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Deep learning hybrid method for islanding detection in distributed generation

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HIGHLIGHTS

- For the first time, deep learning is designed for islanding detection.
- The noises can be effectively eliminated by the feature extraction method proposed.
- The competitive performance of the islanding detection method were proved.

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ABSTRACT

The increasing penetration of distributed energy brings significant uncertainty and noises to microgrid operation, which enlarge the difficulty of microgrid monitoring. For as much as the detection of islanding is prone to be interfered by grid disturbance, island detection device may make misjudgment thus causing the consequence of distributed generations (DGs) out of service. The detection device must provide with the ability to differ islanding from grid disturbance. In this paper, the concept of deep learning is introduced into the classification of islanding and grid disturbance for the first time. A novel deep learning framework is proposed to detect and classify islanding or grid disturbance. The framework is a hybrid of wavelet transformation, multi-resolution singular spectrum entropy, and deep learning architecture. As a signal processing method after wavelet transformation, multi-resolution singular spectrum entropy combines multi-resolution analysis and spectrum analysis with entropy as output, from which we can extract the intrinsic different features between islanding and grid disturbance. With the features extracted, a deep learning based algorithm is proposed to classify islanding and grid disturbance. Simulation results indicate that the method can achieve its goal while being highly accurate, so the DGs mistakenly withdrawing from power grids can be avoided.

1. Introduction

1.1. Motivations

In a microgrid with increasing distributed energy, the islanding condition resulted from line fault and other reasons might cause serious hazards. Islanding conditions must be detected in order for protection devices to function. Minor disturbances, such as minor voltage or frequency changes, are sometimes misidentified as islanding or fault conditions and trigger protection devices to malfunction [1–3]. This malfunction is harmful in that it severely disrupts the normal operation of a distribution system. Hence it is vital to precisely detect islanding and fault scenarios and distinguish them from minor disturbances.

With the increasing penetration of distributed generations (DGs), however, islanding detection faces unprecedented challenges. On the one hand, renewable generation brings significant uncertainties and noises to a distribution system [4,5]. This increases the intensity of disturbances and creates a barrier to the accuracy of islanding detection. On the other hand, if minor disturbances are misidentified as islanding conditions, DGs would be forced out of service, which can be extremely dreadful. Hence an accurate islanding detection method becomes decisive to the security of a distribution system with high penetration of DGs.

Islanding detection methods can be divided into communication methods, active methods, and passive methods [6,7]. The high cost of the communication method is barrier to its application. The active method has an adverse effect on grid operation due to injection signals. The mainstream method is the passive method. It extracts voltage and

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frequency signals at the point of common coupling (PCC) and compares the signals with a given threshold value. It is quite convenient, but the threshold values are usually set empirically, which might be misleading and unreliable. Meanwhile, using conventional wavelet energy coefficients as eigenvectors is susceptible to the noise caused by an increasing amount of power electronics equipment.

The voltage value and frequency at the point of common coupling are extracted for wavelet transformation, then the absolute values of the coefficients are acquainted for the comparison with the set threshold values of voltage and frequency in [7,8]. It is recognized as islanding only if the two numerical values exceed the threshold values simultaneously, else as other grid disturbance. Nonetheless, the threshold value is set by experiments and experience, and the two values of real islanding do not necessarily exceed the threshold value at the same time. With the same flaws, an average absolute frequency deviation value based active islanding detection technique is utilized in [9]. In [10], wavelet energy coefficients in different frequency bands of the transient phase current signal are extracted as eigenvectors by wavelet transformation, with which the islanding is detected by means of decision tree, neural network, support vector machine and other pattern recognition technology. This method is a novel and quick way to recognize islanding. However, using wavelet energy coefficients as eigenvectors is susceptible to noise. Moreover, contrastive analysis and classification of islanding and similar disturbance are not conducted in that paper.

This paper aims to propose a method that can detect islanding and grid disturbances accurately with high penetration of distributed energy.

1.2. Contributions

The contributions of this paper include the following:

(1) We propose a novel feature extraction method for islanding detection. The method combines multi-resolution singular spectrum entropy with wavelet decomposition. Multi-resolution singular spectrum entropy is good at digging the essential feature of signals from islanding and disturbance conditions irrespective of how wavelet coefficients are set. It is found to be effective in eliminating noise interference. The method is proved to outperform the popular wavelet energy coefficient method in feature extraction.

