Islanding detection in a distributed generation integrated power system using phase space technique and probabilistic neural network

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Abstract
The high penetration level of distributed generation (DG) provides numerous potential environmental benefits, such as high reliability, efficiency, and low carbon emissions. However, the effective detection of islanding and rapid DG disconnection is essential to avoid safety problems and equipment damage caused by the island mode operations of DGs. The common islanding protection technology is based on passive techniques that do not perturb the system but have large non-detection zones. This study attempts to develop a simple and effective passive islanding detection method with reference to a probabilistic neural network-based classifier, as well as utilizes the features extracted from three phase voltages seen at the DG terminal. This approach enables initial features to be obtained using the phase-space technique. This technique analyzes the time series in a higher dimensional space, revealing several hidden features of the original signal. Intensive simulations were conducted using the DigSilent Power Factory software. Results show that the proposed islanding detection method using probabilistic neural network and phase-space technique is robust and capable of sensing the difference between the islanding condition and other system disturbances.

1. Introduction
Distributed generation (DG) is one of the most promising alternatives for conventional centralized electric power generation. The need for DG is rising worldwide because of the restructuring of the electric power industry and the increase in electric power demand. In fact, several utilities worldwide already have a significant DG penetration level in their power systems. However, numerous issues still need to be seriously considered when DGs are connected to the utility grid. One of the main issues is islanding detection. An islanding condition occurs when the DG continues supplying power into the network after the loss of mains. Subsequently, the utility loses control of the islanded part of the distribution network. This occurrence can negatively affect the network and DG itself by posing safety hazards to utility personnel and the public, as well as by giving rise to power quality problems and serious damage to the network and DG, even if the main power is restored within a short time [1]. To prevent equipment damage caused by unintentional islanding, the IEEE 1547–2003 standard [2] stipulates a maximum delay of 2 s for the detection and disconnection of DGs to de-energize the islanded network. Therefore, research and development studies on loss of mains protection for safer operation are of great interest.

Numerous islanding detection techniques are available. These methods are mainly divided into two categories, namely, remote and local. Remote methods require a communication scheme, whereas local techniques are based on local information. In other words, remote systems use communication, whereas local ones utilize observation. Although remote techniques are highly reliable, implementing such methods is difficult because of the utilization of direct communication between the DGs and utility through such technology as fiber optic and wireless communication networks. Moreover, the practical implementation of these schemes can be inflexible, complex, and expensive because of the high penetration of DGs in complex systems. Therefore, for simplicity and applicability, a more cost-effective local technique is preferred in this study.

The core concept of local islanding detection techniques remains the same as that of some system parameters that are supposed to be steady during the grid-tie operation but significantly change during the transition state from the grid connected to island mode operation. Local methods have two categories, namely, passive and active. Both techniques are used to monitor whether the grid voltage/frequency exceeds the limits imposed by the relevant standard [3]. From the power quality perspective, the passive islanding detection method is preferable even in cases in
which the negative contribution of the active techniques can be considered negligible. Conventional passive techniques utilize the measurement of electrical quantities, such as voltage, current, or frequency, to estimate the system island state using under/over voltage (UVP/OVP), under/over frequency (UFP/OFP), and vector shift (VS) functions. Some inverters may include any combination of these protection schemes as built-in functions. However, these schemes may not be acceptable as adequate interface protection above certain limits of installed DG capacities. Meanwhile, frequency-based schemes are widely used in passive detection schemes to detect islanding condition involving synchronous generators. The frequency is constant under normal conditions. Hence, detection of the islanding condition is possible by checking the rate of frequency changes. The frequency relays are based on the under- and over-frequency criteria for the calculation of the frequency of the DG terminal voltage waveforms. Typically, the under- and over-frequency range is set to \pm 0.5 Hz. Three types of frequency-based relays are available for islanding detection, namely, frequency relay, rate of change of frequency relay [4, 5] and vector surge (or shift, jump) relay. However, the primary weakness of the UVP/OVP and UFP/OFP is the dif

To reconstruct the data of a time series in a higher dimensional space, the technique is based on the mathematical method, which requires the modification of the phase locked loop needed by inverters for utility synchronization. Teoh and Tan [8] proposed a harmonic measurement technique for the same purpose by monitoring the change in the total harmonic distortion (THD) at the point of common coupling (PCC). If the THD value exceeds a pre-defined threshold, the inverter disconnects the DGs from the network.

