Application of Islanding Detection and Classification of Power
Quality Disturbance in Hybrid Energy System

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Abstract. Islanding and power quality (PQ) disturbances in hybrid energy system become more serious with the application of renewable energy sources. In this paper, a novel method based on wavelet transform (WT) and modified feed forward neural network (FNN) is proposed to detect islanding and classify PQ problems. First, the performance indices, i.e., the energy content and SD of the transformed signal are extracted from the negative sequence component of the voltage signal at PCC using WT. Afterward, WT indices are fed to train FNNs midfield by Particle Swarm Optimization (PSO) which is a novel heuristic optimization method. Then, the results of simulation based on WT-PSOFNN are discussed in MATLAB/SIMULINK. Simulations on the hybrid power system show that the accuracy can be significantly improved by the proposed method in detecting and classifying of different disturbances connected to multiple distributed generations.

1. Introduction
Under the new situations and circumstances of a worldwide avocation of energy conservation and reduction of pollutant emission, the renewable energy sources have caused extensive concern. Distributed Generation (DGs) like wind turbine, photovoltaic (PV) can satisfy the expand energy demand, reduce the environment pollution and promote the coordinated development of environment and economy [1]. As penetration level of DG connected to utility grid increases, there are various issues needed to be considered such as islanding situation and power quality (PQ) problems [2]. Islanding operation forms because of fault or other reasons in power system when DG fails to detect power state and can not quickly cut off from public Grid and supply local loads instead [3]. This results to negative influence on public power system, such as the safety hazards to utility personnel, PQ disturbances and serious damages of equipment. Hence, it is important to detect islanding and PQ disturbances correctly and efficiently to increase the reliability of power supply [4].

Recently, several approaches have been proposed in detection islanding and classification of PQ disturbances which could be roughly divided into three groups: active, passive, and communication-based methods [5]. Generally, active methods analyze the changes of output signals by injecting a small disturbance into the system [6]. And the passive methods for effective detection of disturbances are based on observing system parameters and selecting appropriate thresholds. Active
methods can bring about PQ problems, while passive methods are affected by non-detection areas and need to select the suitable threshold [7].

Nowadays, new methods have been proposed about wavelet transform (WT), artificial neural network (ANN), and the hybrid of the two [8]. The wavelet transform (WT) is useful in detecting PQ problems and analyzing signal in both time and frequency domains [9]. Artificial neural networks (ANNs) can be used to classify different PQ problems according to the results of WT [10].

In FNNs, the main object is to find the appropriate combination of connection weights and biases for purpose of achieving the least error in the process of learning. A wide variety of heuristic optimization methods have been adopted by training FNNs: Simulated Annealing (SA), Genetic Algorithms (GAs) [11], Particle Swarm Optimization (PSO) algorithms [12], and Differential Evolution (DE) [13]. In addition, SA and GA, suffering from low convergence speed, could avoid trapping in local minima. According to [14], in the aspect of avoiding the drawbacks of convergence speed, PSO is one of the effective and reliable training algorithms.

Based on the above analysis, this paper proposes an islanding detection and classification method based on Wavelet Transform (WT) and modified FNN in hybrid power system. Discrete wavelet transform (DWT) is used to decompose the negative sequence voltage signal at PCC into different frequency bands [15]. The energy content and SD of the wavelet details calculated will be fed to a trained FNN which will be able to predict the event by understanding the pattern of input feature vector. Apart from being efficient and accurate [15], the presented method makes no difference with the power quality and high classification accuracy compared to traditional techniques.

This thesis is organized as below: Grid-connected multiple DGs is presented in Section II and the proposed Wavelet Transform – PSOFNN based islanding detection technique is fully described in Section III. Then, the simulated results and discussions are described in Section IV. The conclusion is showed in Section VII.

