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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

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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 ± 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 difficulty in detecting when the load and generation in an islanded distribution system is nearly equal. This situation may incur the risk of large non-detection zones (NDZ). Therefore, in the literature, some improvements have been proposed to mitigate large NDZ problems. In [6], a method is proposed to reduce the NDZs of UVP/OVP and UFP/OFP by comparing the P–V and P–Q characteristics of inverters equipped with a constant current controller.

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:

$$\mathrm{DWT}_{\psi} f(m,n) = \sum f(k) \psi *_{m,n}(k) \quad (1)$$

where, $\Psi_{m,n}$ is the discretized mother wavelet given by

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_o^m}} \psi\left(\frac{t - b_o a_o^m}{a_o^m}\right) \quad (2)$$

$a_o(>1)$ and $b_o(>0)$ 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]

$$||ED_{1a}|| = \left[\sum_k d_k^2\right]^{1/2} \quad (3)$$

where, ED_{1a} 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