Comprehensive review of IDMs in DG systems

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Abstract: Distributed generation (DG) offers solution to the ever increasing energy needs by generating energy at the consumer end, in most cases, by means of renewable energy sources. Islanding detection is an important aspect of interconnecting a DG to the utility. This study presents comprehensive review of various islanding detection techniques along with their relative advantages and disadvantages. A broad classification of islanding detection methods (IDMs) is laid out as classical methods, signal processing (SP)-based methods, and computational intelligence-based methods with a focus on SP-based methods and computational intelligence-based methods. The evolution of SP techniques used for islanding detection is presented along with the merits and shortcomings of each technique. Furthermore, the advent of computational intelligence methods based IDMs are discussed along with their merits and demerits. An insight into various islanding methods based on quantitative measures of performance indices such as detection time, detection accuracy, and efficiency are tabulated and presented. Finally, the prospective direction of research for IDMs is also presented.

1 Introduction

With a surge in demand for energy and the depleting fossil fuel resources, it has become the need of the hour to come up with solutions to meet the insatiable need for energy consumption. The increasing load demand will further increase the cost of transmission and distribution, in addition to the generation cost. However, in the recent past, the cost of distributed generation (DG) sources is coming down, thereby making DG sources an economical solution by connecting them at the distribution end [1]. This approach results in saving the cost needed for expanding transmission and distribution facilities [2]. DG, mostly with renewable energy sources and energy storage devices, at the consumer side, is one such solution to meet the future energy demands [3]. This approach has no detrimental effects on the environment [4]. However, one of the issues with renewable sources is their intermittent nature [5]. The intermittent nature of renewable sources makes it difficult to operate and control them [6]. These fluctuations not only affect the power quality and the system dynamics, but also possess some challenges to seamlessly integrate them to the grid. The primary concerns in regard to islanded systems are: (i) in the absence of stiff source (grid), the frequency and voltage variations tend to be significant, if not regulated (ii) islanding may create hazards to utility line workers by causing a line to remain energised, (iii) out-of-phase re-closure may lead to significant damage to the DG in the islanded part, and (iv) islanding may affect the automatic restoration of service for the nearby consumers [1].

One such challenge is the islanding phenomenon. Islanding in any DG system is a condition wherein the distributed energy resource is isolated from the grid and still continues to supply to the local consumers. Islanding can either be planned or unplanned.

Microgrids can operate either in grid-connected or isolated mode and each mode has strikingly different strategies to achieve optimal performance. In grid-connected mode of operation, the primary goal is optimal and economical operation. In planned islanding, a controllable operation, the microgrids still supply power to the local loads to ensure continuity of supply while the utility is disconnected. Unplanned islanding on the other hand is an uncontrollable operation and hence it is undesirable. It may arise due to several reasons such as line tripping, human error, or equipment breakdown. Unplanned islanding seriously affects the microgrid operation and hence it must be detected and disconnect the DGs. Various islanding detection methods (IDMs) have been proposed over the years with a primary goal to detect islanding event adhering to the international standards.

Furthermore, this paper is organised as follows: in Section 2, various international standards for islanding detection are summarised. In Section 3, classification of IDMSs is discussed. Section 4 gives a brief account of classical IDMs. In Section 5,
IDMs based on signal processing (SP) techniques are presented. In Section 6, computational intelligence-based IDMs are reviewed. Section 7 gives the conclusion of the techniques discussed.

2 International standards

Several international standards currently exist across the globe for interconnecting a DG to the utility. All these standards, more or less, demand stringent requirements for islanding detection in terms of detection time, q-factor, frequency range, and nominal voltage values. These standards are used as a benchmark while developing new techniques for islanding detection. A digest of various international standards is given in Table 1.

3 Classification of IDMs

IDMs can be broadly classified as classical methods, which include all the local methods such as passive, active, and hybrid methods, remote methods, SP methods, and intelligent/computational intelligence-based methods. Classification of IDMs is shown in Fig. 1. Although the main focus of this paper lies in SP and intelligent islanding techniques, classical IDMs are also discussed for the sake of completeness; therefore, brevity is maintained while addressing classical methods.

4 Classical methods

4.1 Passive methods

Passive IDMs, as the name suggests, passively monitor a range of electrical quantities at the point of common coupling (PCC) and check if they are below the preset threshold value. Consequently, if the monitored electrical quantity goes beyond the threshold value, which is most likely in the event of loss of grid, an islanding event is detected as depicted in Fig. 2. Various passive IDMs reported in the literature are discussed below and a summary of passive IDMs is presented in Table 2:

i. Voltage unbalance (VU): During an islanding event, even if the load variations are nominal, an unbalance in the voltage arises as a result of the topological changes in the system. An islanding detection scheme based on this technique is proposed by monitoring the negative and positive-sequence components [7].

ii. Total harmonic distortion (THD): Whenever there is a loss of mains, an immediate effect is changes in the loading of the DG. These changes in loading result in variation of the harmonic content in the current. Therefore, by monitoring the harmonic distortion, islanding event can be detected [7].

iii. Over/under voltage and over/under frequency (OUV/OUF): In grid-connected mode of operation, the active and reactive power requirements of the load, \( P_{\text{load}} \) and \( Q_{\text{load}} \), are supplied by the DG \( (P_{\text{DG}} \text{ and } Q_{\text{DG}}) \) and the mismatch between the two is supplied by the grid

\[
\Delta P = P_{\text{load}} - P_{\text{DG}}
\]

\[
\Delta Q = Q_{\text{load}} - Q_{\text{DG}}
\]

However, in the event of islanding, to maintain the active and reactive power balances, the voltage and frequency will change such that \( \Delta P = 0 \) and \( \Delta Q = 0 \), respectively [8]. The variations of these two parameters are monitored to detect an island.

iv. Rate of change of power (ROCOF): An islanding event has a direct consequence on the load change; therefore, by monitoring variations in the power output of the target DG islanding event can be detected [9].

v. Rate of change of frequency (ROCOF): When a DG source is operating in the islanding mode, the power mismatch will lead to a change in the frequency [9]. Therefore, by monitoring the ROCOF over few cycles and comparing it with the threshold value, islanding event can be detected [10].

vi. ROCOF over power (ROCOFOF): ROCOF technique has difficulties detecting the islanding situations especially when the power mismatch between the load and islanded DG is very small. To overcome this drawback, a method based on \( df/dP \) is proposed to detect islanding event even under small power mismatch cases [11].

vii. Phase jump detection (PJD): PJD essentially monitors the phase difference between output voltage and current of a grid-tied inverter [12]. Phase-locked loops (PLLs) are used to synchronise the inverters with the voltage at the PCC. This is achieved by a PLL by detecting the zero crossing of the voltage at PCC. However, during an islanding event the inverter output current remains unchanged while the voltage at the PCC, as a consequence of islanding, is no longer stiff. This will result in a phase jump of the voltage since the phase angle of the load is still the same. By detecting this phase jump, islanding event can be detected [13].

