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An intelligence-based islanding detection method using DWT and ANN

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Abstract: In this paper, a new method based on artificial neural network (ANN) and discrete wavelet transform (DWT) is proposed for electrical islanding detection. Transient signals produced during an event are used in the proposed method. ANN is trained to classify the transient events as islanding and nonislanding. The required features for classifying are extracted through DWT of voltage and current transient signals. The proposed method is then simulated on a medium voltage distribution system of CIGRE with 2 kinds of DGs. Results show that this method can detect electrical islands more rapidly and accurately.

Key words: Discrete wavelet transform, electrical islanding detection, neural network, distributed generation, distribution system and transient signals

1. Introduction

An important requirement for the connection of distributed generation (DG) to distribution networks is the protection system's ability to detect islanding. Islanding is the state under which part of an electric power system that contains both load and DG is energized solely with DG while it is isolated from the rest of the system [1]. Islanding is either intentional, as for maintenance and load shedding, or unintentional, as with faults and equipment failures. Unintentional islanding is not acceptable; because of some concerns, DGs must be disconnected if it does occur [2,3]. The system in Figure 1 contains the utility system on the left and the DG-fed distribution system on the right. There are various customer loads between these 2 electrical power sources. An islanding event occurs whenever any of the breakers B1, B2, and B3 are opened.

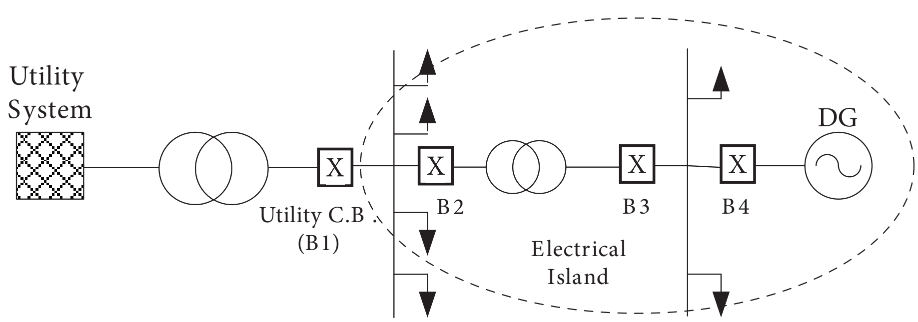

Figure 1. A general view of electrical islanding.

According to IEEE Std. 1547.1, the DG must be stopped within 2 s of the formation of unintentional islanding in order to avoid possible damage to local electrical loads or DGs, due to asynchronism during grid

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reconnection. In addition, it is necessary to guarantee the safety of workers or customers during maintenance operations of the electrical system. Moreover, the grid cannot control voltage and frequency, which may damage the equipment. Islanding detection techniques can be classified into local and remote methods. Local techniques are divided into passive and active methods.

Remote techniques are based on communication between the grid and the DGs. Several communication-based techniques have been proposed, including power line carrier (PLC) [4,5], transfer trip [6,7], and supervisory control and data acquisition (SCADA) [8]. Communication-based methods have a negligible nondetection zone (NDZ) and better reliability, but are more expensive than the local methods [9]. NDZ can be defined as the operating region in which islanding cannot be detected. NDZ can be represented in terms of power mismatch or the load parameters R, L, and C.

Passive methods rely on monitoring a certain parameter and then setting thresholds on the selected parameter. Several passive techniques have been proposed, including under/over voltage [10], under/over frequency [10], voltage phase jump/voltage vector shift/frequency phase jump [11], voltage and/or current harmonics [12], rate of change of frequency (ROCOF) [13], rate of change of voltage [14], rate of change of real/reactive power and power factor [14], and voltage imbalance [15]. Despite their simplicity and ease of implementation, passive methods are known to suffer from large NDZs.