The scheme reported in [7] is based on the monitoring of phase differences between the inverter terminal voltage and output current. The method is easy to implement because it merely requires the modification of the phase locked loop needed by inverters for utility synchronization. Teoh and Tan [8] proposed a harmonic measurement technique for the same purpose by monitoring the change in the total harmonic distortion (THD) at the point of common coupling (PCC). If the THD value exceeds a pre-defined threshold, the inverter disconnects the DGs from the network.

The application of computational intelligence in islanding detection is a new trend in passive islanding detection algorithms. These approaches mainly aim to estimate the off-grid operation as soon as possible by neither communicating with any other utility component nor giving any concession on power quality. In addition to swift estimation, the technique provides high computational efficiency with good reliability and accuracy. Some existing intelligent methods combine signal processing and neural network techniques. For instance, fast Fourier transform (FFT) with integration of the immunological principle to respond to inverter islanding was proposed in [9]. Nonetheless, FFT is unsuitable for non-stationary signals that appear during islanding. To overcome its limitations, FFT is replaced with wavelet features and artificial neural network (ANN) classifier for robust islanding detection, as described in [10]. In the research conducted by Samantaray et al. [11], the feature vector was extracted using discrete wavelet transform (DWT) from the current signal seen at DG terminal. Various classification techniques, such as decision tree, radial basis function (RBF), and probabilistic neural network (PNN), were then trained as classifiers. Samantaray et al. claim that PNN is highly effective in islanding detection and is more reliable than other classification techniques because it has already been tested with the simulation model and real-time digital simulator.

A new technique called phase space method is becoming popular for use in various classification and detection algorithms. The technique is based on the mathematical method, which reconstructs the data of a time series in a higher dimensional space. In power system research, the technique was first utilized for power quality detection problems in 2008 [12, 13]. Moreover, the phase space approach has also been applied to distance relays. The speed of the phase space fault detection technique was found to be only 4 ms, which is considered suitable for real-time implementation. However, this technique has not been thoroughly applied to islanding detection. Some preliminary applications of the phase space technique in islanding detection were explored in [14, 15].

The proposed approach is an extension of [14] and [15]. This approach aims to adopt phase space and neural networks for islanding detection. The present works differ from the preliminary work in [14, 15] because of the use of enhanced phase space features, an effective classifier, and improved results with extensive comparative studies. The proposed method involves two major steps. In the first step, features are extracted using phase space at the target DG location. This step is then compared with conventional signal processing technique, such as wavelet transform with six decompositions of the DWT of the voltage signals obtained at the target DG location. The main purpose of this step is to identify the best algorithm that can be used to extract the features under islanding detection conditions. In the second step, a classification task is performed under islanding conditions using PNN. The performance of PNN is compared with that of a conventional neural network, such as RBF, for training in differentiating the islanding event from other system disturbance events. The error measurement indices are studied to identify the best features and classification technique to be used in islanding detection.

2. Conventional discrete wavelet based method

A commonly used DWT-based islanding detection method was introduced by Lidula and Rajapakse to solve the limitation of windowed Fourier transforms in islanding detection [16–18]. The method assumes that the event-specific characteristics embedded in the transient current or voltage waveforms are not directly distinguishable. Therefore, these characteristics have to be pre-processed to extract features that assist fast classification response. DWT is used for this purpose. DWT of discrete signal \( f(x) \) is mathematically defined as follows:

\[
\text{DWT}_f(m, n) = \sum_k \psi_{m,n}(k)
\]

where, \( \psi_{m,n} \) is the discretized mother wavelet given by

\[
\psi_{m,n}(t) = \frac{1}{\sqrt{a_0^{mn}}} \psi\left(\frac{t - b_m a_0^n}{a_0}\right)
\]

where, \( a_0 > 1 \) and \( b_0 > 0 \) are fixed real values, and \( m \) and \( n \) are positive integers.