4.2 Active methods

Despite having very short detection times, passive IDMs possess inherent shortcomings such as the presence of non-detection zone (NDZ) and the setting of threshold value for islanding detection. Especially with threshold setting, too low a value will lead to nuisance tripping while slightly larger threshold setting will result in missed islanding event. To overcome the shortcomings of passive techniques, active methods are proposed. Active methods take advantage of the fact that response of the grid to a perturbation can vary drastically under normal conditions and islanded conditions. Active islanding, as shown in Fig. 3, injects a

| Table 1 International standards for anti-islanding |
|-------------|-----------|-------------|
| Standard    | \( Q \)  | Detection time | Voltage range |
| IEEE 929-2000 | 2.5      | within 2 s    | 59.3–60.5 Hz   | 0.88–1.1 pu |
| IEEE 1547    | 1        | within 2 s    | 59.3–60 Hz     | 0.88–1.1 pu |
| IEC 62116    | 1        | within 2 s    | 59.3–60 Hz     | 0.88–1.15 pu |
| UL 1741      | 1        | within 2 s    | 59.3–60.5 Hz   | 0.88–1.1 pu |
| UK G83/2 (DGs up to 16 A/phase) | 0.5 | within 0.5 s  | 47.5–51.5 Hz (stage 1) | 0.87–1.1 pu (stage 1) |
| UK G83/3 (17 kW/phase or 50 kW/three phase) | 0.5 | within 0.5 s  | 47.5–51.5 Hz (stage 1) | 0.87–1.1 pu (stage 1) |
| Canadian C22.2 No. 107-01 | 2.5 | within 2 s    | 59.5–60.5 Hz   | 0.88–1.06 pu |
| German VDE 0126-1-1 | 2 | within 0.2 s  | 47.5–50.2 Hz    | 0.88–1.15 pu |
| French       | 2        | instantly     | 49.5–50.5 Hz    | 0.88–1.06 pu |
| ERDF-NOI-RES 13E Japanese JIs | 0 within 2 s (active IDM) | setting value | setting value |
|             | 0.5–1 s (passive IDM) | setting value | setting value |
| Korean       | 1        | within 0.5 s  | 59.3–60 Hz     | 0.88–1.1 pu |
perturbation into the grid parameters, continuously at set intervals, and analyses the response. If the parameter exceeds a set threshold value in the analysed response, active methods classify it as an islanding event.

**Fig. 1 Classification of IDMs**

**Fig. 2 Block diagram of passive IDM**

**Table 2 Summary of passive islanding detection techniques**

| Technique            | NDZ  | Impact on power quality | Detection time  | Error detection rate |
|----------------------|------|-------------------------|-----------------|----------------------|
| VU                   | large| none                    | 53 ms           | low                  |
| harmonic distortion  | large for high Q | none | 45 ms | high                |
| OUV/OUF              | large| none                    | 4 ms–2 s        | low                  |
| ROCOP                | small| none                    | 24–26 ms        | high                 |
| ROCOF                | small| none                    | 24 ms           | high                 |
| ROCOFOP             | <ROCOF| none            | 100 ms          | low                  |
| phase jump detection| large| none                    | 10–20 ms        | low                  |
Various active IDMs reported in the literature are given below and a summary of these techniques is presented in Table 3:

i. Impedance measurement method: In this method, the magnitude of the inverter output current is continuously varied and the corresponding change in the voltage is monitored [14]. The variation is calculated as \( \frac{dv}{dt} \), as equivalent impedance seen from the inverter. If the value exceeds a certain threshold, it will be classified as an islanding event [15]. However, the difficulties that arise in setting the threshold value make it impractical to implement.

ii. Active frequency drift (AFD) method: Once an inverter is synchronised to the grid, the voltages at the PCC and the inverter current remain fixed. However, when there is a loss of mains, a small disturbance caused in the inverter’s output current will lead to a change in the zero crossing of the voltage giving rise to a change in the phase. This forces the inverter to drift the current to eliminate phase error. This process will lead to a point, where the frequency at the PCC is higher than the threshold value leading to detection of an islanding situation [12].

iii. Frequency jump (FJ) method: FJ, just like AFD, also introduces a dead zone in the inverter's output current waveform, but not in every cycle; for instance, a dead zone in every three cycles [12]. Despite the dead zones introduced to the current waveform, the voltage at PCC remains unchanged when it is connected to the grid. When islanding occurs, the voltage at PCC no longer remains stiff and the islanding is detected by the variation in voltage frequency [16]. Both AFD and FJ techniques fail to perform well for multiple inverters operating in parallel.

iv. AFD with positive feedback (AFDPF) method: A method to minimise the existence of NDZ in AFD is proposed in [17] by employing positive feedback to increase the chopping frequency with increasing frequency deviation from the nominal value as follows:

\[
 cf_k = cf_{k-1} + F(\Delta \omega_k) \quad (3)
\]

where \( cf_{k-1} \) and \( \omega_{k-1} \) are chopping fraction and frequency in the previous cycle, respectively, and \( F \) is a function which maps sampled frequency error \( \Delta \omega_k = \omega_k - \omega_n \). This function, when properly chosen, adds significant improvements to AFD. However, the power quality is slightly affected and NDZ still prevails for loads with high-quality factor.

v. Sandia frequency shift (SFS): SFS is an extension of AFD, wherein a positive feedback is applied to the frequency of the inverter's voltage and its chopping frequency is defined as [12]

\[
 cf = cf_k + K(f_{PCC} - f_{grid}) \quad (4)
\]

where \( cf_k \) is the chopping frequency when there is deviation in frequency, \( K \) is the accelerating gain, \( f_{PCC} \) is the frequency of the voltage at PCC, and \( f_{grid} \) is the grid frequency. SFS offers least NDZ in comparison with all the other active methods [16].

vi. Sandia voltage shift (SVS) method: SVS is yet another method that employs positive feedback, in this case to the amplitude of voltage at the PCC, for islanding detection. When the utility is disconnected, by applying a positive feedback to the voltage at PCC, there is a corresponding change in the inverter's output current and power which can further accelerate the voltage drift to detect the islanding condition [12]. Despite its ease of implementation and an efficiency comparable with SFS, SVS has some drawbacks such as slight degradation of power quality and reduction of inverter's efficiency as a consequence of changing output power and its effect on maximum power point tracking [16].

vii. Slip mode frequency shift (SMS) method: In SMS method, the output current of the utility connected converter, which is expressed as (5), is controlled as a function of the frequency of the voltage at the PCC [18].

\[
 i_{CON} = I \sin(2\pi f_t + \theta_{SMS}) \tag{5}
\]

where \( f \) and \( \theta_{SMS} \) are PCC voltage frequency and phase angle for the SMS technique, respectively. \( \theta_{SMS} \) is further set as given below:

\[
 \theta_{SMS} = \frac{2\pi}{360} \theta_m \sin \frac{\pi f - f_{grid}}{2f_m - f_{grid}} \tag{6}
\]

where \( f_{grid} \) is the nominal grid frequency, \( \theta_m \) and \( f_m \) are maximum phase angle and the corresponding frequency at which it occurs, respectively.

During grid-connected mode of operation, the phase angle \( \theta_{SMS} \) is almost zero for rated utility frequency. However, during islanding mode of operation the phase angle is entirely dependent on the external perturbation and the variation in the phase angle can be used to detect an islanding event [19].

