noise significantly affects the performance of any algorithm due to its presence in the system as well as due to measurement error. The system considered for the study of islanding detection is shown in Fig. 1. It shows the photovoltaic (PV) system connected to the utility at PCC with certain local load.

To analyse the influence of noise on the detection schemes, consider that the PCC voltage is contaminated with noise. The PCC voltages without and with the presence of 20 dB noise are presented in Fig. 2a. As presented in this figure, voltage swell has occurred at 0.2 s resulting 50% rise in voltage and white Gaussian noise of 20 dB is added to the signal at 0.3 s. The corresponding root-mean-square (RMS) value of voltage for the three-phase PCC voltage signals is presented in Fig. 2b.

As observed from Fig. 2b, the RMS value of voltage increases with the inception of swell. For noise-free condition, RMS value increases to 350 V after swell, whereas with the contamination of noise in the signal, it goes up to 400 V. Under such situation, let the specified threshold for islanding is 450 V, then RMS value with the noisy signal may go closer to threshold value, and hence reliability of the set threshold decreases. Therefore, to obtain a reliable

![Fig. 1 Grid interactive DG system for islanding detection](image1)

![Fig. 2 Effect of noise on voltage](image2)
threshold for the islanding detection scheme, the entire analysis is performed on a noisy environment.

3 Total variation-based signal decomposition

Total variation-based signal decomposition is an effective technique for signal analysis under noisy environment [28, 29]. TVF has numerous successful applications which are well-documented in the field of image processing [30]. Researchers have also used TVF for fault diagnosis [28]. The output of the decomposition is obtained by optimising a particular cost function involving a quadratic data fidelity term and a convex regularisation term [31]. The derivation of the algorithm is based on the min–max property and the majorisation-minimisation (MM) procedure [32].

The MM is an approach to solve optimisation problems which are too difficult to solve directly [33]. In this approach, instead of minimising the cost function \( F(x) \) directly, the method solves a sequence of optimisation problems, \( G_k(x), k = 0, 1, 2, \ldots \) This procedure consists of two steps. In the first step (majorisation), each sequence of optimisation problem called surrogate function that locally approximates the objective function with their difference minimised at the current point. Then in the second step (minimisation), the surrogate function is minimised. A parallel argument can be made for maximisation problems by replacing the upper-bound minimisation step by a lower-bound maximisation step [34].

Total variation can be defined as the changes in signal between signal values.

The total variation of an \( N \)-point signal \( x(n) \) is as follows:

\[
\text{TV}(x) = \sum_{n=2}^{N} |x(n) - x(n-1)| = \| D x \|, \quad (1)
\]

where \( 1 \leq n \leq N \), \( D \) gives the first-order differential and \( \| \cdot \|_{1}(m \geq 1) \) represents the \( l_{m} \) norm.

Consider the signal \( x \) corrupted by additive white Gaussian noise \( n \): which is \( y = x + n \), where \( x \) is the signal and \( n \) is the noise.

The estimation of the signal \( x \) using TVF is given below:

\[
J(x) = \| y - x \|^2 + \lambda \| D x \|^2, \quad (2)
\]

where the first term \( \| y - x \|^2 \) represents the data fidelity and \( \lambda \) is referred to as the regularisation parameter. Here, the objective is to extract the original signal \( x \) which minimises the objective function (2) with respect to (3) which is given below:

\[
x \in \mathbb{R}^{N}, x = \arg \min_{x} J(x) \quad (3)
\]

In this analysis, the matrix \( D \) is defined as follows:

\[
D = \begin{bmatrix}
-1 & 1 \\
-1 & 1 \\
& \ddots \\
& \ddots & -1 & 1 \\
& \ddots & \ddots & -1 & 1
\end{bmatrix}
\]

From the matrix \( D, DD^T \) is obtained as follows:

\[
DD^T = \begin{bmatrix}
2 & -1 & \cdots & \cdots & -1 \\
-1 & 2 & -1 & \cdots & \cdots & -1 \\
& \ddots & \ddots & \ddots & \ddots & \ddots \\
& & \ddots & \ddots & \ddots & \ddots \\
& & & \ddots & \ddots & \ddots \\
& & & & \ddots & \ddots & \ddots
\end{bmatrix}
\]

As stated above, during the filtering, the MM method is used because of its effectiveness in solving difficult optimisation problems. Moreover, it has a fast rate of convergence. Therefore, the optimised objective function of (3) can be represented in the following manner. The detailed procedure is described in [33]

\[
X_{k+1} = y - D^T \left( \frac{1}{\lambda} \text{diag}(|Dx|) + DD^T \right)^{-1} D y \quad (4)
\]

