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Islanding Detection in a Hybrid Renewable Energy System Microgrid by Utility Side Voltage and Current Measurements

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Abstract

The integration of microgrids into utility networks is often accompanied by several challenges among which is unintentional islanding. Islanding occurs in a microgrid when the utility grid is disconnected from the microgrid by the opening of the utility circuit breaker at the point of common coupling (PCC). An islanding detection method based on monitoring the voltage and current at the utility circuit breaker during the transient period prior to islanding is presented in this paper. In the proposed method, the negative sequence components of the voltage and current are acquired at the utility circuit breaker. The features used to distinguish islanding from non-islanding conditions are extracted from these negative sequence components using the discrete wavelet transform (DWT). These features which are the energy and standard deviation of the detail coefficients together with the load on the microgrid constitute a feature vector which is used to train an artificial neural network (ANN) to detect islanding. Simulation has been carried out using a hybrid renewable energy system microgrid which consists of a solar PV array, wind power system, diesel generator, and battery storage. The results illustrate that the method is reliable and fast.

Keywords: artificial neural network, discrete wavelet transform, islanding, microgrid, non-detection zone

I. INTRODUCTION

There has been an increase in the use of distributed generation (DG) nowadays due to emerging energy problems, environmental issues, the development of semiconductor-based power converters [1] as well as privatisation and deregulation of the electricity market [2] amongst others. DG has several advantages such as reduction of transmission/distribution line losses, voltage profile improvement as well as overall improvement of power quality and reliability. However, DG also introduces some problems in the electricity network such as unintentional islanding, reverse power flows, and protection concerns. In order to maximise the benefits of DG and for better control, the DG units are usually integrated into a microgrid [2]. A microgrid is a local electrical network that consists of power generation sources, loads, a means of delivering power from the generation units to the loads, and may be connected to a larger utility power system that operates to balance the power supply and demand within the microgrid [3]. Therefore, a microgrid can support local loads in islanding mode, unlike grid-connected DG units which are shut down during islanding. Islanding occurs when a DG device or microgrid continues to supply local loads after it has been disconnected from the utility grid.

The utility usually dictates the voltage and frequency of the microgrid in the grid-connected mode, and the DG units can share the active and reactive powers [4]. However, in islanding mode, the DG units should regulate the voltage and frequency of the microgrid and supply the load demands. Islanding is, therefore, one of the most critical problems in microgrids and can occur intentionally or unintentionally. The occurrence of faults in the utility network is the main cause of unintentional islanding. The effects of islanding on the microgrid include voltage and frequency instability, power quality problems, synchronization difficulties during reconnection to the utility grid as well as operator safety hazards. It is therefore imperative that islanding events be accurately detected and within 2 s of their occurrence according to IEEE 1547-2003 standards [5]. This paper presents an islanding detection approach based on monitoring the transient signals at the utility side prior to islanding in order to ensure safe operation of the microgrid and utility grid.

Section II of this paper presents a summary of the various islanding detection schemes. In section III, the theoretical background of the proposed technique is presented. Section IV is a description of the system under study. The proposed islanding detection method is presented in section V. Section VI is the simulation results and discussion, and section VII is the conclusion.

II. ISLANDING DETECTION METHODS (IDMs)

The most important performance indices of IDMs are the detection time and non-detection zones (NDZs) [1]. A good islanding detection method should have a short detection time that satisfies the IEEE 1547-2003 standards and is free of NDZs. NDZs refer to the operating range of active power (ΔP) and reactive power (ΔQ) mismatch between the utility grid and microgrid where the given technique is not able to detect islanding [6]. Most IDMs work reliably during conditions of sufficient power exchange between the microgrid and utility grid but might fail to detect islanding during conditions of minimal exchange [7]. In the grid-connected mode, if there are no power mismatches ($\Delta P=\Delta Q=0$) there will be no changes in the voltage amplitude or frequency of the microgrid after the outage of power in the utility grid and over/under voltage and over/under frequency relays will not be able to detect islanding.