1. Variation of active (P) and reactive (Q) power methods: During an islanding condition, the changes in the real power output of an inverter, caused due to variation of temperature and/or irradiance, flow into the load. This will directly affect the inverter output current and the voltage at the PCC. The variation of the output power caused by the active power variation injected by inverter can be expressed as follows [20]:

\[
 P_{DG} = P_{load} = \frac{V^2}{R} \quad \tag{7}
\]

The variation in voltage can be derived from (7) as

\[
 \Delta V = \frac{\Delta P_{DG}}{2} \sqrt{\frac{R}{P_{DG}}} \quad \tag{8}
\]

In (8), since \( R \) and \( P_{DG} \) are constant, the variation in voltage is directly dependent on variation in \( P_{DG} \). Similarly, relation between variation in reactive power (Q) and variation in frequency is given as

\[
 \Delta Q = K_i(f_n - f) \quad \tag{9}
\]

where \( K_i \), \( f_n \) and \( f \) are gain, nominal value of frequency, and the estimated value of frequency, respectively.

1. Negative-sequence current injection method during grid-connected mode of operation, if a negative-sequence current component is injected it will entirely flow into the grid since the grid offers low impedance. Therefore, the injected negative-sequence current will have no effect at all on the voltage at PCC. However, in the event of an islanding
condition, the injected negative-sequence current will flow into the local load, resulting in an unbalance in voltage at the PCC. An islanding event can be detected when unbalance exceeds the set value [21]. The voltage imbalance to detect islanding event is defined as

\[ VI = \frac{V_n}{V_p} \times 100\% \]  

(10)

where \( V_n \) and \( V_p \) are instantaneous magnitudes of negative-sequence and positive-sequence voltages in abc reference fame, respectively. The advantages of this method include short detection time, no NDZ, and a higher accuracy than positive-sequence voltage injection method.

2. High-frequency signal injection method: An IDM based on injection of high-frequency low-magnitude voltage signal is proposed in [22]. High-frequency impedance can be measured by injecting various forms of excitations such as rotating or a pulsating voltage vector. The advantages of this method are negligible effects on power quality due to the injection of high-frequency voltage signal, accurate, and fast islanding detection.

3. Virtual capacitor/inductor method: IDMs are proposed where the grid-connected power inverter serves as a virtual capacitor when the frequency is slightly lower than the nominal frequency [23] and as a virtual inductor when the frequency is slightly higher than the nominal frequency [24], during an islanding event. Therefore, the amplitude and frequency of the voltage varies even when the real and reactive power mismatch is negligible, resulting in better islanding detection.

4. Phase PLL perturbation: Velasco et al. in [25] have proposed a method which adds a current harmonic to the inverter reference current. By modifying the phase signal of the PLL, a perturbation is generated such that the angle of the inverter reference current \( \theta_{INV} \) is as below:

\[ \theta_{INV} = \theta_{PLL} + k \cos(\theta_{PLL}) \]  

(11)

where \( k \) is the rate of disturbance introduced in the system. Since a PLL is used to generate the perturbation signal, it is always proportional to the injected current. Another advantage of this method is that it does not affect the zero crossing of the signal.

5. Positive feedback-based IDM: In [26], active IDMs based on the output impedance is proposed for current loop disturbance technique and power loop disturbance technique. An islanding event is detected based on the violation of the Nyquist criteria for impedance ratio. An active DC distribution system is considered for implementing the IDMs.

### 4.3 Hybrid methods

As opposed to passive IDMs, active methods could significantly minimise the NDZ, and thereby improve the detection accuracy. However, the injection of a disturbance signal, in addition to, increasing the complexity of system, also affects the power quality. To avoid continuously injecting a disturbance signal, hybrid techniques are devised by combining passive techniques as a primary detection technique and active method as a secondary detection technique as depicted in Fig. 4. Hybrid methods inherit the desirable features of both passive and active techniques. The following are various hybrid methods reported in the literature:

i. **VU and frequency set point method:** This islanding detection technique combines positive feedback, an active technique, and VU/THD, a passive method, thus making it a hybrid method. At the outset, the three-phase voltages are continuously monitored at the output terminal of the DG and VU is calculated. Owing to its higher sensitivity, VU is used as a detection parameter in ROCOF and ID. Since VU may arise due to an islanding or a sudden variation in load, frequency set point is lowered whenever VU is above the threshold value to properly discriminate an islanding event from other disturbances. The detection time is reported to be 0.21 s [27].

ii. **Voltage and real power shift (RPS):** This hybrid technique is a combination of average rate of voltage change and RPS, a passive method and an active method, respectively. Initially, voltages are continuously measured at the DG terminals and whenever a \( \frac{dV}{dt} \neq 0 \) is detected, the magnitude of average rate of change of voltage, \( AV \), for five cycles is calculated to check for an islanding. If \( AV > V_{SMAX} \), where \( V_{SMAX} \) is the maximum set point, then it can be classified as an islanding event, and if \( AV < V_{SMIN} \), where \( V_{SMIN} \) is the minimum set point, then islanding is not suspected. However, if \( V_{SMIN} < AV < V_{SMAX} \), then the change could be due to an islanding or some other disturbance in the system. At this point, RPS is used to determine whether the system is islanded or not [28].

iii. **Voltage fluctuation injection:** This hybrid islanding detection scheme comprises of two indices based on passive detection methods, namely ROCOF and ROCOV, and one parameter, namely correlation factor, that gives the correlation between the variation in the terminal voltage of the DG source and the voltage perturbation source. In this method, the passive islanding detection scheme is used as a primary detection scheme and the active technique is used as a backup scheme. This method can detect islanding within 0.216 s [29].

iv. **Hybrid SFS and Q–f method:** In this hybrid method, a combination of \( Q-f \) droop, a passive method, and SFS, an active method, are used. To overcome the instability of SFS and to minimise the NDZ, the optimum value of gain is determined by applying bacterial foraging optimisation algorithm. The \( Q-f \) droop curve scheme is further added to the above technique to enhance the overall effectiveness of the hybrid detection technique [30].

### Table 3 Summary of active islanding detection techniques

| Technique                        | NDZ    | Impact on power quality | Detection time | Error detection rate |
|----------------------------------|--------|-------------------------|----------------|---------------------|
| impedance measurement            | small  | degrades                | 0.77–0.95 s    | low                 |
| AFD                              | large  | degrades                | within 2 s     | high                |
| frequency jump                   | small  | degrades                | 75 ms          | low                 |
| AFDPF                            | smaller than AFD | slightly degrades | ~1 s | lower than AFD |
| SFS                              | smallest | slightly degrades     | 0.5 s          | low                 |
| Sandia voltage shift             | smallest | slightly degrades     | 0.5 s          | low                 |
| SMS                              | small  | degrades                | ~0.4 s         | low                 |
| variation of P and Q             | small  | degrades                | 0.3–0.7 s      | high                |
| negative-sequence current injection | none   | degrades                | 60 ms          | low                 |
| high-frequency signal injection  | smallest | slightly degrades     | few ms         | low                 |
| virtual capacitor                | smallest | slightly degrades     | 20–51 ms       | low                 |
| virtual inductor                 | smallest | slightly degrades     | 13–59 ms       | low                 |
| phase PLL perturbation           | smallest | negligible             | 120 ms         | low                 |

