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A new artificial neural network based method for islanding detection of distributed generators

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ABSTRACT

This paper presents an artificial neural network (ANN) based method for islanding detection of distributed synchronous generators. The proposed method takes advantage of ANN as pattern classifiers. It is capable of identifying the islanding condition based on samples of the voltage waveform measured at the distributed generator terminals only, which is an important advantage over other ANN-based anti-islanding methods. Moreover, the proposed method is robust against false operation. In order to create a training data set for the ANN, a data selection procedure has been proposed, so that the ANN could be trained more effectively, which has contributed positively to the good performance of the method. The concept of the time-performance region has been introduced to assess the method performance, as well as the non-detection zones. A detailed discussion about the data sampling rate to feed the proposed method has also been conducted, so that the computational burden can be faced as an important factor to assess its performance.

Introduction

One of the main requirements of distribution utility companies related to connecting distributed generators is the detection of islanding events. Islanding occurs when part of the distribution system becomes electrically isolated from the main supply, and it remains energized by distributed generation (DG) in the isolated subsystem. Failure to detect islanding may lead to power quality issues [1], equipment damage and safety issues concerning the electrical company workers. Therefore, DG connection codes worldwide require that all islanded distributed generators are disconnected as fast as possible after an islanding occurrence [1–3].

Typically, a distributed generator should be disconnected within 100–2000 ms after loss of the main supply [1–3]. To reach this objective, islanding detection can be performed using several methods, such as communication-based schemes, as well as active and passive techniques.

Communication-based schemes use telecommunication devices, which send a trip signal to the generators when islands are formed. There are different technologies that can be used such as SCADA (Supervisory Control and Data Acquisition), transfer trip or PLCC (Power Line Carrier Communication) systems [4–7]. Although these schemes are considered effective, they are costly [7].

In active schemes, disturbances are injected locally into the system and their responses are used to detect islanding conditions. Examples of such methods include active frequency drift [8], Sandia voltage and frequency shift methods [9] and DG voltage variation [10,11]. This type of anti-islanding protection may present poor performance caused by signal interference if there are multiple distributed generators equipped with active schemes. Besides, they may also hinder power quality [1,7].

Finally, passive schemes depend on the local measurements of voltage and current signals. These schemes may use the under/over voltage and under/over frequency relays [1,5,7]; non-conventional measurements, such as the rate of change of active power [12]; phasor measurement units [13]; or hybrid techniques, as described in [14,15]. The technique presented in [14] combines voltage imbalance and total harmonic distortion of the current to detect DG islanding, and the technique described in [15] applies system impedance estimation to improve anti-islanding relay performance. Usually, passive anti-islanding schemes are simple to operate and easy to implement. However, they may present large non-detection zones (NDZ) if not properly adjusted [16]. If settings are too sensitive, islanding will be detected successfully (small NDZ) but the probability of nuisance tripping increases. Therefore, efficient islanding detection techniques must discriminate islanding events from other disturbances, such as load switching and short circuits. In this context, intelligent-based islanding detection methods have been

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proposed recently. For example, in [17] data mining is used to extract information from multiple system parameters to identify and classify possible islanding conditions. In [18] the relevant spectral features of negative sequence voltage and current signals collected from the system are used as input of a fuzzy expert system, which identifies the operation status as islanding or non-islanding. In [19], the DG voltages are processed using the Wavelet Transform to calculate indexes based on wavelet singular entropy to identify the operation status.

In addition, artificial neural networks (ANN) have been used for islanding detection. In [20], various parameters are measured using a hybrid active–passive technique in order to secure the detection of islanding for any possible network topology, DG penetration level and operating conditions. The authors consider synchronous distributed generators. The proposed technique uses ANN to extract information from the data sets of measured parameters after they are obtained via a massive event analysis using network simulations. An adaptive neuro fuzzy inference system using the rate of change concerning active power of distributed generators is proposed for islanding detection in [21]. In [22], a probabilistic neural network approach was proposed to detect islanding based on several measurements, such as rate of frequency change, rate of voltage change, rate of power change, total harmonic current distortion and rate of power factor change for islanding detection. An ANN based islanding detection method is proposed in [23] for wind farm power generation systems. The method uses the second harmonic of the processed voltage and current measurements to feed an ANN, which identifies the operation status.