On the basis of (4), the TVF output can be obtained. As observed from (4), the parameter \( \lambda \) plays a vital role in deciding the performance efficiency of the filtering procedure. It controls smoothing of a signal. For larger noise levels, large value of lambda needs to be selected for obtaining better smoothing of a signal [33]. There are various ways to find lambda such as manually by the trial-and-error method [35], the unbiased predictive risk estimator method [36], the Stein unbiased risk estimator method [37], the generalised cross-validation method [38], the \( L \)-curve method [39], the variational Bayes’ approach [40] and the Lagrange multipliers based method [41]. In this paper, a relatively large value of lambda is chosen by trial-and-error method so as to remove all unwanted components from the residual signal so that boundaries of islanding events can be determined accurately. On the basis on the results obtained for different kinds of islanding as well as non-islanding events, the lambda parameter \( \lambda \) is fixed as 1000.

4 Challenge behind islanding detection in the presence of high-quality factor load

The variations in the signal magnitude during islanding are very less when load of high-quality factor \( (Q) \) is connected. This happens because the load resonance frequency is same with that of system’s nominal frequency. Therefore, most of the detection schemes based on variation in magnitude of the signal fails to detect islanding and suffers from high non-detection zone (NDZ). High-quality factor of load indicates energy loss relative to the amount of energy stored within the system. Thus, higher the \( Q \) factor, lower the rate of energy loss, and hence oscillations will reduce slowly, i.e. they will have a low level of damping [42]. Under such scenario, the deviation in the PCC voltage after islanding is very nominal. Therefore, it forms a critical case for islanding detection. Some of the passive and hybrid schemes based on Sandia frequency shift, slip mode frequency shift and phase jump detection (PJID) have been successfully applied for islanding detection under high-quality factor load [43, 44]. PJID involves monitoring of sudden change in phase difference between the PV output voltage and current when islanding occurs [43]. However, PJID scheme may suffer from frequent nuisance tripping due to the occurrence of transients during motors starting, if the specified threshold value is low [45]. Also, the scheme fails when the load is purely resistive, i.e. the angular difference between voltage and current is zero. To overcome this, in the proposed scheme, the rate of change of positive sequence voltage phase angle (ROCOPSA) of PCC voltage is considered. The reason behind the selection of ROCOPSA is that the effect of transient does not drive the positive sequence angle to cross the threshold. Moreover, positive sequence voltage takes care of unbalanced system as well. The islanding detection capability of ROCOPSA for high \( Q \) is illustrated below in Fig. 3.

The minimal variations occurred in signal due to high \( Q \) value may not be sufficient to trigger the anti-islanding relay based on magnitude, but these variations bring enough difference in the phase of the signal. To verify this, PJID voltage and its corresponding positive sequence angle is analysed under different load quality factors. Figs. 3a and b represent the PJID voltage and its positive sequence angle for load quality factors of 1 and 2, respectively. As noted from these figures, there are small variations in the magnitude, whereas significant deviation is observed in the positive sequence angle during islanding. Therefore, in the proposed scheme, the rate of change of positive sequence of the PCC voltage is also considered to make the islanding decision.
Proposed islanding detection approach

5.1 Detection algorithm

The islanding detection algorithm starts with the extraction of modal voltage component of voltage signal at PCC. The voltage signal is acquired from the measurement bus placed at the PCC. According to IEEE std. 929-2000, PCC is the point at which the electric utility and the customer interface occurs. Typically, this point is the customer side of the utility revenue meter \[46\]. Also, it can be simplified as the point where the microgrid is connected with the main grid through a breaker mechanism. The location of PCC is marked in Fig. 1. The measured PCC voltage signal is further used to extract the modal voltage signal.

Consider that the signal consists of noise component. The signal is further processed through the TVF.

As observed from Fig. 2, the presence of noise affects the operating region of anti-islanding relay. Hence, removal of noise from the signal gives pure component of the signal and this synthesised signal is used for feature extraction. Various features can be extracted from the TVF output which includes energy \((E_g)\), standard deviation \((S_d)\), entropy \((E_t)\), variance \((V_a)\), skewness \((S_{kn})\) and kurtosis \((K_{ts})\). These statistical parameters are considered because they explain the irregularities and asymmetrical behaviour of the signal in a best possible way \[47\]. In the proposed study, it is found that among the above-mentioned features, energy and skewness are sufficient for differentiating islanding and non-islanding events. The values of energy and skewness are compared with their threshold values for islanding detection as shown in Fig. 4.