A suitable sampling frequency and mother wavelet are obtained by experimentation and trial and error. For a selected sampling frequency of 10 kHz and mother wavelet (DB4 wavelet), the transformation is applied to six levels of decomposition to extract the detailed information of the sample voltage signal [16, 17]. The six details extracted from the wavelet decomposition contain a large amount of information to assist in islanding detection. Therefore, the energy content of each level is obtained to construct the feature vector. Wavelet energy is obtained by integrating the square of wavelet coefficient over a time window of 0.01 s. The energy content for the first detail can be calculated by [19]

\[
\|E_{D_1}\| = \left[ \sum_k d_k^2 \right]^{1/2}
\]

where, \( E_{D_1} \) is the energy content of \( D_1 \) for voltage signal at phase-A. \( d_k \) is the kth coefficient in the first decomposition level. Once all
energy contents are acquired, the sum of energies of the three phases is calculated to create a six-dimensional-feature vector at each decomposition level of the voltage waveform. This feature extraction method is illustrated in Fig. 1 along with details of phase A. Next, two classes of events, namely, "non-islanding" and "islanding," are considered for training the neural network classifier. More details on this method can be found in [16,17].

3. Proposed feature extraction algorithm

This section introduces the proposed islanding detection algorithm based on the phase space technique. First, the concept of phase space technique is described. Then, the feature extraction method using various ANN methods is elaborated.

3.1. Overview of phase space technique

The aim of phase space method is to analyze the time series in a higher dimensional space called phase space. In mathematics and physics, a phase space is a space in which all possible states of the system are presented. In this state, each possible state of the system corresponds to a unique point. The use of phase space is convenient to describe dynamic systems. Each orthogonal coordinate of phase space represents one of the system instantaneous states [20]. Nonetheless, measuring the entire variability of a dynamic system is impractical. Unintentionally, Takens has proven in [21] that phase space can be reconstructed from a time series with a single component using the embedding theorem.

A d-dimensional dynamical system can be illustrated by d first-order differential equations. The solution to these equations, \( \mathbf{s} \in \mathbb{R}^d \), is a state in the corresponding phase space, where \( \mathbb{R} \) indicates the Euclidean space. The measured function, \( x = h(s) \), transforms a collection of states to a scalar time series. A positive number \( \tau \) is used to show the delay of this time series. Function \( F_i(s_i) = s_{i+\tau} \) is defined to evaluate the state at time \( i \) and the delay coordinate. Hence, the embedding \( \phi : \mathbb{R}^d \rightarrow \mathbb{R}^d \) is defined as follows:

\[
\phi(h, F, \tau)(s_i) = \{ h(s_i), h(s_{i+\tau}), \ldots, h(s_{i+(d-1)\tau}) \} = \mathbf{x}_i
\]

Thus, the trajectory matrix of dimensioned \( d_E \) and delay \( \tau \) can be expressed as [13, 22, 23]

\[
X = \begin{bmatrix}
  x_1 & x_{1+\tau} & \cdots & x_{1+(d_E-1)\tau} \\
  x_2 & x_{2+\tau} & \cdots & x_{2+(d_E-1)\tau} \\
  \vdots & \vdots & \ddots & \vdots \\
  x_M & x_{M+\tau} & \cdots & x_{M+(d_E-1)\tau}
\end{bmatrix}
\]

(5)

where, \( \tau \) is delayed, \( \mathbf{x}_i \) (\( i = 1, 2, \ldots, d_E \)) are column vectors that form the coordinate of each \( d_E \) dimension, and the row vectors \( \mathbf{x}_i \) (\( i = 1, 2, \ldots, M \)) represent individual points in the phase space [20]. The correlation dimension is defined as [24]

\[
C(r) = \lim_{N \to \infty} \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \theta(r - |x_i - x_j|) \quad (i \neq j)
\]

(6)

where, \( x_i \) and \( x_j \) are two arbitrary points and \( \theta(a) \) is the Heaviside step function with a value of zero for negative algorithm and one for positive algorithm.