Active methods introduce deliberate changes or disturbances to the connected circuit and then monitor the response of the system in detecting an islanding condition. Active methods include slip-mode frequency shift [16], active frequency drift (AFD) [17], Sandia frequency shift [18], voltage imbalance, varying terminal voltage, voltage pulse, Sandia voltage shift [19], automatic phase shift (APS) [20], reactive error export [21], and impedance monitoring [22]. Active methods typically have a smaller NDZ but can degrade the power quality of the system [23]. In addition, some active methods require the implementation of additional controllers which intensify the complexity of the islanding detection method [24,25].

Although there are a number of islanding detection techniques available, unfortunately there is no single method with a zero nondetection zone in all possible scenarios and with minimal power quality erosion [26,27]. As a result, the power systems engineering community is undecided on which type of islanding detection to use [28]. Zero power flow between the island and the utility is one of the most difficult states of islanding detection. The objective of this paper is to develop an islanding detection technique that can operate well under the zero power flow condition as well as other operating conditions.

Classification-based methods have been introduced for islanding detection in [29–34]. In [29], the magnitude of a specified DWT coefficient is compared with a threshold. These determined threshold values are obtained through trial and error and based on the skill of experts. In [30], 3 pattern recognition methods, including decision tree (DT), neural network, and support vector machine, were studied on the IEEE 7-bus system. A method based on DWT is discussed in [31], which is particular for single phase photovoltaic (PV) systems. An intelligence-based method is investigated in [32], which uses the decision-tree (DT) classifier, but with a complex set of 11 features for classification, including total harmonic distortion of current/voltage, gradient of the product of voltage and power factor, etc. It has only 83.33% islanding detection accuracy. An intelligence-based method with synchronous-based DG was proposed in [16]. Eleven parameters as features were fed to a DT classifier. The method introduced in [33] uses a DT classifier in identifying the islanding condition, with 4 levels of DWT. In [34], a wavelet–ANN technique for islanding detection is introduced for a system with induction-based DG (wind farm).

This paper proposes a new algorithm for islanding detection using DWT for extraction of the required features for classifying, and ANN for classifying the events as islanding and nonislanding. The rest of the paper is organized as follows: Section 2 provides the theory of the DWT and ANN. The case study is introduced in Section 3. Section 4 presents the proposed islanding detection method. Section 5 provides the simulation. The last section touches upon the conclusion.

2. Theory of the DWT and ANN

Voltage and current transient signals of a power system are thought to have unique characteristics that signify the cause of transient occurrence. The method proposed here is based on the principle that the transient state has certain characteristics that can be used to present a new method for distinguishing island occurrences from other occurrences. Of course, the features presented in transient signals are not directly diagnosed and so there should be a process to extract these features to speed up response in classifying. To this end, wavelet transform seems to be suitable.

Some important classification methods include support vector machines, neural network, and decision tree. Although studies have been carried out to compare them, due to a number of factors and possibilities, we cannot definitely state which method should be preferred in every situation. The proposed method uses neural network for pattern recognition and classification. Neural network has advantages, including variety, simplicity, and capability of fast training.

2.1. Features extraction by DWT

DWT is used as a means for analyzing transient signals. Using DWT, a signal can be broken down into some signals in distinct frequency bands, which are called wavelet coefficients. It is more suitable for study of transient states in comparison with other methods such as Fourier transform (FT). A suitable study of Fourier and wavelet transforms can be obtained in [35]. Mathematical definition of DWT for a signal $f(k)$ is stated in Eqs. (1) and (2) as:

$$DWT_{\psi} f\,(m,n) = \sum_{k} f\,(k)\,\psi^{*}_{m,n}(k), \tag{1}$$

in which $\psi_{\mathrm{m,n}}$ is the discrete mother wavelet as:

$$\psi_{m,n}\,(k) = \frac{1}{\sqrt{a_0^m}}\psi\left(\frac{k-nb_0a_0^m}{a_0^m}\right) \tag{2}$$

a_0 (>1) and b_0 (>0) are constant real numbers, and m and n are positive integer numbers. DWT breaks down a signal to an approximate and a detail. The approximate is again broken down in order to generate another step, and this process is repeated. In fact, the original signal, by passing through 2 high pass and low pass filters, will be decomposed into 2 signals as approximate and detail, which are shown in Figure 2. In this figure, D and A signals include high and low frequencies of the main signal (S), respectively. In the next step, this breaking is continued with the breaking down of signal A. A suitable survey of wavelet can be obtained from [35].