2. Grid-connected multiple DGs

To describe the proposed method for islanding detection, a hybrid distribution (HS) system model is built by MATLAB. The HS designs a photovoltaic power plant with a rated power of 250 kW with constant light of 1000 $W/m^2$ and a wind power plant with a power rating of 1.5 MW with constant wind speed of 12 $m/s$. The photovoltaic array comprises of 86 parallel strings. Each of them consists of 7 Sun Power SPR-415E modules connected in series. A 3-level IGBT bridge based on PWM is used to control the converter. Wind turbine with power of 1.5MW and PV with power of 250kW connects to a 10 kV distribution system. Dome-fed induction generators (DFIG) wind turbines are made up of wound-rotor induction generators and an AC/DC/AC IGBT-based PWM converter [16]. A typical hybrid distribution system with two distributed generators is presented in Figure 1. The hybrid power system consists of PV and Wind Power plant connected to a 10 kV Grid at point of common coupling (PCC) [6]. PQ disturbances considered in this study are Line to Line (L-L), Line to Ground (L-G) fault, Line to Line to Ground fault and Non-Linear load switching.
3. Detection and classification approach

In this chapter, the detection and classification method based on Wavelet Transform - PSOFNN is explained. The proposed method is on the basis of the analysis of transient process and identification of PQ events such as faults, switching and so on [15]. After the wavelet decomposition of the negative sequence voltage signal at the PCC [6], the eigenvalues of different scales are calculated and sent to a trained modified FNN model in order to classify different PQ disturbances.

3.1. Discrete Wavelet Transform (DWT)

WT decomposes data and functions in the time–frequency plane and is a choice for analyzing non-stationary signals emerged when island occurs [6].

In this paper, the negative sequence components of voltage signals at PCC are used as the input signals of the wavelet transform. When fault occurs, it can be noticed that the decomposition coefficients of the input signals by WT provide valuable information and represent the influence of any disturbances [17]. Daubechies 4 (dB4) mother wavelet was proved to perform well in feature extraction for islanding detection [17].

Given a function \( v(t) \), the continuous wavelet transform (CWT) could be described as follow [6]:

\[
CWT(v, x, y) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} v(t) \varphi^{*} \left( \frac{t-y}{a} \right) dt
\]

(1)

Where \( x \) and \( y \) are scaling and translation constants, and \( \varphi \) is the wavelet function. Through the discrete wavelet transform, wavelet transform of sampling waveform could be gained:

\[
DWT(v, x, y) = \sum_{k} v(k) \varphi^{*} \left( \frac{n-kx_{0}}{x_{0}} \right)
\]

(2)

3.2. The Choice of features

To detect islanding and PQ disturbances, characteristic indicators like the energy content of the signal and Standard Deviation (SD) are extracting from negative sequence voltage by WT.

Figure 1. A hybrid power system with multiple DGs.
The Parseval’s theorem states that the total energy of the signal in the time domain is equal to the total energy of the signal in the frequency domain, that is, the total energy of the signal after Fourier transform remains unchanged. Mathematical framework is shown as follows [18]:

$$E_{signal} = \frac{1}{T} \int_{0}^{T} |v(t)|^2 dt = \sum_{k=-\infty}^{\infty} |c(k)|^2 + \sum_{j=-h}^{h} \sum_{k=-\infty}^{\infty} |d_j(k)|^2$$

(3)

$$c_j(k) = \sum_{m=-\infty}^{\infty} c_{j+1}(m) h(m-2k)$$

(4)

$$d_j(k) = \sum_{m=-\infty}^{\infty} c_{j+1}(m) h_1(m-2k)$$

(5)

$$h_k(k) = (-1)^k h(1-k)$$

(6)

Where $T$ represents the period of time, $c_j(k)$ and $d_j(k)$ are the quadrature mirror filters (QMF), $h(k)$ and $h_1(k)$ represent the scaling function and wavelet function.

The energy of signal and SD [19] for the detail coefficients is calculated in Equation (7) and Equation (8).

$$\|X\|_2 = (\sum_{i=1}^{N} |x_i|)^{1/2}$$

(7)

$$SD = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu)^2$$

(8)

Where the amplitude of $i_{th}$ sample of Wavelet Transform of sampling signal is $x_i$, $N$ represents the number of samples and $\mu$ is the mean of the Wavelet Transform of signal.