As discussed in Section 4, to provide robust and reliable detection scheme under high \(Q\)-factor loads, the ROCOPSA value of PCC voltage is used in the detection algorithm. Hence, whenever the TVF-based detection criteria give an NO signal to islanding, to cross-check the decision, the ROCOPSA value is verified. The threshold for differentiating the islanding and non-islanding scenarios is decided depending on the simulation results under different network conditions. The flowchart of the proposed scheme is presented in Fig. 4. The combined operation of both the criteria (i.e. \(E_g\), \(S_{kn}\) and ROCOPSA) makes the proposed detection scheme a reliable and accurate technique.

5.2 Threshold selection

Extraction and selection of features is a crucial process since it decides the accuracy of a detection scheme. Similarly, proper selection of threshold plays a key role to maintain the accuracy of the detection scheme. The parameters, showing the substantial variations to differentiate islanding and non-islanding cases, are considered in the proposed algorithm. Therefore, energy content and skewness are selected as the monitoring parameters for effective islanding detection. To determine the threshold of the proposed algorithm for islanding, different islanding conditions as well as various non-islanding disturbances are simulated in MATLAB/Simulink. Among the various operating conditions, some of the conditions are critical. For example, for zero-power
In this section, the performance of the proposed scheme is evaluated based on the MATLAB simulation of the studied system of Fig. 1 under various network conditions. The scheme is tested for islanded operating conditions of the DG as well as for various switching events and power quality disturbances. To verify the robustness of the proposed scheme, different possible islanding conditions are chosen. It includes islanding under zero-power mismatch, high load quality factor, occurrence of islanding during power quality (PQ) disturbances (namely, sag and swell) and occurrence of islanding in a weak grid scenario. Non-islanding test scenarios include different load switching disturbances in addition to the plausible disturbances of grid. Threshold values considered for energy, skewness and ROCOPSA are 70.0, 5.0 and 7.0, respectively. The various operating conditions are discussed below.

6.1 Islanding detection under zero-power mismatch condition

In this section, the performance of the proposed algorithm is evaluated under islanding condition with zero-power mismatch in a noisy environment, as it is a critical case. For inception of islanding, the main Circuit breaker (CB) between the utility and the DG is opened at the 500th sample. Under this condition, the modal voltage component of PCC voltage is presented in Fig. 5a. Then, it is passed through the TVF-based signal decomposition process to obtain the TVF output as shown in Fig. 5b. As observed from Figs. 5a and b, the signal, even under the influence of noise, is showing significant variations after islanding with zero-power mismatch. Thus, the proposed scheme clearly demarcates the pre-islanding and post-islanding events. Therefore, the scheme owns the capability of eradicating NDZ significantly.

6.2 Islanding detection for varying load quality factor ($Q_f$)

This section examines the efficacy of the detection scheme under different load quality factors. The modal voltage signal, its corresponding TVF output and ROCOPSA are presented under varying quality factor of load in Figs. 6a–c, respectively. As observed from the TVF output (Fig. 6b), the variations in voltage magnitude are very small for high-quality factor load ($Q_f = 2$) and are not enough to enable the features to cross the threshold. However, the value of ROCOPSA for critical condition of $Q_f = 2$ is much above the set threshold (i.e. 7). Moreover, for the non-islanding scenarios, the value of ROCOPSA is much below the set threshold (i.e. 7). Therefore, threshold value of ROCOPSA has been fixed as 7. Thus, the ROCOPSA value is sufficient to hit the threshold even under high-quality factor load as shown in Fig. 6c. Hence, the inclusion of ROCOPSA in the proposed algorithm enables it to achieve successful islanding detection even under wide variation of load quality factor.

6.3 Islanding detection under PQ disturbances

The objective behind this section is to assure that the proposed islanding detection scheme should not be sensitive to PQ disturbances under grid-connected mode. In other words, the

### Table 1 Performance evaluation on studied system of Fig. 1

| Sl. no. | Threshold Condition | Energy (R/ $\Omega$) | Skewness |
|---------|---------------------|----------------------|----------|
| 1       | islanding with zero-power mismatch | 375.0398 | 1.1722 |
| 2       | islanding with unbalance and non-linear load | 151.6595 | 3.8604 |
| 3       | islanding ($X/R = 5$) | 187.0276 | 2.8682 |
| 4       | islanding ($X/R = 15$) | 350.3568 | 1.2826 |
| 5       | islanding in the presence of sag | 237.3039 | 2.5319 |
| 6       | islanding in the presence of swell | 246.9956 | 2.1875 |