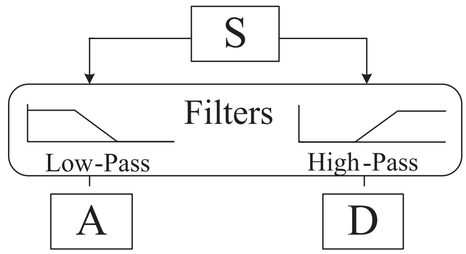

Figure 2. A general view of wavelet transform.

2.2. Classification of events by neural network

Methods of distinguishing patterns have been built on the basis of mathematical approaches, and classification of information is carried out on the basis of previous experiences or statistical information of patterns. The classifying consists of 2 main sets of information:

1. Training information set, including classes and corresponding features.

2. Test information set, testing accuracy of classifying.

In past decades, serious attempts have been made to simulate biological neural networks, which led to introducing ANN [36]. The general structure of a neural network is shown in Figure 3. In the simplest form of a layered network, single layer feed-forward network, we have an input layer of source nodes that projects onto an output layer of neurons (computation nodes), but not vice versa. By adding one or more hidden layers, whose computation nodes are correspondingly called hidden neurons, the network is enabled to extract higher order statistics. The function of the hidden layer is to intervene between the external input and the network output in some useful manner. Training on the basis of presented patterns is the main capability of an ANN. The output of the neural network is obtained from Eq. (3):

$$y = f\left(w, x\right) = \sum_{i=0}^{n} w_i x_i \tag{3}$$

x_i and y are the ith input and output, respectively. By optimizing all variables (w_i) in the training steps, ANN finds the closest answer, so that the sum of error squares will reach the least acceptable level in terms of Eq. (4):

$$E_p = \sum_{p} \frac{1}{2} \left(t_{pj} - o_{pj}\right)^2 \tag{4}$$

where t, o, j, and p are target, real value of output, jth output neuron, and training inputs, respectively. The type of neural network used in this article is a multilayer feed-forward network. This type of neural network is commonly referred to as multilayer perceptrons (MLPs). MLPs have been applied successfully to solve some difficult and diverse problems by training them with a highly popular algorithm known as the error back-propagation algorithm. These networks have been successfully used in the solution of difficult pattern-recognition problems [37]. Standard back-propagation is a gradient descent algorithm, as is the Widrow–Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function [37].

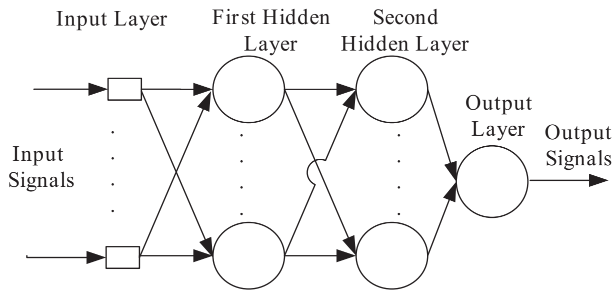

Figure 3. General structure of a neural network.

3. Case study

The system under study in this article is the CIGRE medium voltage (MV) distribution system, which is shown in Figure 4. It is derived from a German MV distribution network [38]. The benchmark network retains the characteristics of a real network. This distribution system consists of 2 DGs: one with an induction generator (DG1) with a capacity of 1.5 MVA at bus-7, along with a capacitor compensator with a capacity of 0.48 MVAR; the other, a synchronous generator (DG2) with a capacity of 1 MW and 100 kVAR at bus-9. All loads have been considered as fixed impedance. The case study has 2 circuit breakers, S1 and S2, which are normally kept open. The network structure can be changed from a radial to a loop circuit by closing S1 and S2. In this paper, by closing and opening S1 and S2, 4 different states of operation are considered. In addition, a power