3.3. Modified FNN: PSOFNN

Artificial neural networks (ANNs) had been successfully applied in many aspects in power systems operation and control. One of functions of ANN is often designed as classifiers because of the ability of learning, complex nonlinear mapping and parallel computing [20].

Artificial neural network is extensively interconnected by a large number of simple processing units (called neurons) [21] that solve specific problems in parallel. A simple neuron with input vector $P$ is shown in Figure 2. The goal of Artificial Neural Networks (ANN) is that the network shows some desired behaviors by adjusting these parameters. Therefore, you can train the network to perform particular functions by changing the parameters.

![Figure 2. A simple neuron.](image-url)
In this paper, PSO is applied to update the weights and biases of a network for the purpose of minimizing the mean square error (MSE) so as to the network will implement particular functions [21].

PSO is a heuristic optimization approach which is proposed by Kennedy [22], which searches for the target minimum by a number of particles in the space.

Every particle updates its position according to the current position and velocity in order to minimize the distance to global best position. It can be described as follows [23]:

\[ v_i^{t+1} = w v_i^t + c_1 \times \text{rand} \times p(\text{pbest}_i - x_i^t) + c_2 \times \text{rand} \times (\text{gbest} - x_i^t) \]  

\[ x_i^{t+1} = x_i^t + v_i^{t+1} \]

Where \( v_i^t \) is the velocity of particle \( i \), \( w \) is a weighting function, \( c_j \) is an acceleration coefficient, \( \text{rand} \) is a random number between 0 and 1, \( \text{pbest}_i \) is the pbest of agent \( i \) at iteration \( t \), and \( \text{gbest} \) is the best solution.

The fitness function is introduced as follows [24]:

\[ f(s_j) = (1 + \exp(-((\sum_{i=1}^{n} w_{ij} x_i - \theta_j))))^{-1}, \quad j = 1, 2, ..., h \]  

\[ s_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j \]  

\[ o_k \sum_{i=1}^{h} w_{ij} f(s_j) - \theta_j, \quad k = 1, 2, ..., m \]  

\[ E_k = \sum_{i=1}^{m} (o_k - d_i)^{2} \]  

\[ E = \sum_{k=1}^{q} \frac{E_k}{q} \]  

\[ \text{fitness}(X_i) = E(X_i) \]

Where \( n \) is the number of the input nodes, \( w_{ij} \) is the connection weight from the \( i_{th} \) node in the input layer to the \( j_{th} \) node in the hidden layer, \( h_j \) is the bias of the \( j_{th} \) hidden node.

A typical FNN with two layers is shown in Figure 3.

Figure 3. FNN with 2-3-1 structure.

Moreover, the matrix encoding strategy is used in this paper. The example of Figure 3 is shown as follows [24]:
\begin{equation}
\text{particle}(\cdot, i) = \left[ W_i, B_i, W'_i, B'_i \right]
\end{equation}

\begin{equation}
W_i = \begin{bmatrix} w_{13} & w_{23} \\ w_{14} & w_{24} \\ w_{15} & w_{25} \end{bmatrix}, \quad B_i = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}, \quad W'_i = \begin{bmatrix} w_{36} \\ w_{46} \\ w_{56} \end{bmatrix}, \quad B'_i = \begin{bmatrix} \theta_i \end{bmatrix}
\end{equation}

Where $W_1$ and $B_1$ are respectively correspondent with weight matrix and bias matrix in the hidden layer, $W'_2$ and $B'_2$ are respectively correspondent with transpose of weight matrix and bias matrix in the output layer.

4. Simulink results and discussions

This section consists of the waveforms obtained on computer simulation of various events in MATLAB/Simulink. SD and the content of energy are calculated to train PSOANN. Simulation time is 1.5 seconds. Disturbances are introduced from 0.6 to 0.9 seconds.