IDMs are broadly classified into two categories; remote and local techniques. The remote techniques depend on a communication channel between the utility grid and the microgrid and are implemented at the utility side of the network. These techniques are the most reliable but their implementation is expensive due to the extra costs required in terms of communication equipment [6]. They are therefore reserved for large scale units and are not compatible for use in microgrids [3]. Local IDMs are often implemented at the microgrid side and monitor system variables such as current, voltage, frequency, harmonics, and active power at the DG units' buses to detect islanding. Islanding is detected when these parameters reach a pre-set threshold. These methods can be further divided into passive and active methods.

II.I. Passive Islanding Detection Methods

Passive IDMs monitor the system parameters and act on a pre-set threshold. These methods include: the use of voltage unbalance and total harmonic distortion of current [8], [9], unusual change in active power and frequency [10], change in reactive power [11], phase jump and vector shift detection [12], total harmonic distortion and voltage unbalance [12]. Other passive IDMs include over/under voltage and over/under frequency (OUV/OUF) [9], and the rate of change of frequency (ROCOF) [13]. Furthermore, new research on passive islanding detection methods using advanced tools like the wavelet transform [14] has also been carried out. In other methods, the wavelet transform is used together with a decision tree classifier [15], or neural network [11], [12] to determine the occurrence of islanding. These passive IDMs are easy to implement but most of them have significant NDZs or high error detection ratios.

II.II. Active Islanding Detection Methods

The active techniques inject disturbances in the distribution network so as to distort the current/voltage waveform, causing a change in its amplitude, phase or frequency. In the grid-connected condition, the distortions get absorbed by the grid. However, when the DG is islanded, these distortions are designed to drive the operating point of the island to a level that triggers the system protection devices. Some of the active islanding detection techniques use impedance measurement. Here, a new frequency component is injected into the inverter output current and the voltage at the corresponding frequency is measured and used to determine the impedance [16]. Other active techniques involve the injection of a negative sequence current signal at the PCC [17]. Some other methods introduce positive feedback to cause perceptible changes in phase or in voltage [13]. In other methods, phase-locked loop circuits (PLLs) are used to introduce a disturbance in the inverter reference or inverter output. When islanding occurs, the phase in voltage or in current moves out of a pre-set threshold value, thereby causing the inverter to trip [18], [19]. These active IDMs are more effective than the local methods and are generally free from NDZs. However, they are not as fast as some of the passive methods because of the system's inherent reaction time, and the cost of implementation is higher [3]. Moreover, the disturbances injected into the network can degrade the power quality [9].

There are also hybrid islanding detection methods that combine active and passive methods to make use of their advantages. In these methods, a disturbance is only injected into the microgrid when islanding is probable. Hence, they pose less power quality problems compared to active methods. Some of these methods include: positive feedback versus voltage unbalance [20], voltage versus reactive power shift [21], and adaptive reactive power disturbance and passive criteria [22]. These methods have lower islanding detection time and smaller NDZs.

III. THEORETICAL BACKGROUND OF THE PROPOSED TECHNIQUE

Islanding detection methods such as the ones mentioned above have generally been motivated by efforts to integrate distributed generation units into electrical grids especially inverter based units like solar PV systems. Hence, these methods are usually implemented within the source. However, advances in technology have led to the creation of microgrids with multiple sources; some of which are non-inverter-based. There is, therefore, a need to modify these methods to suit the multiple sources in microgrids. So rather than implementing the IDMs on each inverter or source, the IDMs should be implemented at the PCC. It is, therefore, the intent of this paper to propose an IDM which can be applied to microgrids. The method is focused on detecting the loss of power at the utility interconnection point (PCC), where the IEEE 1547–2003 interconnection standards are applied.