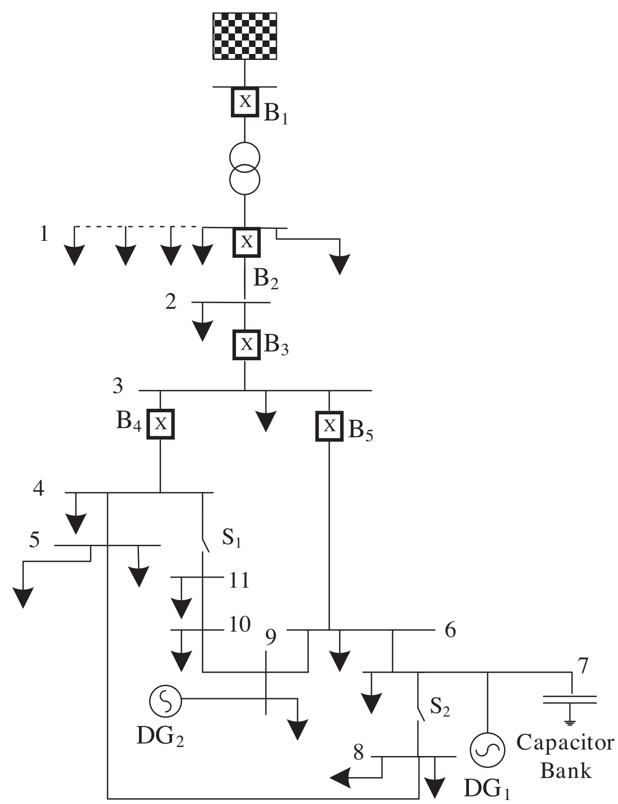

Figure 4. CIGRE medium voltage distribution system.

balance state is also taken into consideration. This is the state in which generation and consumption in the island region are equal. Due to this equality, the fluctuation of the electrical parameters such as frequency and voltage is quite low. Furthermore, it causes elimination of some of the features of signals and complicates the detection of the islanding event. The 5 states of operation considered in this paper are as follows: 1) S1 and S2 are open, 2) S1 and S2 are closed, 3) S1 is closed and S2 is open, 4) S1 is open and S2 is closed, and 5) power balance state.

Events are divided into islanding and nonislanding. In the system under study, 355 different states (71 states in 5 different network structures) are considered; 71 states are mentioned, which include 58 nonislanding states and 13 islanding states.

The 58 nonislanding states include the following items:

1. Normal operation.
2. Faults including 3-phase, 2-phase, 2-phase to ground, and single line to ground (4 faults in 11 buses).
3. Switching all loads (2 buses).
4. DGs switching (2 DGs).
5. Capacitor switching (1 bus).

The 13 islanding states include the following items:

1. Opening breakers B2 and B3 after the occurrence of each of the 4 types of faults on bus-2 (4 states).
2. Opening breakers B3, B4, and B5 after occurrence of each of the 4 types of faults on bus-3 (4 states).
3. Opening breakers B4 and B5.
4. Opening breakers B3, B4, and B5.
5. Opening breaker B1.
6. Opening breaker B2.
7. Opening breaker B3.

Of these 355 states, 264 states are used for training and 91 states are used for testing the neural network. To protect the test against all transient states and for assessment of the proposed algorithm, test information has been randomly selected. In the proposed algorithm test, a series of choices has been randomly made to avoid the errors that may occur due to reliance on a particular data set.

4. Proposed islanding detection method

For extracting the special features of each event, currents and voltages of 3 phases at terminals of both DGs are measured and recorded. DWT is applied to transient voltage and current signals to extract the necessary features for the classifying process. Current and voltage signals are sampled with a frequency of 10 kHz. It is to be noted that while going through this process, in terms of accuracy of classification, speed of detection, and cost and capability of the hardware needed, it was found that the frequency is suitable and there is no need for higher frequencies.