\[
\theta(a) = \begin{cases} 
0, & \text{if } a < 0 \\
1, & \text{if } a \geq 0
\end{cases}
\]

(7)

The number of pairs \( (x_i, x_j) \) calculated by Eq. (6) satisfies \( |x_i - x_j| < r \). A small \( r \) suppose that \( C(r) \) behaves as \( C(r) \alpha r^d \), such that \( d_E \) is the correlation dimension and estimated by

\[
d_E = \lim_{\tau \to 0} \frac{\log |C(r)|}{\log r}
\]

(8)

The embedding dimension is defined by \( 2d_E = [2d_E + 1] \). In the proposed method, the delay is selected to demonstrate the geometric data of the perturbation signal. In the sinusoidal waveform given by \( F(t) = A \sin(\omega t + \phi) \), the sample signal can be expressed by \( F(k) = A \sin(\omega k \Delta t + \phi) \). In this case, \( N_s = 2\pi/(\omega \Delta t) \) is the sampling rate in each period. Embedding the signal to a phase space of \( d_E = 3 \) with a delay of a quarter of its period \( \tau = N_s/4 \) shows that the embedded signal is an ellipse. Using \( x, y \) and \( z \) to represent the coordinates of the phase space \( x_1, x_2, x_3 \), respectively, the embedded signal in the phase space can be defined by the following equations:

\[
\begin{align*}
  x + y &= 0 \\
  x^2 + y^2 &= A^2
\end{align*}
\]

(9)

Eq. (9) in the \( xy \)-plane and \( yz \)-plane constitutes a circular waveform with radius that is the amplitude of the original signal and center that is the source of the plane, whereas the portrait of the \( xz \)-plane is a line segment.
Euclidean norm of each point on xy-plane signifies \( E(k) = \sqrt{x^2 + y^2} \). Euclidean norm for points belonging to the normal part of the signal should be within the range of \( [A(1 - \gamma), A(1 + \gamma)] \), where \( \gamma \) is the threshold introduced to tolerate the noise corruption. Points in which \( E \) falls out of this range are detected as disturbances. The beginning to ending samples of the disturbances are recorded using detection schemes. In this paper, \( E_x \) is utilized to extract special features to characterize islanding and non-islanding events. The corresponding features are then used as inputs for the neural network.

4. Phase space features extraction

Feature extraction is one of the critical tasks in developing multiple-parameter-based islanding detection. The aim of the proposed phase space features is to identify the specific signature of the voltage signal, which can differentiate between islanding and any other event condition. In this study, five features are extracted from the voltage signal using Euclidean norm \( (E_x) \). The selected features are described in Table 1.

The features with a mean value of \( E_x \) during the period of fault or after a first transient period to the next transient period of disturbance are obtained from the following equation [14,15]:

\[
E_x = \frac{\sum_{i=1}^{n} E_x}{n}
\]

(10)

where, \( n \) is number of the sample points. Meanwhile, feature with area can be calculated as

\[
\text{Area} = \int_{b}^{a} E_x dt
\]

(11)

where, \( a \) and \( b \) are the limits indicating the beginning and the end of disturbance, respectively.

Fig. 2 shows an example of a voltage waveform during a three-phase fault at DG2 and corresponding phase space representation. The signal in Fig. 2(a) is extracted using the Euclidean norms of phases A, B, and C, which are added up, as illustrated in Fig. 2(b). By normalizing the \( E_x \), as shown in Fig. 2(c), the values for mean, maximum, minimum, duration, and area under curve of \( E_x \) are extracted, as depicted in Fig. 2(d). These five input features can be rearranged as a vector according to Table 1.