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4.4 Remote methods

Remote techniques employ communication between the utility and the DG to detect an occurrence of an islanding event. This requires additional instrumentation in order to establish a communication link between the utility and the DG, which is an expensive affair. However, the upside of these methods includes the absence of NDZ, no degradation of power quality, and it is effective in multi-DG environment. Various remote IDMs are presented here:

i. Power line carrier communication (PLCC): This technique employs two devices: a signal generator connected at the substation end and a signal detector connected at the target DG terminals. The signal generator continuously transmits a signal through the power line itself to all the distribution feeders. This signal will be detected by the signal detectors present at the DG location. However, if the signal detector fails to detect the signal for more than a set duration, it can be concluded that an islanding has occurred and the DGs will be eventually tripped [31]. Since the transmitter is expensive, considering the economic aspects, this method is used in cases where the DG system density is high. The detection time of this method is about 200 ms [32].

ii. Signal produced by disconnect (SPD): This method is similar to PLCC technique since this method also uses the concept of signal transmission from the utility end to the DG location. However, the difference between the two schemes lies in the fact that SPD uses microwave link, telephone line, or other means for communication. Therefore, when the detector at the DG end fails to receive a signal for a set duration, then it will be classified as an islanding event [12]. The disadvantage, however, of this technique is that it requires a huge investment for setting up the communication links.

iii. Supervisory control and data acquisition (SCADA): Islanding detection by means of SCADA is accomplished by measuring the voltage at the target DG location. If a voltage is sensed when the utility is disconnected, SCADA system will take necessary action to tackle the islanding event by sending signals to the corresponding DG [12]. This method can eliminate NDZ and greatly enhance the efficiency of the system. However, this method suffers with slow detection speeds, increased expenditure on instrumentation and communication links, and a complex installation procedure which is not justified for smaller DGs.

5 SP techniques

On one hand, passive methods offer the advantage of fast response time, but on the other hand, they have a large NDZ which is undesirable. Active methods do not have issues with NDZ as much as passive methods do, but they, in varying degrees, have a negative influence on power quality of the system and hence are employed with caution. Minimisation of the NDZ of passive methods can greatly enhance their overall performance and hence make them a viable alternative to active methods. SP methods come in handy to achieve the task of minimising NDZ since they are capable of extracting hidden features of any given signal and unveil a great deal of information about the state of the system. On the basis of the knowledge of the extracted features, an islanding event can be classified, as explained further.

SP-based IDM, as shown in Fig. 5 monitors various parameters at the PCC and applies an SP technique to derive hidden features, which are further used for islanding detection. Different SP methods for islanding detection by feature extraction are explained further and a summary of these techniques is presented in Table 4.

5.1 Fourier transform (FT)-based methods

FT is a popular technique used for frequency-domain analysis, wherein a signal is characterised by a series of sinusoidal signals of different frequencies. However, FT does not have the ability to resolve any transient information associated with dynamic variations [56]. Therefore, to overcome this problem time–frequency analysis is proposed. Short-time FT (STFT), a modification of FT, segments a signal into small frames, wherein each frame can be treated as stationary. A moving window technique is further applied to evaluate all these frames, which allows us to have a time–frequency analysis of the signal [57]. The disadvantage, however, is that STFT cannot be applied to non-stationary signals due to the fixed window width [58]. However, by selecting an appropriately small window, STFT can be used to identify transients in voltage disturbance signals [59].

Discrete FT (DFT) is a technique that is employed to perform frequency-domain analysis on discrete time signals, which are sampled from continuous time signals. Fast FT (FFT) is an algorithm that is used to compute the DFT with a significant enhancement of computational efficiency [60]. In spite of its computational efficiency, FFT suffers from limitations such as the depiction of high-frequency components as low-frequency components [61]. An IDM based on DFT is reported in [33] with a detection time of 1 ms even under the circumstances, where the difference between power generated by the photovoltaic (PV) and power consumption by load is insignificant. This method uses variation of harmonic component in the grid voltage to detect islanding. A total of 256 components are used. Another IDM reported in [62] employs FFT to calculate the harmonic content of the equivalent reactance seen at the DG location, which is further given as an input feature for an intelligent classifier. FFT with artificial neural network (ANN) to detect islanding event is discussed in [63]. In this method, harmonic signature of the output voltage of the inverter is used as an input feature for ANN. Goertzel algorithm (GA), a type of DFT, which has the fastest technique for pitch detection in comparison with DFT and FFT, is
utilised for islanding detection has been reported in [34]. In this method, a disturbance is injected into the grid and the variation of the harmonic component, which is calculated by DFT-based GA (DFT-GA), in the voltage at PCC is monitored. The detection time using DFT-GA is reported to be under two cycles.

### 5.2 Wavelet transform (WT)-based methods

WT, just like FT, is a technique used for the analysis of a signal [64]. However, the difference lies in the fact that, in wavelet analysis, the signal is characterised in terms of small waves, called wavelets, which are generated from a fixed function called mother wavelet. These wavelets are localised in both time and frequency, thus making WT a suitable candidate for time–frequency analysis of signals [65]. Owing to the fact that wavelets have short windows at high frequencies and large windows for low frequencies, it can depict the dynamic behaviour, transients, and discontinuities. This can be effectively used for islanding detection. Also, WT can be used for non-stationary signals. WT can be classified as continuous (CWT) or discrete (DWT). In [35], CWT and Mallat decomposition are used to detect islanding event and to filter the noise from signal, respectively. To reduce the computational burden arising from the numerous coefficients in CWT, alternate techniques such as DWT have been investigated for islanding detection.

Daubechies mother wavelet-based DWT is used for islanding detection by effectively capturing the changes in the signal at the DG terminals [36]. To detect an islanding event, a three-level decomposition with Daubechies mother wavelet using a four-coefficient filter is programmed into an field programmable gate array. The variation in the computed coefficients from the voltage signal is used for islanding detection. Some of the reported advantages are: improved islanding detection capability and ease of programming.

A hybrid IDM has been reported in [37], which monitors voltage and current at PCC. This work is extended in [38], where, in addition to the passive method used, it also monitors the high-frequency components introduced by the DG inverter and the associated filter and controller for islanding detection. The harmonic performance of a given pulse-width modulation technique depends on the effect of pulse width, its position within carrier interval, and pulse sequence within and across carrier interval on harmonics induced by the phase leg switched waveform and harmonic cancellation, if any, between individual leg outputs. On the other hand, varying the switching frequency attenuates the harmonics through low-frequency filtering and has no influence on the magnitude of the harmonics [66]. The purpose of an LCL filter is to reduce the harmonic injections. However, if the resonant frequency of the filter is sufficiently lower than the switching frequency, then the filter is not effective. This is due to the fact that the effect of capacitor is not influential in averaged model that is used for stability studies [67].

DWT with bi-orthogonal 1.5 mother wavelet has been used on the high-frequency components introduced by the PV inverter at PCC as it offered good response times and time–frequency resolution. In addition to the above-mentioned advantages, this method requires fewer sensors and has enhanced computational efficiency.