Daubechie's 1 (Dbl) is used as the mother wavelet. Successful application of the Daubechie's mother-wavelet family for extracting features of transient states of power systems have been reported in a number of studies [31,35,39]. On initial investigation of comparison of islanding detection with some mother-wavelets of this family, Dbl proved to be suitable.

Disturbance is carried out at zero second. Typically, considerable differences exist between islanding and nonislanding events, but threshold alone cannot distinguish between them. Hence, a more valid technique involving classification methods is required.

Straight application of wavelet coefficients (which are fundamentally curves) as an input to ANN is impossible. Thus, the energy values related to DWT coefficients in a time window that contains the transient are applied as specifications for the ANN. Energy of DWT coefficients is calculated by the sum of their square over a time window equal to 0.01 s. The proposed method applies a sliding window, thus maintaining the transient state data. Sliding window size was obtained based on some investigations that considered the precision and operation time.

At every decomposition stage, the 3 phases' energies were summed in the specific frequency intervals. The processes of DWT and ANN, for phase-a current only, are indicated in Figure 5. After the sampling of DG1 and DG2 signals, DWT is used for analysis of voltage and current signals. At each level of DWT, the energies of the 3 phases were summed to form a combined "3-phase energy" value. Only the decomposition of phase-a current is shown in detail to reduce the complexity of the figure. The so-calculated "3-phase energy" values of the currents and voltages create a $2m$ feature space (m levels of currents and m levels of voltages) for each DG, if the output of$m$ levels from the DWT is used. Finally, for detection of an islanding event, these $2m$ features applied to the ANN classifier. Two different plans for the proposed algorithm are considered.

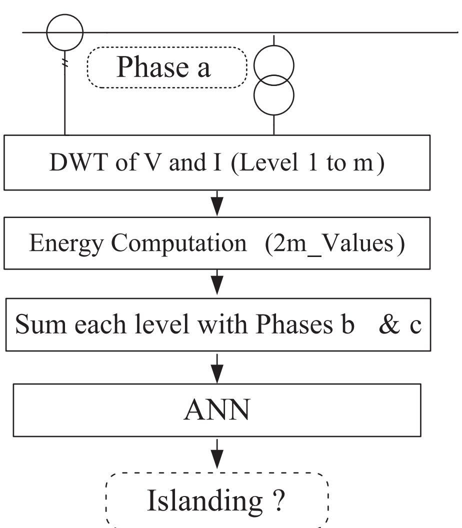

Figure 5. Features extraction by DWT and classification by ANN.

Plan 1: In this plan, the relay of each DG will be independently trained and tested by voltages and currents of corresponding DG. The number of inputs to ANN in this relay is 2 times the number of the level of DWT.

Plan 2: the measured voltage and current signals of the 2 generators (DG1 and DG2) are used for training a relay. The number of inputs to ANN in this relay is 4 times the number of the level of DWT.

5. Simulation and results

For simulation of the distribution system under study, DIgSILENT software has been used. The required DWT and ANN were programmed with MATLAB software. One example of the simulated cases is presented in Figure 6. This case is related to the opening of the B2 and B3 switches after a 3-phase fault occurred on bus-BB2 when the S1 and S2 were open. DG1 voltage and current waveforms are shown in Figure 6a. Wavelet transform of these waveforms, levels 1 to 3, is shown in Figure 6b, Figure 6c, and Figure 6d, respectively.