Fig. 3 shows the samples of input features obtained for islanding and non-islanding conditions based on the abovementioned procedure for DG1 and DG2, as shown in Fig. 4. Fig. 3 (a) shows that the feature values for islanding events are F1, F2, F3, F4, and F5 and range from 1.58 to 1.73, 0.31 to 0.39, 0.92 to 0.98, 0.14 to 0.23, and 0.27 to 0.35, respectively. These feature value combinations and their ranges are significantly different from non-islanding event feature values, such as capacitor bank switching and three phase fault events, as shown in Fig. 3(b) and (c). Capacitor bank switching events feature values for F1, F2, F3, F4, and F5 range from 1.49 to 1.55, 0.8 to 0.94, 1.03 to 1.07, 0.66 to 0.90, and 0.71 to 0.84, respectively, whereas three-phase fault event values range from 0.75 to 1.00, 0.48 to 0.81, 0.95 to 1.27, 0 to 0.48, and 0.42 to 0.72, respectively. Therefore, these unique case features, such as islanding and all other non-islanding events, are useful inputs for intelligent classifiers, such as neural networks.

5. Distributed network with multiple DGs

The test system model consists of radial distribution system with two identical DG units, which is fed by 120 kV, 1000 MVA source at a 50 Hz frequency [14,15], [19], [25]. The DG units are placed within a distance of 30-km with a distribution line of \( \pi \)-sections, as shown in Fig. 4. The details of the studied system are given in Table 2.

Using the topology shown in Fig. 4 and data in Table 2, the system with multiple DGs is modeled and simulated using power system simulation tools DigSilent®. The voltage signals are retrieved at the target DG location for islanding and non-islanding conditions (other disturbances). The possible situations of islanding and non-islanding conditions studied are given as follows:-

- Load switching and capacitor switching at PCC point and DGs units;
- Loss of mains at the PCC bus;
- Fault at PCC point, DGs units, and distribution lines;
- Tripping of main circuit breaker for islanding condition;
- Tripping of other DGs apart from the target one; and
- Events that can trip breakers and reclosers, as well as island the DG under study.

The above conditions are simulated under possible variations in operating condition, such as the following:

- Normal DG loading, minimum DG loading and maximum DG loading; and
- Different operating points of the DG that causes NDZ.

The above conditions in the system, as shown in Fig. 4, can form three islands and can be tested with three possible NDZ conditions, as shown in Fig. 5, by varying consumer and DG loading conditions.

5.1. Obtaining data for training and testing

For any artificial intelligent classifier, such as ANNs, obtaining the training and testing data samples, as well as the input parameter settings, is important. The input to the classifier can be obtained using wavelet or phase-space features addressed in the aforementioned sections for various disturbance events. The classifier output or target parameters, which can be islanding or non-islanding conditions, can be obtained from simulation with a value definition for each event. Table 3 shows the predefined event class parameters based on the type of event class.

When adopting five phase-space features, two classifiers are used to represent the features corresponding to DG1 and DG2, as illustrated in Fig. 6. Each classifier uses 3611 samples, which correspond to training and testing. For training, 2166 samples (60%) are used, whereas 722 samples (20%) are applied for testing and validation. Meanwhile, for wavelet cases, six features with two classifiers for DG1 and DG2 are used [16], [18]. The structure of wavelet-based ANN is shown in Fig. 7. The sample data used in phase space are again used for training and testing in the wavelet-
based ANN classifier. However, all wavelet features are pre-processed using $-\log(x)$. This process is conducted to normalize the features in the range between 0 and 1. Table 4 illustrates the distribution of training and testing data used in the development of wavelet and phase-space islanding detection methods. With the same data trained and tested for both cases, the performance of the classifier type and feature extraction method in islanding detection can be compared.

6. Artificial neural network for index prediction

ANNs are computational models of a biological process. Such a model has several interesting and attractive features, which can be used to identify various events [26]. Among various forms of ANN, radial basis function neural network (RBFNN) and probabilistic neural network (PNN) have been selected as the classification tools.
in this study. A brief explanation of these variants of ANNs is given below.