In [39], Daubechies db4-based DWT is applied for negative-sequence components of voltage and current at the target DG terminals and the classification of islanding event is determined by

| Table 4 Summary of SP-based IDs |
|--------------------------------|
| **Category**                  | **Reference** | **SP method** | **Tested system** | **Detection time** | **Efficiency/accuracy** | **Sensitivity to noise, dB** |
| FT                            | [33]          | DFT           | PV system         | 1 ms              | —                      | —                        |
| WT                            | [34]          | DFT-GA        | single-phase two-stage PV | < two cycles      | —                      | —                        |
| [35]                          | CWT           | grid-tied DG  |              | 0.6 s            | —                      | —                        |
| [36]                          | DWT           | DG at petroleum company | 0.05–1 s     | —                | —                      | —                        |
| [37, 38]                      | DWT           | PV (low power) |              | 0.5–30 cycles    | —                      | 5% mismatch (P)          |
| [39]                          | DWT           | wind farm (doubly-fed induction generator ) |              | one cycle         | —                      | 50% mismatch (P)         |
| [40]                          | DWT           | PV            |              | 2.5 cycles       | —                      | 0–20% mismatch (P)      |
| [41]                          | DWT           | wind DG       |              | <0.2 s           | —                      | 0–25% mismatch (P)      |
| [42]                          | DWT           | PV            |              | 0.05 s           | —                      | 0–±20% mismatch (P)     |
| [43]                          | DWT           | PV            |              | > one cycle      | —                      | —                        |
| [44]                          | DWT           | synchronous DG |              | 5.5 ms           | —                      | 0% mismatch (P)         |
| [45]                          | WPT           | wind farm     |              | 0.06 s           | —                      | —                        |
| [46]                          | WT (MRA)      | inverter-based DG | —            | —                | —                      | −37.3–+21% mismatch (P) |
| [47]                          | WSE           | three wind farms and gen. set |   | 10 ms           | —                      | 0–80% mismatch (P)      |
| [48, 49]                      | ST            | PV, fuel cell, and wind | 26–28 ms | —                | —                      | 20                       |
| [50]                          | ST (CUSUM)    | wind farm     |              | 25 ms            | 100% at DG-1           | 40% mismatch (P)         |
| [51]                          | HST           | PV, fuel cell, and wind | —            | —                | —                      | —                        |
| [52]                          | TT-T          | PV, fuel cell, and wind | —            | —                | —                      | 20                       |
| [53]                          | HHT           | inverter-based DG | < two cycles | —                | 0–80% mismatch (P)      | —                       |
| [54]                          | MM            | PV and wind (IEEE-30 bus) | 22 ms      | 98.4% at DG-1    | 60% mismatch (P)       | 20                       |
| [55]                          | MMRI          | wind and diesel generator | ≤20 ms    | 100% at DG-1     | 0–40% mismatch (P)     | —                       |

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the variation in energy coefficients and standard deviation (SD). In this method, the detection time for islanding event classification is reported as one cycle. The compactness and localisation properties of Daubechies db4 are used to minimise the NDZ in [40]. Another feature of db4 is that it makes use of second-level wavelet coefficients (d2) to identify the spectral changes in higher-frequency components, whereas db4 DWT and db3 DWT are used for islanding detection of wind turbine-based grid-connected PV DG [42], respectively. Dyadic DWT, a DWT technique based on Mallat's pyramid algorithm [68], has been used to detect islanding event because of its simplicity and non-redundancy [43]. DWT with Haar wavelet as a mother wavelet is used for loss of grid detection in multi-DG environment. Haar wavelet requires fewer decomposition levels, thus least detection time [44]. The detection time reported is 5.5 ms.

While CWT generates too many coefficients and reduces the computational efficiency, DWT ends up mixing high frequencies, which results in loss of information. Wavelet packet transform (WPT) is proposed [45] to overcome these challenges. In this method, node ROCOP index is defined based on WPT and ROCOP output at the DG terminals.

Multi-resolution analysis (MRA) based on WT is reported in [46] for islanding detection. MRA based on WT extracts harmonic features by partitioning the entire harmonic spectrum into different frequency bands and the harmonic features for each band are generalised. In this technique, WT-based MRA is applied on voltage signals at the DG terminals to decompose them into different scales, wherein for each scale a series of wavelet coefficients are generated that correspond to a certain frequency bandwidth. Islanding is detected based on the change in the ratio of the wavelet coefficients. A variation of 43% in wavelet coefficients is seen before and after islanding. Wavelet singular entropy index (WSEI)-based islanding detection is proposed in [47]. WSEI encompasses the advantages of the WT, singular value decomposition, and Shannon entropy. To calculate WSEI, first WT is applied to the three-phase voltages at the DG terminals and a coefficient matrix is generated. Second, a singular value matrix is computed for the coefficient matrix, which is used to determine the WSE of individual phases. Finally, WSE of three phases is added to calculate the WSEI which is used for detecting loss of grid.

### 5.3 S-transform (ST)-based techniques

As a means to overcome the shortcomings of WT such as sensitivity to noise and consequently its inability to detect islanding events under a noisy environment, ST has been proposed [69]. ST consolidates the properties of STFT and WT and it is based on a moving and scalable Gaussian window to perform a time-frequency representation of a time-series signal in different frequency representations. ST also gives multi-resolution while keeping the phase of respective frequency components unaffected, which comes in handy for disturbance detection in a noisy environment [71].

Ray proposed a method to detect islanding in a hybrid power system based on ST [72]. In this method, ST is applied to the acquired voltage signal and S-matrix is obtained. From the S-matrix, energy and SD are computed. An islanding event is positively detected when the energy and SD are above the fixed threshold value. Threshold values, for the configuration in which wind, fuel cell and PV are considered, are set as 0.071 pu for energy and 0.042 for SD. The threshold values, both energy and SD, are found to be higher for smaller DGs and lower for large DGs. In other words, the threshold values are inversely dependent on the DG rating. In [48], negative-sequence voltage is extracted for islanding event detection. Furthermore, the performance of ST-and WT-based detection techniques are compared on the basis of simulation results and ST-based method is reported to have detected islanding events even under noisy conditions. An extension of this work is reported in [49]. Another method that employs cumulative sum detector (CUSUM) based on ST is reported in [50]. In this method, ST is applied to the negative-sequence current and voltage signals acquired from the target DG terminals and the spectral energy content of the same is calculated. CUSUM is calculated from the spectral energy, which forms the basis for islanding detection. The threshold value of CUSUM (voltage) is 0.6 for non-islanding and 1.6 for islanding. It is also reported that the detection accuracy is marginally influenced by the DG location. The reported results show that the islanding detection accuracy is 100% when the DG location is far away from the PCC and it is 92.3% when the DG location is far away from the PCC. The rating of the DGs is same.