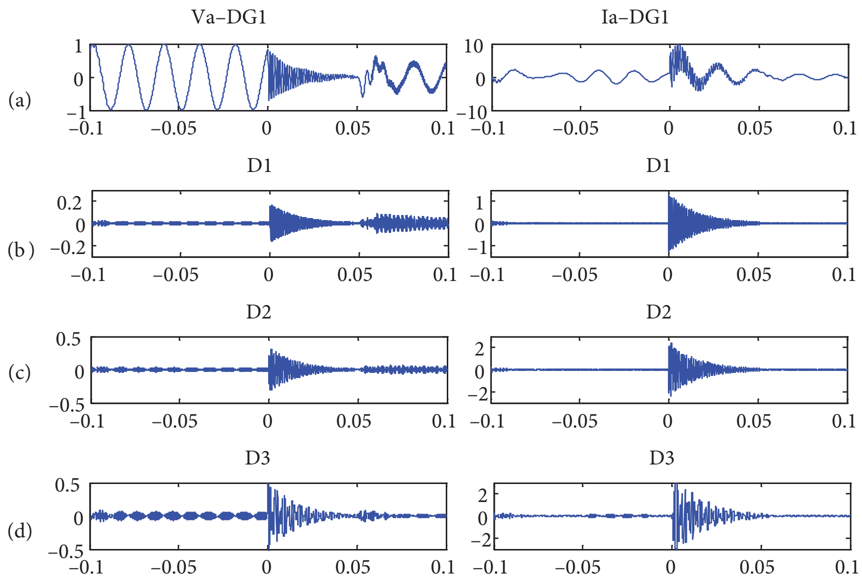

Figure 6. (a) Voltage and current of DG1; (b, c, and d) levels 1 to 3 of wavelet transform.

For access to levels of DWT that are acceptable in terms of accuracy, speed, and calculation costs, the first to ninth levels of wavelet coefficients were considered. Accuracy of Plan 1 and Plan 2 in levels 1 to 9 of wavelet coefficients is shown in Figure 7. In this figure, accuracy is defined as the ratio of the number of true detected cases to the total number of test cases in percentage form.

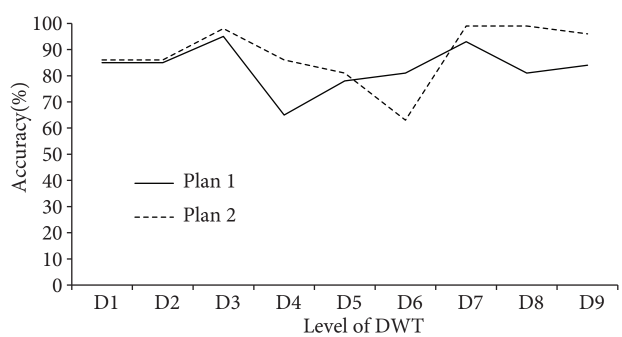

Figure 7. Accuracy diagram of the 2 plans in 1 to 9 wavelet levels.

Given the 3 criteria and comparing the accuracy of different levels with average accuracy of levels 1 to 9, it was found that level 3 is the most suitable level. In Table 1, the average of accuracy in levels 1 to 9 for Plan 1 and Plan 2 are presented. As seen in Table 1, Plan 2 is more accurate than Plan 1.

The accuracy of both plans to the third level of DWT coefficients is presented in Table 2. On detection of an occurrence, the first plan is said to be successful if both DGs have correctly diagnosed the phenomenon.

This point could be a justification for the decreased accuracy of the first plan in comparison with the second plan.

Table 1. Average accuracy of Plans 1 and 2 (%).

Plan average accuracy	Plan 1	Plan 2
D1 to D9	82.9	88

Table 2. Accuracy of both plans for islanding detection (%).

Level	Plan 2	Plan 1
D1	85.7	84.6
D2	85.7	84.6
D3	97.8	94.5

The problem with Plan 2 (despite its high accuracy in comparison to Plan 1) is that the 2 states that were diagnosed as erroneous were island states. Nonrecognition of an island will have serious risks for the consumer, power company, and DG.

The number of false detections of Plans 1 and 2 based on different structures of operation is shown in Table 3. As presented in Table 3, Plan 2, when compared to Plan 1, could decrease the total number of incorrect detections from 5 to 2 (60%). In addition, the incorrect detections in the power balance state could decrease from 3 to 1 (66%). The presented results show that Plan 2 tends to show higher accuracy in the detection of islands. The flowchart of the passive islanding detection algorithm proposed in this article is shown in Figure 8. After sampling voltage and current signals of DGs (200 samples per cycle), DWT tools are used for extraction of wavelet coefficients at levels 1 to 3. The corresponding energies are then calculated, and at each level, the energies of the 3 phases of each signal are summed together. Finally, features are applied to the ANN classifier for detection of islanding events.