6.1. Radial basis function neural network

RBFNN is an established and convenient neural network that has been used since the late 1980s for classification and prediction. For instance, RBFNN has been utilized in solving power system such as power transfer allocation [27], speech recognition system [28], fault location [29], protection of transmission lines [30] and transient stability assessment of power system [31]. General architecture of RBFNN consists of three layers namely an input layer, a hidden layer and an output layer as illustrated in Fig. 8. The input layer feeds the feature vector value to each neuron in hidden layer which consists of radial basis activation function. Finally, the output layer basically sums the weighted basis functions without any activation function. Assuming a single neuron at the output layer, the output of the

Fig. 3. Samples of selected phase space features for islanding and non-islanding events on DG1 and DG2 in the studied system. (a) Grid disconnection events (islanding condition), (b) Capacitor switching events (non-islanding condition) and (c) Three phase fault event (non-islanding condition).
Table 2
System model description.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>External grid</td>
<td>Represented by a 120 kV, 1000 MVA source</td>
</tr>
<tr>
<td>L1</td>
<td>Load with 15 MW and 3 MVar</td>
</tr>
<tr>
<td>L2 and L3</td>
<td>Load with 8 MW and 3 MVar</td>
</tr>
<tr>
<td>DG1 and DG2</td>
<td>1200 Vdc</td>
</tr>
<tr>
<td>T1</td>
<td>Transformer 120/25 kV</td>
</tr>
<tr>
<td>T2 and T3</td>
<td>Transformer 25/0.6 kV</td>
</tr>
<tr>
<td>Line 1</td>
<td>25 kV with 10 km length</td>
</tr>
<tr>
<td>Line 2 and Line 3</td>
<td>25 kV with 20 km length</td>
</tr>
<tr>
<td>PCC</td>
<td>Point of common coupling</td>
</tr>
<tr>
<td>A and B</td>
<td>Point near by the respective DG (A is point near DG1; B is point near DG2)</td>
</tr>
</tbody>
</table>

Fig. 4. Power distribution system with multiple DGs.

Fig. 5. Possible islands and NDZ region in the test system.
RBFDN in Fig. 8 can be calculated as

$$
\eta(x, w) = \sum_{k=1}^{6} w_{ik} \phi(||x - C_k||_2)
$$

(12)

where, \(||x - C_k||_2\) represents the Euclidean distance between the input vector \(x\) and the center \(C_k\). \(\phi(\cdot)\) represents a basis function, \(w_{ik}\) represents the weights in the output layer, \(S\) represents the number of neurons (and centers) in the hidden layer.

In this study, the Gaussian function is used as the RBFNN and it is given by

$$
\phi(||x - C_k||_2) = e^{-||x - C_k||^2/\sigma^2}
$$

(13)

where, \(\sigma\) is the spread parameter which controls the radius of the cluster represented by the \(C_k\). Practically, if value of \(\sigma\) is too big or small, it will cause degradation in the performance of RBFNN.

6.2. Probabilistic neural network as model classification

PNN is a type of neural network that is popularly used for classification, which is fundamentally developed based on Bayesian formulation [32]. PNN was widely used in power system applications due to its fast training capability and accuracy in classification. Mathematically, an input vector is utilized to define a category and the network classifiers are trained using data of known class. The PNN use the training data to develop a distribution function that is used to evaluate a tendency of feature vector within several given category. Basically, the Bayes formulation for this PNN can be given by [33]

$$
P(x|y) = \frac{P(y|x) \times P(x)}{P(y)}
$$

(14)

where \(P(y|x)\) is the probability of event \(x\) while event \(y\) given, \(P(x)\) is the probability of event \(x\), \([P(y)]\) is the overall probability of all events \(y\) and \([P(y|x)]\) is the probability of event \(y\) while event \(x\) given. The relationship of \([P(y|x)]\) is known as a posterior probability where the probability is known only after event \(x\) itself has been occurred.

Fig. 9 illustrates the structure of PNN, where it can be divided into four layers namely, the input layer, pattern layer, summation layer and the output layer. The first layer is input layer that represents the input features. This input layer is fully connected to the second layer called pattern layer. Each pattern in the training set is connected with one neuron. These neurons execute a weight sum of the receiving signal from the input layer. It is then applied to a nonlinear radial basis activation function to provide the neuron output. This activation function was addressed as [33]

$$
\phi(||x_{wi} - 1||_2) = e^{-\frac{||x_{wi} - 1||^2}{\sigma^2}}
$$

(15)

where, \(x_{wi}\) is the weight input of \(x_i\) to neuron and the \(\sigma\) is the smoothing parameter that determines how smooth the surface separating category will be. A reasonable range of \(\sigma\) is in between 0.1 and 10. The used of the Bayesian estimating function in pattern layer allowed the PNN to approximate Bayesian probabilities in categorizing pattern.