In spite of its enhanced performance under a noisy environment [73], ST with Gaussian window fails to effectively localise the transient disturbances. To overcome this problem, a modified version of ST, known as hyperbolic ST (HST), is proposed for analysing power quality events in [74]. As opposed to ST, HST uses a pseudo-Gaussian hyperbolic window which has a frequency-dependent shape in addition to height and width [75]. The resulting asymmetry gives superior time and frequency resolutions both at high and low frequencies. An IDM based on HST in a multi-DG system is presented in [51]. In this technique, negative-sequence component of voltage retrieved from the PCC is considered for islanding detection. The use of negative-sequence components for detecting islanding stems from the fact that during normal operating conditions the impedance offered by the grid to negative-sequence component is very low and hence all negative-sequence components will flow into the grid. However, during islanding conditions the grid is disconnected and all the negative-sequence components now flow into the load. This will lead to an unbalanced voltage which can be easily detected [21]. Furthermore, negative-sequence components are immune to noise to a great extent [49]. From the reported results, it is evident that HST performs better than WT and ST even under noisy conditions.

### 5.4 Time–time (TT) transform-based techniques

TT transformation (TT-T) is a technique based on ST, which presents a one-dimensional (1D) time-series data in a 2D TT-series representation. TT-transform aids in providing an enhanced time localisation of a signal through scaled windows [76].

An IDM based on TT-transform is proposed in [52]. It is shown that TT-transform method has the ability to detect islanding effectively based on the unique contour patterns of various disturbance signals. From the reported results in [52], 2D TT-transformed plots of voltage signal at the PCC have a unique pattern contour for grid-connected and islanded modes of operations. These 2D contour plots exhibit a clear distinction between normal operating conditions and islanded conditions. Therefore, the patterns themselves form the features for islanding detection. TT-transform is dependent on the choice of mother wavelet. For instance, WT has been employed in [51] to extract desired features, which are further used for detecting islanding events. The performance of TT-transform, in comparison with, WT and ST is found to be superior.

### 5.5 Hilbert–Huang transform (HHT)-based techniques

The HHT is an SP technique used for processing non-linear and non-stationary signals [77]. HHT is composed of two steps: in step one, the signal is decomposed into various components called as intrinsic mode functions (IMFs). This is achieved by employing empirical mode decomposition (EMD). In the second step, Hilbert transform is applied to the decomposed IMFs to get the Hilbert spectrum. This entire process is termed as HHT [78]. The merits of HHT over WT, STFT, and ST are discussed in the literature. The advantage of HHT over FT is that HHT has also been noted in [51] to extract only stationary signals [79]. When compared to WT, the nature of decomposition is dependent on the choice of mother wavelet. For HHT, no such assumptions need to be made or in other words HHT performs adaptive decomposition. This is reflected in empirical procedure of generating IMFs. Also, WT cannot achieve fine resolutions in both time domain and frequency domain simultaneously. WT also suffers problems such as leakage of energy, interference terms, and distortion at borders leading to spikes [80]. ST on the other hand is a generalisation of STFT with a scalable Gaussian window, which may not be suitable for all
applications. For instance, at high frequency, the Gaussian window will be too narrow, so the points we practically apply will be too less.

EMD-based IDM is proposed in [53]. In this method, EMD is applied to voltage at the PCC and the first IMF is used to detect islanding events under two cycles.

5.6 Mathematical morphology (MM)-based technique

Morphological filters are basically non-linear signal transformation tools [81]. They are based on MM, a technique based on integral geometry and set theory and deals with the shape of a signal entirely in time domain. This technique is widely used in the field of image processing. The fundamental idea is to use a structural element as a probe to gather the data from the signal. Morphological transform decomposes a given signal into several parts which carry varied physical significance. Two fundamental morphological operators in MM are dilation and erosion [82], from which various compound morphological operators such as closing, opening, top-hat, and hit-miss transforms can be defined. Dilation is an expanding process, whereas erosion is a shrinking transform. New morphological operators such as closing and opening operators are formed by conjugation of erosion and dilation operators [83]. In [54], difference in generalised opening and closing, open, close erosion, and dilation are used for anomaly detection in a signal. MM-based islanding detection is reported in [55], where MM operators such as dilate erode difference filter (DEDF) are applied to the current and voltage signals acquired from the target DG location. Furthermore, these values are applied as an input to new operator defined as average of difference between maximum and minimum values of DEDF. In the next step, a new operator called MM ratio index (MMRI) is defined, which is used for islanding detection. The MMRI is then used as an index for detecting islanding. In [55], the threshold value for MMRI is set to 1.23. Therefore, whenever the computed value of MMRI exceeds 1.23, an islanding event is detected.

6 Intelligent techniques

From the foregoing review of various IDM, it can be clearly noted that passive IDM has the potential to achieve high detection speed, enhanced accuracy, and effectiveness in multiple DG environment when coupled with SP techniques. However, as the DG system complexity increases, it becomes evident that adding intelligence to DGs will greatly enhance the robustness of the system. Since intelligence-based techniques can handle multiple parameters simultaneously, it is possible to train the DG for various islanding cases and enhance the accuracy of detection. While using intelligent techniques, SP technique will extract features from the acquired signal, which, in the next step will be used as an input to the intelligent technique in the form of a feature vector as depicted in Fig. 6. Various intelligent techniques are reviewed and further summarised in Table 5.

6.1 NN-based techniques

A biological NN is a system with multitude of exhaustively interconnected processing units, known as neurones, that work together to solve a given task. An ANN, or more generally referred to as an NN, are defined as processing devices, either algorithms or actual hardware, that are designed based on the neuronal structure of the brain, but on much smaller scales [101]. NNs possess the ability to learn from data and recognise the patterns by means of a function that transforms the data and forwards them as activation functions to the neurones in the next layer. This process continues until the neurone in the output layer is activated, which means the ANN has successfully recognised the given data set. On the basis of its abilities, ANN is employed to classify islanding event by means of transient voltage signals produced at the instant of islanding [84]. DWT is used for extracting features which are used for training the ANN classifier. In [85], a self-organised map NNs (SOM NN) with seven neurones have been used to classify islanding events. This method uses the input signal to the droop of the governor, which carries the frequency deviation information. Training of SOM NN is carried out in two stages with learning rates \( \eta_1 \) and \( \eta_2 \) set as 0.9 and 0.02, respectively, with Gaussian neighbourhood function. A multi-layer perceptron (MLP)-type ANN has been employed for islanding detection in [86]. MLP has been selected owing to its ability to detect voltage and frequency variations. Also, this method uses only voltage at the DG terminals, sampled at 128 and 64 samples per second, as an input feature vector. NN-based islanding detection is used for comparing the performance of other classifiers in [87]. In this method, out of 21 extracted features only 4 are used as an input vector. The selection of features is done by implementing backward sequential feature selection and forward SFS.

Probabilistic NNs (PNNs): In spite of the fact that ANN-based islanding does a decent job of detecting islanding events, it suffers from certain shortcomings such as longer computational times for training and vulnerability to false minima due to the incremental adaptation approach of back-propagation method. These can be overcome by using PNNs. A PNN is defined when an exponential activation function is used instead of sigmoid activation function in an NN [102]. PNN basically has four layers, namely input layer, pattern layer, summation layer, and output layer. A method that employs transient signals generated during an islanding event along with PNN as a classifier is reported in [88], which is tested on a system with an induction generator (IG) and synchronous generator (SG). In [89], PNN in conjunction with space-phase technique for feature extraction has been used to classify islanding events.