Table 3. The number of false detections in various states of operation.

Network structure	Plan 1	Plan 2
Power balanced	3	1
S1& S2 open	0	0
S1 closed & S2 open	0	0
S1 open & S2 closed	1	1
S1 & S2 closed	1	0
Sum	5	2

6. Assessment of proposed method and comparison with other methods

6.1. Assessment of nondetection zone (NDZ) and detection time

The "imbalance factor" is defined as the utility power to the total power consumption in the islanded zone in percentage before islanding has occurred. The islanding detection time of the proposed method was investigated by changing the active and reactive power imbalance. In order to change the active power imbalance, generation power of the synchronous DG is changed from 0.6 to 1 pu and load values are varied. The needed reactive power imbalances were created by varying the capacitors and the load power factors. The results are presented in 3-D plots. Figure 9 shows the detection time for Plan 2. The active power imbalance, reactive power imbalance, and detection time are displayed in the X-axis, Y-axis, and Z-axis, respectively. The events of those that have detection times more than 2 s are considered as nondetected. The 2 plans show similar responses. The nondetection zone (NDZ) of each plan can be found by chopping the surfaces using a horizontal plane at 2 s on the P–Q plane. Figure 9 shows that the proposed relay (Plan 2) has a negligible NDZ, and the detection time of the proposed method is very much independent from the power imbalance.

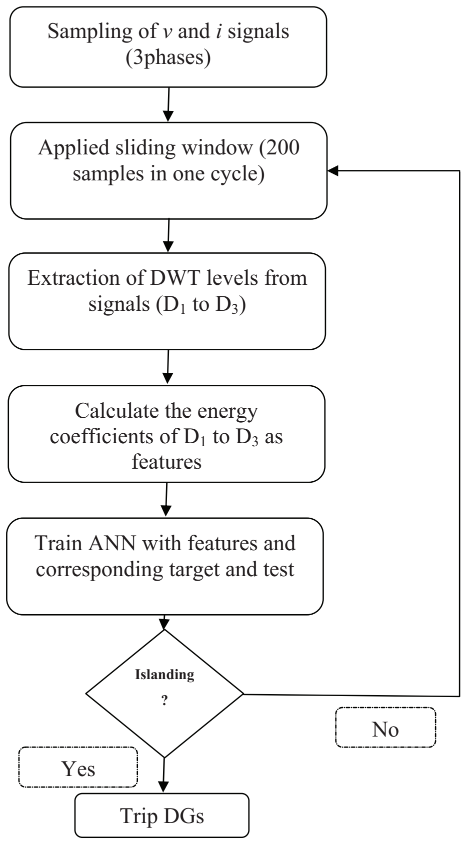

Figure 8. Flowchart of proposed algorithm.

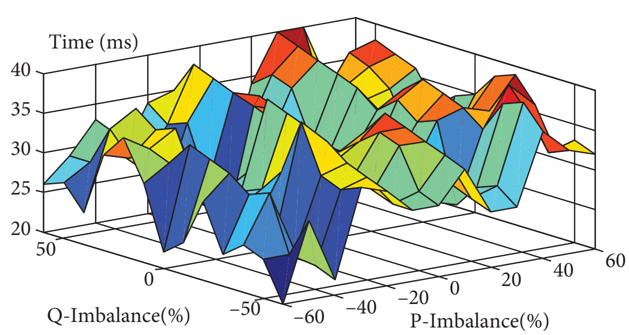

Figure 9. Islanding detection times and NDZ of the proposed method.