### Table 2 Performance evaluation on IEEE 34-bus system

| Sl. no. | Threshold Condition | Energy (R/ $\Omega$) | Skewness |
|---------|---------------------|----------------------|----------|
| 1       | islanding with zero-power mismatch | 181.0330 | 4.1748 |
| 2       | islanding ($X/R = 5$) | 196.7648 | 4.1027 |
| 3       | islanding ($X/R = 15$) | 243.0230 | 3.6840 |
| 4       | islanding in the presence of sag | 151.8511 | 3.0729 |
| 5       | islanding in the presence of swell | 152.0420 | 3.6592 |

mismatch, the magnitude of features is relatively low as compared with the magnitude for non-zero-power mismatch. Such kind of critical conditions is also considered while deciding the threshold. Among the islanding cases, islanding in the presence of unbalanced and non-linear load is also considered. The non-islanding disturbances include the variation in voltage (sag/swell with different magnitudes), introduction of harmonics, occurrence of transient, different load switching (i.e. resistive, inductive and capacitive loads), DG switching, variation in grid frequency etc. The details of various operating conditions which are considered are given in Tables 1 and 2 for studied system in Fig. 1 and 34-bus system, respectively. The extracted features (i.e. energy, skewness and ROCOPSA) are analysed for all the islanding as well as non-islanding scenarios. The value of selected threshold is such that if the obtained value deviates from the threshold, then it falls in the category of islanding events; otherwise, it will be treated as non-islanding case. For feature ‘energy’, the value of threshold is such that if the obtained value is less than the threshold value, then it falls under the category of non-islanding events; otherwise, it will be treated as islanding case. For feature ‘skewness’, if its value is below the pre-specified threshold, then it is considered as an islanding case; else, it is treated as non-islanding event. Similarly, for the higher $Q_f$, the value of ROCOPSA is less as compared with the value for lower $Q_f$. Hence, while deciding the threshold for ROCOPSA, the operating condition of higher $Q_f$ is taken into consideration.

6 Performance evaluation in simple system

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scheme should be able to clearly differentiate between the PQ disturbances and the islanding condition to avoid erroneous operation.

When the signal is under the influence of PQ disturbance (i.e. voltage sag, swell and harmonics contamination), and furthermore islanding condition arises, the responses of the proposed scheme to such scenarios are presented in Figs. 7–9. In Figs. 7–9, the 20% sag, 20% swell and harmonics are created at the 200th sample. Furthermore, islanding situation is created at the 500th sample. The modal voltage signal for simultaneous occurrence of sag/swell/harmonics and islanding event is given in Figs. 7a–9a, respectively. Similarly, the corresponding TVF outputs of Figs. 7b–9b are presented in Figs. 7b–9b, respectively.

For voltage sag condition, as observed from Fig. 7b, during starting of the sag, a momentary small increase in the TVF output is observed. However, during islanding, persistent large variations are observed. Moreover, from Figs. 8b and 9b, the response of TVF output to swell/harmonics and islanding condition is clearly visible.

Many other islanding and non-islanding disturbances are considered and their numerical values of features are presented in Table 1. As observed from Table 1, the values of feature are within the pre-specified threshold for PQ disturbances, and the values deviate from the specified threshold notably for islanding events.

7 Performance evaluation under IEEE 34-bus test system

In this section, the 34-bus standard distribution system is considered for the validation of the proposed detection system. The single line diagram of IEEE 34-bus system is presented in Fig. 10. The network consists of four numbers of PV systems (each of 14.1 kW), connected at bus nos. 12, 15, 22 and 30. Total load connected at different buses to the network is 60 kW, 30 kVar. The loads are combination of balanced, unbalanced, non-linear and dynamic
load. In this system, bus 12 is considered as PCC, where the measurements are obtained for the consideration of islanding scenario of PV system-1. The detailed system parameters of the 34-bus distribution system are obtained from [48]. The modal voltage signal is extracted from the PCC of the intended DG and is processed through the total variation-based approach. After processing of the signal, the feature parameters are obtained and the threshold value is decided by performing extensive simulation to differentiate between islanding and non-islanding events. Hence, threshold selection is system dependent. The threshold value for energy, skewness and ROCOPSA are 80.0, 7.0 and 7.0, respectively. The performance of the proposed detection scheme is tested under various operating conditions as given below.

7.1 Performance under islanding condition with zero-power mismatch
The performance of the proposed detection technique during islanding on a practical microgrid scenario is explained in this section with the consideration of noise. As presented in Fig. 11, islanding condition is simulated with zero-power mismatch at the 500th sample and significant variation is observed in the TVF output of the modal signal during islanding. This variation puts a substantial difference in the extracted features value as given in Table 2. From Table 2, it is observed that the features surpass the respective specified threshold. Hence, the proposed total variation-based approach is successful and reliable in islanding detection, thereby avoiding NDZ.