4.1. Islanding Detection for Multiple DG systems.

Waveforms are shown in normal operation and islanding operation in Figure 4 and Figure 5.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure4}
\caption{signals at normal operation at PCC. (a) Phase Voltage (b) Neg.Seq.Voltage (c) Phase Current}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure5}
\caption{signals at islanding operation at PCC. (a) Phase Voltage (b) Neg.Seq.Voltage (c) Phase Current}
\end{figure}

4.2. PQ Disturbance Detection
Figure 6. Signals at Line-Ground operation at PCC. (a) Phase Voltage (b) Neg. Seq. Voltage (c) Phase Current

Figure 7 signals at Line-Line Fault operation at PCC. (a) Phase Voltage (b) Neg. Seq. Voltage (c) Phase Current

Figure 8. signals at Non-Linear Load Switching operation at PCC. (a) Phase Voltage (b) Neg. Seq. Voltage (c) Phase Current

Figure 9. signals at Line-Line-Ground operation at PCC. (a) Phase Voltage (b) Neg. Seq. Voltage (c) Phase Current
It is evident from Figure 6 to Figure 9 that some differences exist in the negative sequence during different types of events can be noticed. These differences reflect on WT indices like SD and energy of the signal which are shown in Table 1 will be able to classify the events with high prediction accuracy. Meantime, THD changes abruptly during Islanding and it is hard to fix a threshold to detect PQ events. Compared to detection of harmonics method, new proposed approach performs well based on WT.

Table 1. Feature vectors for training.

| Events            | THD(%)  | SD        | Energy        |
|-------------------|---------|-----------|---------------|
| Normal            | 0.94    | 9.6089e-5| 5.2496e-5     |
| Islanding         | 20.46   | 0.0433   | 0.0535        |
| L-L Fault         | 0.3     | 0.1248   | 0.0370        |
| L-G Fault         | 0.39    | 0.0121   | 0.0121        |
| LL-G Fault        | 0.17    | 0.1503   | 0.0215        |
| Non-Linear        | 15.79   | 0.0356   | 0.0271        |

4.3 Classification of PQ Disturbances based on Modified ANN

The data are divided two groups, one for training FNNs and the other for test the accuracy of classification. The example is randomly distributed and divided into training and test cases in the ratio of 70%: 30%. Figure 10 shows the convergence curves of PSOFNN based on averages of the MSE. The prediction result of the trained ANN is then compared with original label of the test example to get the accuracy. The total number of data is 150. Table 2 shows Labels for FNN Training with different events and 97.8% prediction accuracy is obtained.

Figure 10. Convergence curves of PSOFNN.

Table 2. Labels and prediction results.

| Events               | Labels | Accuracy   |
|----------------------|--------|------------|
| Normal Operation     | 1      | 100%       |
| Islanding            | 2      |            |
| Line-Line Fault      | 3      | 44/45 × 100% = 97.8% |
| Line-Ground Fault    | 4      | 44/45 × 100% = 97.8% |
| Line-Line-Ground     | 5      | 44/45 × 100% = 97.8% |
| Non-Linear load      | 6      |            |

5. Conclusion and Future Work
This paper has given a presentation for islanding detection and classifying of various PQ problems in hybrid power system based on WT - PSOFNN method. Various situations such as islanding event, three-phase fault and PQ disturbances had been studied. PSO is employed to optimal the selection of the weights and biases of a network for purpose of minimizing the mean square error MSE. The evaluation index wavelet details are extracted from the negative sequence voltage signal at PCC by DWT and fed to a trained FNN that is able to distinguish between islanding and PQ problems. The Simulink results show that it can predict the type of the events with high prediction accuracy of 97.8%. The results of FNN validate the quality of WT indices taken and the effectiveness of proposed method in detection and classification of islanding and PQ disturbances in the hybrid power system.

Future work should focus on the following issues: 1) Testing more hybrid power system by proposed method. 2) Applying hybrid of PSO and other heuristic optimization methods to achieve higher convergence speed.

6. References

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