The third layer is the summation layers. Each pattern layer neuron transmits its output to a single summation layer neuron which can be formulated as;

$$
R_k(x) = \sum_{i=1}^{18} \phi(||x_{wi} - 1||_2), \quad k = 2, 3, 4, ...
$$

(16)

Each neuron in the output layer receives only two inputs from two summation units. One weight is fixed with the strength of unity and other weight is variable as in (16)

$$
w' = [-h_l/h_A, l_A/n_A, l_B/n_B, l_C/n_C]
$$

(17)

where \(h\) is referred to a priori probability of patterns being in category A or B, \(l\) is referred to loss associated with identifying a pattern as being in one category when it is in reality in the other category, and \(n\) referred to the number of A or B pattern in the training set. The value of \(h_A, h_B, n_A\) and \(n_B\) are determined by data pattern, but the losses must be based on knowledge of the application. Finally the output is determined as follows;

$$
y_{k}(x) = \arg\max\{R_k(x)\}
$$

(18)

Due to the use of priori probability and greedy selection in the output layer, PNN is expected to be better for classification compare to RBFDN.

<table>
<thead>
<tr>
<th>Event type</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal condition</td>
<td>1</td>
</tr>
<tr>
<td>Line to ground fault</td>
<td>2</td>
</tr>
<tr>
<td>Load switching</td>
<td>3</td>
</tr>
<tr>
<td>Three phase to ground fault</td>
<td>4</td>
</tr>
<tr>
<td>Capacitor switching</td>
<td>5</td>
</tr>
<tr>
<td>Islanding</td>
<td>6</td>
</tr>
<tr>
<td>Non- Islanding</td>
<td>7</td>
</tr>
</tbody>
</table>

**Table 3** Classifier output definition.

**Fig. 6.** Summary of phase space based classifier for DG1 and DG2.
In this study, both RBFNN and PNN algorithms are implemented for islanding detection using Matlab’s neural network toolbox functions. Table 5 shows the function names and initialization parameters used for PNN- and RBFNN-based classifiers of DG1 and DG2 in Figs. 6 and 7.

The optimum spread constants given in Table 5 are obtained by systematically increasing the value in steps of 0.1 from 0 to 10, as well as by measuring the training goal during training. Furthermore, the islanding detection algorithms developed with RBFNN and PNN can be evaluated using various error measurement indices, such as mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean squared error (RMSE), as given in Eqs. (19), (20), and (21), respectively [34], [35].

\[
\text{MAPE} = \frac{1}{T} \sum_{i=1}^{T} \frac{|X_i - \hat{X}_i|}{X_i} \times 100\% \quad (19)
\]

\[
\text{MAE} = \frac{1}{T} \sum_{i=1}^{T} |X_i - \hat{X}_i| \quad (20)
\]

\[
\text{RMSE} = \sqrt{\frac{1}{T} \sum_{i=1}^{T} (X_i - \hat{X}_i)^2} \quad (21)
\]

where, \(i = 1, 2, 3 \ldots T\), \(X_i\) = original data; \(\hat{X}_i\) = forecast data.

7. Test results

This section describes the result obtained by applying the proposed islanding detection algorithm along with the results of the conventional wavelet-based method. RBFNN and PNN have been used as a classifier with proposed phase-space input features and wavelet features. The performance of both of the classifier was evaluated by analyzing the performance of error indices and their decision accuracy.
7.1. Result of RBFNN with phase space features

The performance of RBFNN with phase-space features for islanding detection and classification was evaluated by testing with different data after being trained offline. These testing data contain various disturbance cases, including islanding and non-islanding events at normal and NDZ conditions. RBFNN classifier output results are then compared with actual or known target values. Regression analysis of each RBFNN corresponding to DG1 output results are then compared with actual or known target data are shown in Table 3. From the observation, Table 6 shows that the classification result with phase space features.