7.2 Islanding detection under different load quality factors ($Q_f$)
This section investigates the performance of the proposed detection scheme under loading condition with different quality factors. For high-quality factor load ($Q_f = 2$), the modal voltage signal contaminated with noise and its corresponding TVF output are presented in Figs. 12a and 12b, respectively. As noted from Figs. 12a and 12b, the features obtained from TVF output are unable to overcome the pre-specified threshold because of insignificant variations before and after islanding. However, from Fig. 12c, it can be observed that ROCOPSA shows deviation from the pre-specified threshold even for $Q_f = 2$ during islanding.

7.3 Performance evaluation under voltage stability margin
The onset of fault in the system results into fall in system voltage. If the fault is not cleared, the voltage drop may continue in an uncontrolled manner. This scenario is known as the voltage instability condition. However, the nose point demarcates the boundary between voltage stability and instability regions. In such scenario, there is a high probability that the existing voltage-based islanding detection schemes may consider this as the islanding event. Therefore, to verify the behaviour of the proposed scheme under voltage stability margin, voltage sag which results in the reduction of voltage by 90% is created by simulating three-phase-to-ground fault at the 500th sample. The response of modal voltage and corresponding TVF output to this voltage sag is presented in Fig. 13. As noted from this figure, there is a significant difference between the pre- and post-fault voltages. However, the features extracted from the signal are not violating the specified threshold as mentioned in Table 2, Sl. no. 13. This shows that the scheme will not detect this voltage variation event as an islanding condition which is true.

In addition to the above-cited cases, many other islanding disturbances are investigated which are occurrence of islanding in the presence of sag/swell and inception of islanding events in weak grid as well as strong grid scenario. In the list of non-islanding disturbances: switching of resistive, inductive and capacitive loads, occurrence of PQ disturbances namely sag, swell, harmonics and transient are considered. Apart from voltage instability scenario, different symmetrical as well as asymmetrical faults with varying fault resistances are taken into account during analysis. Also, the disconnection of feeder and the tripping of DG other than the intended DG scenario are also taken into account. The performance evaluation of the proposed scheme for all the above-mentioned events is presented in Table 2. As observed from Table 2, the values of features are within the pre-specified threshold for non-islanding disturbances and the values deviate the specified threshold notably during islanding events. Thus, it is established that the selected threshold is quite robust and works satisfactorily for different islanding as well as non-islanding conditions.

8 HIL implementation of TVF algorithm
This section demonstrates the real-time feasibility of TVF algorithm using the personal computer (PC) with the MATLAB software and the Arduino Due with a 32 bit Atmel SAM3X8E ARM Cortex-M3 processor having 512 kB flash memory with 96...
kB SRAM and 84 MHz clock speed [49]. The modal voltage signal is extracted from the test system of Fig. 1, which is simulated in MATLAB. Then, the modal voltage signal is given as an input to the Arduino Due board. With the modal voltage signal as its input, Arduino processes the TVF algorithm in real time to obtain the TVF output signal. The board and the experimental setup used for TVF validation is presented in Figs. 14a and b, respectively. The test system shown in Fig. 1 is built on PC to carry out hardware results. The result obtained for islanding condition is presented in Fig. 14c.

In Fig. 14c, modal voltage signal and TVF output are plotted. Consider that islanding occurs at the 500th sample. As noted from TVF output, after islanding, the disturbances are large enough to drive the monitoring parameter to deviate corresponding threshold.

The experimental results for various non-islanding scenarios such as occurrence of LG fault, adjacent DG switching, fall in voltage up to 90% leading to voltage instability and voltage swell are presented in Fig. 15. For the above-mentioned non-islanding cases, the disturbances are initiated at the 500th sample and the corresponding responses are recorded. As observed from Fig. 15, no significant variation can be noted in the TVF output post-occurrence of non-islanding events.

The hardware and the simulation result can be compared during islanding. In Fig. 5, the modal voltage and its TVF output during islanding condition are presented for simulation analysis. Similarly, the modal voltage signal and its TVF output obtained from hardware for the islanding condition are presented in Fig. 14c. By observing those two figures closely, their identical responses to the islanding condition can be noted. Thus, from this section, it is demonstrated that the HIL results obtained validate the simulation results. Thus, the proposed scheme can work efficiently in the practical distribution network.