6.2 Fuzzy logic (FL)-based techniques

FL is a computational methodology that employs rule-based approach to solve problems rather than mathematical modelling approach. These rule-based FL models are called as fuzzy inference systems. Contrary to the standard conditional logic, which is either 1 or 0, FL interprets truth in various degrees. In [90], a fuzzy-rule-based classifier is used for detecting an islanding event. A decision tree (DT) has been used to find the initial classification boundaries, based on which the membership functions and the corresponding rule base is developed. A total of 11 features are initially acquired. Out of these 11 features, three best features, namely ROCOF, ROCOP, and deviation in frequency are used for detecting islanding. A similar approach is presented in [91], where the classification boundaries are established using DT. These boundaries are further used to define fuzzy membership functions to classify islanding events. An active IDM based on fuzzy inference rules is proposed in [92]. The proposed scheme uses positive feedback in dq-synchronous reference frame. Voltage at the target DG and frequency of the PLL \( (f_{PLL}) \) are used as input features. Fuzzification of these input features is based on the observation of the features at zero mismatch conditions. The membership functions are then categorised as small (S), negative large (NL), positive large (PL), negative medium (NM), and positive medium (PM). Another active method based on d-axis injection method for inverter-based synchronous DGs is presented in [93]. When compared to the grid-connected mode, in islanded
| Technique (reference) | Input features | Tested system | Detection | Detection efficiency/accuracy | Sensitivity to noise |
|-----------------------|----------------|---------------|-----------|-------------------------------|---------------------|
| ANN [84]              | seven wavelet levels of $V$ | three-phase PV inverter | —         | 97.22% (DG1) zero mismatch (P, Q) | —                   |
|                       |                |               |           | 97.77% (DG2) zero mismatch (P, Q) | —                   |
| [85]                  | 240 input vectors | SG            | 200 ms    | 97.9%                          | —                   |
| [86]                  | $V$ at DG terminal (64 and 128 samples/s) | SG | 2.75 s (64) | 99.28% (P, Q) zero mismatch (P) | 30% mismatch (P) |
| [87]                  | $V$, $f$, $Z_1$, and $\phi$ | SG inverter | 0.2 s     | 100% ±30% mismatch (P)         | —                   |
|                       |                |               | 0.3 s     | ±5% mismatch (Q)               | —                   |
|                       |                |               | 0.26 s    | 100%                          | —                   |
| probabilistic NN [88] | signal energy extracted by WT | IG and SG | 32 ms+ process time | 85% (average) | — |
| [89]                  | phase-space features of DG voltage | four SGs | 0.24 s | 100%                          | —                   |
| FL [90]               | $\Delta P, \Delta f, \Delta f$ | two SGs | — | 100% 40% mismatch (P) 20 & 30 dB | — |
| [91]                  | $\Delta P, \Delta f, \Delta f$ | two SGs | — | 100% 20 dB | — |
| [92]                  | $V_0$ and $\alpha_{PLL}$ | single-phase inverter | — | 97.9% 0% mismatch (P) | — |
| [93]                  | $Q - Q_{inv}$ | inverter | 0.68 s | — 0% mismatch (P) | — |
| DT [94]               | HC_odd/HC_even and max. $(dP/dt)$ | SG | 300 ms | 100% 0–25% mismatch (P) | — |
| [95]                  | $V$, $f$, $Z_1$, $\phi$ | SG | — | 97% ±30% mismatch (P) | — |
| [96]                  | $Q_{inv}$ | inverter | — | 95% ±5% mismatch (Q) | — |
|                       |                |               | 96%      | — 96%                          | —                   |
| [88]                  | signal energy extracted by WT | IG and SG | 32 ms+ process time | 90% | — |
| [94]                  | 11 indices | SG | 40–45 ms | 100% 5% mismatch (P) | — |
| [95]                  | change in $I$, $V$, $P$, $Q$, $f$, $\phi$ | SG | — | — 40% mismatch (P) | — |
| [96]                  | energy coefficients of $V$ from DWT | SG | 0.01 s | 98% (both DGs) 0% mismatch (P) | — |
| Naive Bayesian classifier [87] | $V$, $f$, $Z_1$, $\phi$ | SG | — | 100% ±30% mismatch (P) | — |
|                       |                |               | 56%      | ±5% mismatch (Q)               | —                   |
|                       |                |               | 100%     | — 100%                          | —                   |
| SVM [87]              | $V$, $f$, $Z_1$, $\phi$ | SG | — | 100% ±30% mismatch (P) | — |
|                       |                |               | 94%      | ±5% mismatch (Q)               | —                   |
|                       |                |               | 100%     | — 100%                          | —                   |
| [88]                  | signal energy extracted by WT | IG and SG | 32 ms+ process time | 74% (average) | — |
| [97]                  | 21 features extracted at PCC | inverter | 120 ms | 96.66% ±30% mismatch (P) 0% mismatch (Q) | — |
| [87]                  | $V$, $f$, $Z_1$, $\phi$ | SG | — | 100% ±30% mismatch (P) | — |
|                       |                |               | 94%      | ±5% mismatch (Q)               | —                   |
|                       |                |               | 100%     | — 100%                          | —                   |
| [88]                  | signal energy extracted by WT | IG and SG | 32 ms+ process time | 74% (average) | — |
| [97]                  | 21 features extracted at PCC | inverter | — | 83.33% ±30% mismatch (P) | — |
| [98]                  | 62 features from $V$ and $I$ | single-phase PV inverter | 50 ms | 98.94% ±40% mismatch (P) | — |
| [99]                  | $V, \theta, f$, $\Delta f$, $\Delta V$, $\Delta I$ | three SGs | — | 97.3% (Gaussian RBF) 0–100% mismatch (P) | — |
| RFC [87]              | $V$, $f$, $Z_1$, $\phi$ | SG | 0.18 s | 100% ±30% mismatch (P) | — |
|                       |                |               | 98%      | ±5% mismatch (Q)               | —                   |
|                       |                |               | 100%     | — 100%                          | —                   |
| [100]                 | sequence components | PV and wind DG | — | 98.81% 0% mismatch (P) | — |
mode of operation, the disturbance signal will heighten the difference in frequency and hence islanding event can be detected. Furthermore, a wavelet-based fuzzy NN-based controller is employed in place of a traditional PI controller for performance enhancement.