(2) For the first time, a deep-learning-based islanding detection method is proposed for binary-classification of islanding and disturbance conditions in a microgrid with high penetration of distributed energy. Deep learning uses computational models composed of multiple processing layers to learn representations of data with multiple levels of abstraction. The deep learning method proposed is found to dramatically improve the accuracy of islanding detection.

2. Feature extraction based on multi-resolution singular spectrum entropy

2.1. Multi-resolution singular spectrum entropy calculation

(1) By selecting appropriate wavelet basis function and decomposition layer, discrete signal $f(k)(k = 1, 2, \dots, N)$ is processed using Mallat algorithm. The discrete dyadic wavelet transform of the discrete signal can be determined by Eq. (1) [11–15].

$$\begin{cases} c_{j+1}(k) = Hc_j(k) \\ d_{j+1}(k) = Gc_j(k) \end{cases} \tag{1}$$

As in (1), H and G are low pass filter and high pass filter, respectively. c_j and d_j indicate the approximate part and the detailed part of the signal scale. After the decomposition of scale $1, 2, \dots, j$ (j is the decomposition layer), $f(k)$ is decomposed into $d_1, d_2, \dots, d_j, c_j$, which indicate information of different bands from high frequency to low frequency, respectively.

(2) For the decomposed signal of each layer, wavelet transform coefficient reconstruction is conducted by Eq. (2).

$$c_{j-1} = H^* c_j + G^* d_j \tag{2}$$

As in Eq. (2), H^* and G^* are the dual operators of H and G, respectively.

(3) Reconstruct the reconstruction signal of each layer in phase space.

The assumption to reconstruct an n-dimensional phase space. Let the reconstruction signal of layer j be $D_j = \{d_j(k)\}$, from which $d_j(1), d_j(2), \dots, d_j(n)$ is supposed to be the first vector of the n-dimensional phase space. Then, take $d_j(2), d_j(3), \dots, d_j(n+1)$ as the second vector. By this analogy, an $(N - n + 1) \times n$ dimensional matrix $\boldsymbol{A}$ is constructed.

$$\boldsymbol{A} = \begin{bmatrix} d_j(1) & d_j(2) & \cdots & d_j(n) \\ d_j(2) & d_j(3) & \cdots & d_j(n+1) \\ \vdots & \vdots & \vdots & \vdots \\ d_j(N-n+1) & d_j(N-n) & \cdots & d_j(N) \end{bmatrix} \tag{3}$$

(4) For the matrix $\boldsymbol{A}$ of each layer, singular value decomposition (SVD) is conducted to calculate the singular spectrum entropy.

The matrix $\boldsymbol{A}_{(N-n+1)\times n}$ is decomposed using SVD and the result is $\boldsymbol{A} = \boldsymbol{U}_{(N-n+1)} \Lambda_{l\times l} \boldsymbol{V}^{\mathrm{T}}{}_{n\times l}$. The nonzero diagonal elements $\lambda_{ji}(i = 1, 2, 3, \dots, l)(l =)$ from $\Lambda_{l\times l}$ are singular values of the matrix $\boldsymbol{A}$ from layer j. According to the informational entropy theory, definition of the signal singular spectrum entropy is as follows.

$$H_j = -\sum_{i=1}^{l} p_{ji} \log(2 p_{ji}) \tag{4}$$

$$p_{ji} = \frac{\lambda_{ji}}{\sum_{i=1}^{l} \lambda_{ji}} \tag{5}$$

As in Eqs. (4) and (5), H_j is the information entropy of level j; the p_{ji} is the uncertain probability distribution of λ.

2.2. The application mechanism analysis of multi-resolution singular spectrum entropy

Multi-resolution singular spectrum entropy is defined as a kind of wavelet entropy based on different principles and approaches [16,17]. The wavelet reconstruction coefficients matrix uniquely represents the information of the corresponding layer of the signal, and the singular value vector of the corresponding layer uniquely represents the coefficients matrix as well [18]. Therefore, the singular value vector of the corresponding layer uniquely represents the information of the corresponding layer as well. Moreover, resulted from the certain measurement given by entropy, multi-resolution singular spectrum entropy can represent the essential character of the signal, which is exceedingly suitable for the feature extraction of islanding and grid disturbance.

2.3. Feature extraction

Specific processes of the eigenvector extraction are as follows:

(1) Decompose the voltage signals to analyze using wavelet transformation, of which the decomposition layer is j. Then reconstruct the reconstruction signal of each layer in phase space. In this paper, the number of sampling points is 6000. 600-dimensional phase space is