9 Performance evaluation with ST

To show the faster detection ability of proposed scheme, it is compared with ST as it also works well under noisy environment. To compare the performance of islanding detection by both ST and the proposed TVF scheme, the test system of Fig. 1 is considered. In this analysis, the same features which are obtained by the TVF scheme are extracted by the ST decomposition. Then, the time taken by both the methods to issue the trip signal under islanding condition is obtained. Keeping the reactive power mismatch to minimum, the active power mismatch is varied from −40 to 40% and the detection time taken by both the schemes are compared in Fig. 16a. Similarly, considering the active power mismatch to minimum value, the reactive power mismatch between the DG and the load is varied from −40 to 40% and the response times for both the schemes are evaluated in Fig. 16b. To find the detection time
taken by ST, the modal voltage is processed through the ST algorithm. The same features as of TVF are obtained and the time of execution is calculated. Time of execution is the time elapsed between the input signal processing and the issuing of corresponding trip signal. Owing to the shorter algorithm time of TVF as compared with ST, the proposed scheme enables itself to achieve faster response than the ST. The graphical analysis of the comparison between both the schemes in terms of its detection speed in accordance to real and reactive power mismatch is presented in Fig. 16. This is because the effectiveness of the islanding detection scheme is characterised by its NDZ. It is the operating region, where detection of islanding cannot be achieved in a timely manner. Furthermore, NDZ is represented in terms of power mismatch. Thus, power mismatch is one of the most important performance indexes of islanding detection algorithm. Therefore, real and reactive power mismatch scenarios between the load and DG are considered for comparative analysis between the two schemes. As observed from those figures, the TVF-based scheme is providing quicker islanding detection (within 60 ms) for both active and reactive power mismatch as compared with ST scheme. Hence, one can decipher that the proposed TVF-based detection scheme is able to achieve faster detection.

10 Conclusion

This paper presented a passive islanding detection technique using TVF approach of signal processing in combination with ROCOPSA for inverter-based DG systems. For practical system scenario, a noisy environment is taken into account for the analysis. It is found that the presence of noise reduces the reliability of set threshold for islanding detection. Therefore, TVF-based approach is considered for feature extraction and subsequent islanding detection. For the condition of high-quality factor load, the variation in the voltage signal during islanding is very small. Therefore, to achieve successful islanding detection under such condition, the value of ROCOPSA is checked for the events, which were treated as non-islanding by the TVF-based approach. Under the surveillance of two-level detection criteria, the scheme is able to achieve accurate as well as fast detection. The performance of the proposed scheme is tested on simple as well as IEEE 34-bus test system. From Tables 1 and 2 (Sections 6 and 7), it can be concluded that the proposed technique is able to detect islanding under zero-power mismatch, noisy condition and various operating conditions. Moreover, the scheme can accurately distinguish between islanding events and power quality disturbances. As explained in Sections 6.2 and 7.2, for islanding under high-quality factor load, the ROCOPSA value is able to deviate the threshold to register the islanding as validated from Figs. 6c and 12c. The HIL results presented in Section 8 validate that the proposed scheme can be efficiently used in practise. Furthermore, it is demonstrated that TVF-based approach is faster than the ST technique due to its lesser algorithm time. The algorithm times found for ST and TVF are 12.07 and 10.23 ms, respectively. Hence, the TVF-based approach along with ROCOPSA can be used in real time for achieving accurate and successful islanding detection.