<table>
<thead>
<tr>
<th>Class</th>
<th>No of cases</th>
<th>Correct detection</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-islanding</td>
<td>650</td>
<td>631</td>
<td>97.07</td>
</tr>
<tr>
<td>Islanding</td>
<td>72</td>
<td>69</td>
<td>95.83</td>
</tr>
</tbody>
</table>

7.2. Result of RBFNN with wavelet features

Using the similar procedures with phase space features, a RBFNN classifier is trained and tested with wavelet features. Here, the outputs of the network are compared with the actual target data to the corresponding input, as shown in Fig. 11 and Table 7. In this case the correlation (R) value are equal to 0.07091 and 0.1234 for DG1 and DG2 classifiers, respectively, which indicates poor correlation between predefined event class targets and output of the RBFNN. This result indicates that the RBFNN performance with wavelet features is inappropriate because of the low accuracy in detecting the islanding event.

7.3. Results of PNN with phase space features

The performance of RBFNN classifier, especially with wavelet features, is very low. Thus, the RBFNN classifier is replaced with the PNN classifier. In this work, the two PNN classifiers are trained and tested with phase-space features for DG1 and DG2, respectively. The training and testing data remain the same as those used in the RBFNN classifier. Table 8 shows the summary of PNN classification results using the phase-space feature. From the table, it can be noted that the classifier provides 100% accuracy in both cases of islanding and non-islanding class.

7.4. Results of PNN with wavelet features

To improve the performance of the islanding detection algorithm with wavelet features, the RBFNN classifier is again replaced with a PNN classifier by maintaining the same training and testing data. Table 9 shows the classification result of PNN with wavelet features.
features. The performance can be observed to have improved to 80.6% compared with the RBFNN classifier, which achieved 58.33% for islanding events.

The overall classification accuracy is illustrated in Table 10. The classification accuracies of the PNN with phase-space features are observed to be 100% for both islanding and non-islanding conditions. However, only 80.6% and 80.5% accuracy were confirmed for PNN classifier with wavelet features for islanding and non-islanding detection, respectively.

The error between forecasted and original values is compared for both algorithms. MAPE, RMSE and MAE are used as error measurements. Table 11 shows the error measurement for various classifiers using phase-space and wavelet input features. Moreover, the time allocation for training and testing in the PNN and RBFNN is also provided in the table. From the observation, the PNN with phase-space features notably provide the lowest error for the measurement compared with the RBFNN and PNN with wavelet features. Moreover, both the MAPE values of phase space-based RBFNN and PNN are less than 10%, which indicates the high accuracy of the detection [35]. Therefore, the observation reveals that the phase-space features with PNN classifier provide higher accuracy than wavelet features with RBFNN and PNN classifiers. The reason why PNN outperforms RBFNN in this case is that the former estimates the probability density function of the training dataset that minimizes the expected risk of a classification into specific output categories [36]. By contrast, the output of the RBFNN network simply sums the weighted basis function and does not have a specific class neuron in its structure. Therefore, PNN is more suitable for classification purposes, whereas RBFNN is better for regression.

8. Conclusion

This paper presented an algorithm known as the phase-space technique for feature extraction of the three-phase voltage waveforms to classify islanding and non-islanding conditions at the target DG location. The proposed method is tested using several disturbance signals, including islanding operation conditions and various non-islanding conditions that may appear in the network, such as DG power variation, fault, load switching, capacitor
switching, and NDZ condition. Test results show that the proposed islanding detection algorithm with PNN and phase-space features is capable of correctly detecting the islanding operation. To validate the performance, the method is compared with a conventional wavelet-based method with different classifiers, namely, RBFNN and PNN. The comparison shows that the proposed detection method with PNN and phase-space features provides 100% accuracy, whereas the method with PNN and wavelet achieves 80.6% accuracy in islanding region detection. Furthermore, the results also indicate that the PNN classifier outperforms the RBFNN classifier. Moreover, the performance was evaluated using error measurement, and the phase-space and PNN classifiers were found to be more accurate than the wavelet technique and RBFNN classifier.

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