Table 4 indicates the minimum, maximum, and average detection times of both plans. If the detection times are above 2 s, those cases are omitted from computation of the average. The maximum detection time for the proposed relay was 40 ms (2 cycles); this was observed for Plan 1 (induction generator). The average detection time of the proposed relay was less than 35 ms (under 2 cycles). Wavelet energy is obtained by integrating the square of the wavelet coefficient over a time window of 0.01 s. This time window length was selected after preliminary investigations as a compromise between accuracy and response time. It has been proposed that maximum accuracy is achieved with minimum response time. The DWT and energy calculations introduce a delay of approximately 10 to 20 ms. The detection time of the proposed method is between 20 to 40 ms (1 to 2 cycles). The main reasons for the reduction of response time are the decrease of the sampling time window and the use of low levels of DWT.

Table 4. Minimum, maximum, and average detection times.

<table>
<tr><td colspan="6">Plan 1</td><td colspan="3">Plan 2</td></tr>
<tr><td colspan="3">Synchronous generator</td><td colspan="3">Induction generator</td><td rowspan="2">Min.</td><td rowspan="2">Max.</td><td rowspan="2">Avg.</td></tr>
<tr><td>Min.</td><td>Max.</td><td>Avg.</td><td>Min.</td><td>Max.</td><td>Avg.</td></tr>
<tr><td>21</td><td>35</td><td>31</td><td>25</td><td>40</td><td>35</td><td>24</td><td>38</td><td>33</td></tr>
</table>

The detection times of active methods are longer than those of passive methods [40]; additionally, some active methods cannot be used with all DG types. Fast response of telecommunication-based methods is dependent on the communication type used [41]. The drawback of this method is that it is complex and costly.

6.2. Comparison of the proposed method with other methods

In this paper, through study and analysis of a real distribution system, a better algorithm with higher accuracy and speed (lower computation) than previous techniques is obtained. Instead of using 1) a complex set of parameters, 2) the threshold values determined through trial and error, or 3) high or certain DWT levels (heavy computation), this paper analyzes different DWT levels and selects a lower DWT level of transient signals generated during the disconnection of the grid. Moreover, the proposed method is independent of DG type.

The relay proposed in this article could obtain higher accuracy (98%) by using the third level of DWT (there are 6 levels of DWT in total). Lower levels result in reduction of response time. In this article, we have attempted to select a better relay through analysis of 27 different approaches. As a result, the proposed relay has higher accuracy, and because of the use of a lower number of decomposition levels, has become faster and less expensive. The maximum accuracy of other passive methods, summarized in Table 5, is lower than the proposed method's accuracy.

Table 5. Accuracy of several passive islanding-detection relays.

Accuracy (%)	Other passive methods
74.05	Voltage vector shift (VVS) [42]
78.81	Over/under voltage [42]
83.33	Intelligence-based relay [32]
90.24	Over/under frequency [42]
93.81	Rate of comparison of frequency (ROCOF) [42]
96.43	DT classifier based relay [33]
97.8	Proposed relay

Thus, the main advantages of the proposed method when compared with other islanding protection methods are summarized as higher accuracy, faster response time, less sensitivity to load imbalance, and a zero NDZ.

7. Conclusions

A rapid and reliable islanding detection method on the basis of wavelet energy of transient signals has been presented. A trained neural network classifier is capable of successful detection of resultant transient events (as islanding and nonislanding), using energy of DWT coefficients. The proposed relay was assessed in 5 states of network operation, which in fact covers all states. In this paper, 2 different plans, the first with 2 separate relays and the second with 1 general relay, are considered. By analysis performed on the required DWT level of 27 relay designs, a better relay was selected for DGs based on accuracy and speed.

The proposed method could result in nearly 98% accuracy; the accuracy of the proposed relay (98%) is better than that of similar methods and other passive methods in the same case study. With consideration of 0.01 s for sampling time and lower DWT (3 levels), the response time of the relay is under 2 cycles, and it is thus proven to be more rapid. The methodology gives a zero NDZ with any type of DGs, if trained considering the possible power imbalances. Finally, the proposed relay has higher accuracy, faster response time, less sensitivity to load imbalance, and a zero NDZ.

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