11 References

[1] Dugan, R.C., McDermott, T.E.: ‘Distributed generation’, IEEE Ind. Appl. Mag., 2002, 8, (2), pp. 9–25
[2] IEEE Std. 1547-2003: ‘IEEE standard for interconnecting distributed resources with electric power systems’, 2003
[3] DeMango, F., Liserre, M., Aquila, A.D., et al.: ‘Overview of anti-islanding algorithms for PV systems. Part I: passive methods’. Proc. IEEE Power Electronics Motion Control Conf., Porto, Porto, Portugal, June 2006, pp. 1878–1883
[4] DeMango, F., Liserre, M., Aquila, A.D., et al.: ‘Overview of anti-islanding algorithms for PV systems. Part II: active methods’. Proc. IEEE Power Electronics Motion Control Conf., Porto, Porto, Portugal, June 2006, pp. 1884–1889
[5] Timbas, A., Oudalov, A., Carl, N.M.H.: ‘Islanding detection in smart grids’. Proc. IEEE Energy Conversion Congress Exposition, Atlanta, GA, USA, September 2010, pp. 3631–3637
[6] Menon, V., Nehrir, M.: ‘A hybrid islanding detection technique using voltage unbalance and frequency set point’, IEEE Trans. Power Syst., 2007, 22, (1), pp. 442–449
[7] Raza, S., Mohikhi, 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
[8] Karimi, M., Mokhtari, H., Iravani, M.R.: ‘Wavelet based on-line disturbance detection for power quality applications’, IEEE Trans. Power Deliv., 2000, 15, (4), pp. 1212–1220
[9] Gaing, Z.L.: ‘Wavelet-based neural network for power disturbance recognition and classification’, IEEE Trans. Power Deliv., 2004, 19, (4), pp. 1560–1568
[10] Lin, C.H., Wang, C.H.: ‘Adaptive wavelet networks for power quality detection and discrimination in a power system’, IEEE Trans. Power Deliv., 2006, 21, (3), pp. 1106–1113
[11] 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
[12] Ray, P.K., Kishor, N., Mohanty, S.R.: ‘Disturbance detection in grid connected distribution system using wavelet and S-transform’, Electr. Power Syst. Res., 2011, 81, pp. 805–819
[13] Teng, J., Li, Z., Tang, Q., et al.: ‘Detection and classification of power quality disturbances using double resolution S-transform and DAS-SVMs’, IEEE Trans. Instrum. Meas., 2016, 65, (10), pp. 2302–2312
[14] Manikandan, M.S., Samantaray, S.R., Kamwa, I.: ‘Detection and classification of power quality disturbances using sparse signal decomposition on hybrid dictionarying’, IEEE Trans. Instrum. Meas., 2015, 64, (1), pp. 27–38
[15] Mishra, P.P., Bhende, C.N.: ‘Islanding detection using sparse S-transform in distributed generation systems’, Electr. Eng., 2018, 100, (4), pp. 2397–2406
[16] Reddy, M.V., Sodhi, R.: ‘A modified S-transform and random forests-based power quality assessment framework’, IEEE Trans. Instrum. Meas., 2018, 67, (1), pp. 78–89
[17] Shukla, S., Mishra, S., Singh, B.: ‘Empirical-mode decomposition with Hilbert transform for power quality assessment’, IEEE Trans. Power Deliv., 2009, 24, (4), pp. 2159–2165
[18] Tse, N.C.F., Chan, J.Y.C., Lau, W., et al.: ‘Hybrid wavelet and Hilbert transform with frequency-shifting decomposition for power quality analysis’, IEEE Trans. Instrum. Meas., 2012, 61, (12), pp. 3225–3233
[19] Nale, R., Biswal, M., Kishor, N.: ‘A transient component based approach for islanding detection in distributed generation’, IEEE Trans. Sustainable Energy, 2019, 10, (3), pp. 1129–1137
[20] Makwana, Y.M., Bhalja, B.R.: ‘Experimental performance of an islanding detection scheme based on modal components’, IEEE Trans. Smart Grid, 2019, 10, (1), pp. 1025–1034
[21] Dwivedi, U.D., Singh, S.N.: ‘Denoising techniques with change-point approach for wavelet-based power-quality monitoring’, IEEE Trans. Power Deliv., 2009, 24, (3), pp. 1719–1727
[22] Wang, Y., Li, Q., Zhou, F.: ‘Transient power quality disturbance denoising and detection based on improved iterative adaptive kernel regression’, J. Mod. Power Syst. Clean Energy, 2018, 7, (3), pp. 644–657, doi:10.1007/s40565-018-0467-4
[23] Faqhrudlin, O.N., El-Saadany, E.F., Zeineldin, H.H.: ‘A universal islanding detection technique for distributed generation using pattern recognition’, IEEE Trans. Smart Grid, 2014, 5, (4), pp. 1985–1992
[24] Azim, R., Li, F., Xue, Y., et al.: ‘An islanding detection methodology combining decision trees and Sandia frequency shift for inverter-based distributed generations’, IET Gener. Transm. Distrib., 2017, 11, (16), pp. 4104–4113
[25] Alhroob, E., Mohammed, M.F., Lim, C.P.: ‘A critical review on selected fuzzy min-max neural networks and their significance and challenges in pattern classification’, IEEE Access, 2019, 7, pp. 56129–56140, doi:10.1109/ACCESS.2019.2919155
[26] Shrestha, A., Mahmood, A.: ‘Review of deep learning algorithms and architectures’, IEEE Access, 2019, 7, pp. 53040–53065, doi:10.1109/ACCESS.2019.2912200
[27] Sareen, K., Bhalia, B.R., Maheshwari, R.P.: ‘Universal islanding detection technique based on rate of change of sequence components of currents for distributed generations’, IET Renew. Power Gener., 2016, 10, (2), pp. 228–237
[28] Zhang, S., Wang, Y., He, S., et al.: ‘Bearing fault diagnosis based on variational mode decomposition and total variation denoising’, Meas. Sci. Technol., 2016, 27, (7), p. 075101
Nie, X., Qiao, H., Zhang, B., et al.: ‘A nonlocal TV-based variational method for PolSAR data speckle reduction’, IEEE Trans. Image Process., 2016, 25, (6), pp. 2620–2634