6.3 DT-based techniques

A DT is a hierarchical model which is used for classification problems. DT classifier adopts a top-down approach, starting from the root node, which contains the initial classification problem, by recursively splitting the classification problem into internal nodes that test for various parameters until a classification is achieved at the leaf node [103]. In [94], a DT-based pattern recognition classifier has been employed to classify islanding events. The classifier is trained by a large data set for the DG under test and 11 parameters are used for classifying the events. The system that is tested in [94] is made use of in [95] to classify islanding events by employing DT classifier. The difference, however, is that in [95] the selection of parameters to classify islanding state is based on the ease of measurement. Accordingly, current (I), voltage (V), reactive power (q), active power (P), frequency (f), and power factor (pf) are selected. Initially, the selected parameters are acquired for several simulated cases. Iterative Dichotomiser 3 algorithm is used to create a DT that selects the best parameter, in terms of sensitivity, for islanding detection. In this case, two parameters, current and power factor, are selected. For easier interpretation, the output of the DT is also given as if-then rules. Vatani et al. [62] propose an islanding detection algorithm based on two indices, namely harmonic content of the reactance seen at the target DG and maximum ROCOF, i.e., max df/dt. A DT classifier employs these indices to classify islanding states. The performance of the DT-based algorithm is further compared with ANN- and SVM-based techniques and it is reported that DT classifier performs better. A DT classifier with DWT for feature extraction has been used in [96] to propose an optimum relay for islanding detection. This algorithm makes use of energy coefficients of transient voltage signal extracted from the target DG. Transient signal generated during fault isolation is used to compute the energy coefficients which are used for classifying the islanding events by a DT classifier in [88]. A four-fold cross-validation is carried out to obtain better performance. A universal islanding detection algorithm is proposed in [87], in which various classification techniques including DT were used for detecting islanding events.

6.4 Naïve Bayesian classifier

Naïve Bayes (NB) classifier is a classification technique that is based on Bayes’ theorem. NB classifier assumes that the presence of a particular feature in a set is independent of the presence of any other variable in that set. Despite the fact that feature independence is a poor assumption in most cases, NB classifier often performs on par with other established classifiers [104]. NB technique works particularly well with large data sets. An IDM is proposed in [97] which employs NB classifier for classification of islanding events, whereas validation is done by using support vector machine (SVM) and k-fold cross-validation techniques. NB classifier with four-fold cross-validation is proposed in [87]. A total of 21 features were extracted from the PCC out of which four best features were selected using backward feature selection and forward feature selection. The proposed technique has been tested on three different cases: (a) inverter-based DG, (b) synchronous-based DG, and (c) multiple DGs. In case of inverter DG, NB classifier is reported to have a classification accuracy of 82 and 52% with all the 21 extracted features and four best features, respectively. Nevertheless, NB classifier performed extremely well with SG-based DG and multiple DGs with a reported accuracy of almost 100%.

6.5 SVM classifier

SVM is the supervised learning algorithm, meaning it requires a set of data to train the algorithm. Once trained, the SVM will use kernel techniques to project the input space to a higher-dimensional feature space and identify the optimal hyperplane that classifies the data with minimum error and maximum distance between the hyperplane and nearest vector [103]. SVM classifiers or simply called as support vector classifiers are unaffected by the sample dimensions. An SVM classifier for islanding detection is proposed in [98]. Autoregressive signal modelling is applied to the voltage and current signals at the PCC to extract a total of 62 features, which are used as an input feature vector for the SVM classifier, with radial basis function (RBF) as a kernel. In [99], SVM classifier is proposed for islanding event classification, especially for the cases where vector surge relay fails to operate positively. A five-fold cross-validation method is used to establish the SVM regularisation parameter (C), bandwidth of RBF kernel (σ), and degree of the polynomial kernel (p). Furthermore, the proposed method is tested with linear, Gaussian RBF, and polynomial kernels.

6.6 Random forest classifier

Random forest classifier (RFC) is an ensemble learning technique that constructs DTs during the training phase, where each DT is constructed by using random subset of the actual data. Moreover, then these DTs are used to classify any input data set. An IDM based on RFC is reported in [87]. In this technique, C4.5 DTs are constructed based on the entropy and InfoGain, which are further used to classify islanding events. The performance of RFC is compared with other classifiers and it is reported that RFC has better performance compared with other classifiers in terms of average accuracy, NDZ, and detection time. Another RFC-based IDM is presented in [100]. This method uses the extracted sequence components from the voltage signal that is acquired at the PCC to classify islanding and non-islanding states.

6.7 Adaptive ensemble classifier

An adaptive ensemble classifier-based IDM is proposed in [105], which employs phase-space technique for feature extraction. This method analyses time series in a higher-dimensional space known as phase space, in which all of the possible states of the system are represented by a corresponding unique point. The signal from the PCC is embedded into the phase space with dimension of three and the Euclidean norm of the signals is added and normalised to create a feature vector that is used as an input to a custom designed adaptive ensemble classifier based on extreme learning machine. This paper also proposes new performance indices for islanding detection. The average decision speed is 1.11 cycles with an average accuracy of 98.87% [105].

Apart from islanding detection, supervised learning can also be used for predictive detection of an islanding event. Predictive detection of islanding refers to the idea of investigating the potential causes that can result in islanding. Multivariate statistics and supervised learning techniques are used for analysing and understanding the anomalous signatures in the signals acquired from PCC just before an islanding is about to occur. This exploratory study is conducted on a modified IEEE-13 bus system and it has been concluded that a three-phase short-circuit fault, for instance, is not a precursor to an islanding event. Such predictive detection can detect the anomalies that are precursor to an islanding event and trip the DG system even before that islanding has occurred [106].

7 Conclusion

In a nutshell, this paper explains the significance of islanding detection and various IDMs are classified as classical, SP-based, and intelligent techniques. Although the focus of this paper is in SP and intelligent techniques, the methodology, merits, and demerits of classical islanding methods are discussed briefly, with all the necessary references. SP techniques as a means to improve the efficiency and accuracy of passive techniques are presented. The evolution of various SP methods employed for islanding detection along with their strengths and shortcomings are discussed. This is followed by the discussion of intelligent techniques and they, together with feature extraction by means of SP techniques, can
play a role in adding robustness to the passive techniques and make them indispensable in a complex hybrid DG network with high density of DGs. This robustness is due to the fact that intelligent techniques can handle multiple parameters, which is very essential in detecting islanding events during critical situation such as at near zero power mismatch, in a multiple DG environment, or in a high-density complex DG system.

The following is a summary of the discussion on IDMs along with some quantitative results:

- **Passive IDMs** have fastest detection times in the order of 4 ms, and do not pose any threat to the power quality of the system. However, passive IDMs possess NDZ which is a drawback under certain conditions.
- **Active IDMs** overcome the disadvantage of NDZ and have reported detection times in the range of 1.5–9 ms with a very good detection accuracy. The downside of active IDMs is that they affect the power quality of the system.
- **Hybrid IDMs** inherit the advantages of both passive and active IDMs by employing them together. Hybrid IDMs have detection times in the order of 0.2 s.
- **Remote IDMs** use communication as a means to detect islanding and hence it does not have any NDZ. However, they tend to be more expensive to implement. Reported detection times for remote IDMs are in the range of 200 ms.
- **SP methods** are great tools to extract hidden features from the PCC signals, and thereby enhance the detection capabilities of passive IDMs by reducing NDZ. SP-based IDMs have a detection times in the order of 1–28 ms depending on the SP method.
- **Intelligent IDMs** overcome the need for setting a threshold value, which is imminent for all the above methods. Also, as the system becomes more complex intelligent methods have a great advantage compared with traditional methods. Detection times of intelligent IDMs are reported in the range of 10–300 ms.

In addition to detecting islanding events, intelligent techniques, along with SP techniques, open up promising avenues in the direction of predictive detection of islanding events. In predictive detection, the precursors to islanding are identified using statistical tools and intelligent algorithms such that a DG can be disconnected even before an islanding event has occurred.

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