Hybrid active–passive techniques, such as in [20], may be costly and complex to implement, and the methods proposed in [21–23] either consider several parameters as inputs for the ANN or require the measured parameters to be processed. These inputs may not be readily available in practical situations or may introduce excessive computational burden to the method. To combine the simplicity of passive methods with the advantages of using ANN, this paper presents an ANN based DG islanding detection method that has the advantage of depending only on the voltage measured at the DG point of common coupling. Since the ANN training data set includes different kinds of events such as islanding, load switching and system frequency variation, the method is able to avoid nuisance trips and offer a suitable response to islanding events. Thus, comparing with Ref. [20–23] the proposed algorithm presents the following advantages: (a) there is no pre-processing since the ANN uses only voltage samples; (b) it doesn't require communication link; (c) accurate discrimination between load switching and islanding condition.

This paper focuses on distributed synchronous generators. However, the method can be applied to any distribution system with other DG technologies. The ANN training procedures are described for this generalization to take place. It is import to highlight that differently from [24] that discusses only the training process of ANN, this paper applies and evaluates the ANN by using practical test cases. Besides, different sampling rates are used and their impacts on the algorithm performance are discussed. The accuracy of the algorithm is checked by using the NDZ (no detection zones), which allows selecting the best ANN configuration for specific situations, regarding accuracy *versus* computational load.

This paper is organized as follows. Section 'Proposed ANN-based method for islanding detection' presents the fundamentals of the method, as well as the distribution feeder used in this paper. In Section 'Method assessment and application', the proposed method is assessed by applying it to several islanding and non-islanding cases. The main findings are presented in Section 'Conclusions'.

Proposed ANN-based method for islanding detection

The main concept of ANN is based on the representation of neural activity in the human brain. The most popular design for ANN is the multilayer feed-forward network, known as MLP (Multi-Layer Perceptron). Such networks have an input layer, an output layer and one or more hidden layers. Each layer has a number of nodes or neurons, which consist of multiple inputs and a single output. A weight is associated to each input, while the input signal is multiplied by these weights. The neuron is responsible for the combination of these weighted inputs and, in accordance with an activation function, the output is determined [25].

The challenge of developing an ANN based algorithm starts by the training set definition, i.e. enough data for the training and validation processes should be provided to make the ANN able to respond correctly to islanding situations. One of the most suitable algorithms used in the ANN training process is the *Backpropagation*. It is a supervised learning method, which requires a dataset of the desired output(s) from known input(s), forming the training set [26].

Based on the above-mentioned concepts, the proposed method was developed according to the following: (a) definition of the distribution feeder; (b) selection of an ANN architecture; (c) definition of an ANN sampling rate for data acquisition; (d) ANN training process; and (e) method overview.

Distribution feeder

The distribution system used in this paper is presented in Fig. 1. The distribution feeder was modeled as an RL series circuit and the transformers were modeled using a T circuit. Synchronous generators were represented by a sixth-order three-phase model in the *dq* rotor reference frame [27]. The generator was modeled with an automatic voltage regulator represented by the IEEE – Type 1 model. Usually, distributed generators do not participate in the frequency regulation of the system and, therefore, they operate at constant active power or droop mode [1]. In addition, the turbine and governor dynamical models were neglected, as the simulation period considered is only 1 s. Thus, the mechanical power was considered constant in this work. The loads were modeled as constant impedance type [27]. All the system parameters can be found in [16].

The simulations were run by using the *SimPowerSystems toolbox* of *Matlab*. The islanding event is simulated by opening the circuit breaker #1 at bus 2.

Selection of the ANN architecture

The ANN used in the proposed method is the MLP with four layers: eight perceptrons in the first layer; four in the second; two in the third; and one in the output layer. This ANN was selected after performing tests on several architectures and assessing the capacity to detect frequency and voltage variations of each ANN. These signals were generated by using the *SimPowerSystems toolbox* of *Matlab* and were used to train and perform the tests.

Definition of the ANN sampling rate

Four different sampling rates were tested: 960, 1920, 3840 and 7680 Hz (16, 32, 64 and 128 samples per cycle of 60 Hz). It is important to mention that the data window acquisition is a full cycle of 60 Hz for all sampling rates. Another characteristic is that the algorithm acquires the data cycle-by-cycle. Although the four sampling rates were tested, only 64 and 128 samples/cycle were used in this paper, because they led to the best results.