Fan, H., Li, C., Guo, Y., et al.: ‘Spatial-spectral total variation regularized low-rank tensor decomposition for hyperspectral image denoising’, IEEE Trans. Geosci. Remote Sens., 2018, 56, (10), pp. 6196–6213

Figueiredo, M.A.T, Dias, J.B., Oliveira, J.P., et al.: ‘On total variation denoising: a new majorization-minimization algorithm and an experimental comparison with wavelet denoising’, Proc. IEEE Int. Conf. Image Processing, Atlanta, GA, USA, 2006, pp. 2633–2636

Selenick, I.W., Bayram, I.: ‘Total variation denoising’, White Paper, NYU-Poly, 2010

Selenick, I. W.: ‘Total variation denoising (an MM algorithm) NYU polytechnic school of engineering lecture notes’, 10th September, 2012. Available at http://eweb.poly.edu/iseslesni/lecture_notes/

Sun, Y., Babu, P., Palomar, D.P.: ‘Majorization-minimization algorithms in signal processing, communications, and machine learning’, IEEE Trans. Signal Process., 2017, 65, (3), pp. 794–816

Langer, A.: ‘Automated parameter selection for total variation minimization in image restoration’, J. Math. Imaging Vis., 2017, 57, (2), pp. 239–268

Lin, Y., Wohlbberg, B., Guo, H.: ‘UPRE method for total variation parameter selection’, Signal Process., 2010, 90, (8), pp. 2546–2551

Blu, T., Louisier, F.: ‘The SURE-LET approach to image denoising’, IEEE Trans. Image Process., 2007, 16, (11), pp. 2778–2786

Ramani, S., Liu, Z., Rosen, J., et al.: ‘Regularization parameter selection for non-linear iterative image restoration and MRI reconstruction using GCV and SURE-based methods’, IEEE Trans. Image Process., 2012, 21, (8), pp. 3659–3672

Hansen, P.C.: ‘Analysis of discrete ill-posed problems by means of the L-curve’, SIAM Rev., 1992, 34, (4), pp. 561–580

Babacan, S.D., Molina, R., Katsaggelos, A.K.: ‘Parameter estimation in TV image restoration using variational distribution approximation’, IEEE Trans. Image Process., 2008, 17, (3), pp. 326–339

Chen, K., Piccolomini, E.L., Zama, F.: ‘An automatic regularization parameter selection algorithm in the total variation model for image deblurring’, Numer. Algorithms, 2014, 67, (1), pp. 73–92

Kuhn, W.B., Bouté, A.P.: ‘Measuring and reporting high quality factors of inductors using vector network analyzers’, IEEE Trans. Microw. Theory Tech., 2010, 58, (4), pp. 1046–1055

Singam, B., Hui, L.Y.: ‘Assessing SMS and PJD schemes of anti-islanding with varying quality factor’, 2006 IEEE Int. Power and Energy Conf., Putra Jaya, 2006, pp. 196–201

Akhalghi, S., Sarailoo, M., Akhalghi, A.: ‘A novel hybrid approach using SMS and ROCOF for islanding detection of inverter-based DGs’. 2017 IEEE Power and Energy Conf. Illinois (PECI), Champaign, IL, 2017, pp. 1–7

Bower, W., Ropp, M.: ‘Evaluation of islanding detection methods for utility-interactive inverters in photovoltaic systems’. Sandra report SAND, 3591, 2002

IEEE 929-2000: ‘IEEE recommended practice for utility interface of photovoltaic systems’, 2000

Saini, M., Beniwal, R.: ‘Detection and classification of power quality disturbances in wind-grid integrated system using fast time-time transform and small residual-extreme learning machine’, Int. Trans. Electr. Energy Syst., 2018, 28, (4), pp. 1–23

Kersting, W.H.: ‘Radial distribution test feeders’, IEEE Trans. Power Syst., 1991, 6, (3), pp. 975–985

Fanniakh, M., Elhaifyani, M.L., Zouggar, S.: ‘Hardware implementation of the fuzzy logic MPPT in an Arduino card using a Simulink support package for PV application’, IET Renew. Power Gener., 2019, 13, (3), pp. 510–518