III.I. Signal Processing and the Wavelet Transform

The signals encountered in real-world applications are non-stationary signals (their frequency content varies with time). Therefore, conventional signal processing techniques like the Fourier transform are not suitable for their analysis. This is because the time domain representation of a signal does not provide quantitative information on the frequency content of the signal. The Fourier transformed frequency representation, on the other hand, provides frequency content but doesn't indicate the time localization of the frequency components. Consequently, analysing a non-stationary signal requires a transformation technique that can simultaneously provide a two-dimensional time and frequency representation. Of the various time-frequency representation techniques, the wavelet transform provides information about a signal in the time-frequency domain simultaneously [23].

Wavelet analysis is a mathematical tool that uses short duration oscillating waveforms called wavelets with zero mean and sharp decay to zero at both ends, in place of stationary sinusoidal waveforms like in Fourier analysis. The wavelets are dilated and shifted to vary their time-frequency resolution. In wavelet analysis, the wavelet function is compared with the input signal to get a set of coefficients that show how the two signals match. The coefficients are calculated using the continuous wavelet transform (CWT). The CWT of a function x(t) at a scale $(a > 0), a \in R^{+*}$ and translational value $b \in R$ is given by the integral

$$X_{\omega}(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t)\overline{\psi}\left(\frac{t-b}{a}\right) dt \qquad (1)$$

where $\psi(t)$ is a continuous function in both time and frequency domain called the mother wavelet, and the overline represents the complex conjugate operation [24]. The mother wavelet serves as a source function for the generation of daughter wavelets which are simply the scaled and translated versions of the mother wavelet. The scale parameter determines the oscillator frequency and length of the wavelet, and the translation parameter dictates its shifting position.

The discretisation of the CWT gives rise to the discrete wavelet transform (DWT). The DWT is therefore defined by using the discrete values of the scaling and translation parameters. To achieve this, set $a = a_0^m$ and $b = nb_0 a_0^m$
This gives:

$$\psi_{m,n}(t) = a_0^{\frac{-m}{2}} \psi(a_0^{-m}t - nb_0) \qquad (2)$$

where $(m, n \in \mathbb{Z})$, and m and n are the frequency and time localization respectively.
The DWT of a discrete function x(k) can, therefore, be defined as

$$DWT(m,k) = \frac{1}{{a_0^m}^{1/2} \sum_n x(n) \psi\left(\frac{(k - nb_0 a_0^m)}{a_0^m}\right)} \qquad (3)$$

To implement the DWT, Mallat in [25] developed an approach called the Mallat algorithm (Mallat's Multi-Resolution Analysis, MRA). Here, the signal to be processed is passed through finite impulse response (FIR) high-pass filters (HPF) and low-pass filters (LPF) having different cut-off frequencies at different levels. The low-frequency content is known as the approximation (a) while the high-frequency content is known as the detail (d) in wavelet analysis. This approach can be repeated to further decompose the approximation gotten at each level until the desired level is attained.

III.II. Artificial Neural Network (ANN) as Classifier

Artificial neural networks (ANNs) are computational networks that attempt to simulate, in a comprehensive manner, the decision-making process in networks of neurons (nerve cells) of the organic central nervous system [26]. Neurons are usually ordered into layers, appropriately interconnected by means of unidirectional (in some cases bi-directional) weighted signal channels, known as connections (synaptic weights) [27].

The neurons work in parallel to solve specific problems. Fig.1 [28] shows the architecture of a typical ANN with input signals: $x_1, x_2, \ldots, x_n$, weights: $w_1, w_2, \ldots, w_n$ and an output signal: Y. Weights are the fundamental means of long-term memory in ANNs. A neural network (NN) 'learns' by repeated adjustments of the weights in order to adapt the system to a particular input-output transformation task. The neuron calculates the weighted sum of the input signals and compares the outcome with a threshold value θ [28]. Therefore, the output of a neuron with a sign activation function can be evaluated as

$$Y = \text{sign}\left[\sum_{i=1}^{n} x_i w_i - \theta\right] \qquad (4)$$

Other activation functions such as the softmax, step, linear and sigmoid functions [27] can also be used.

Machine learning algorithms are classified into two main categories: supervised, and unsupervised learning. ANNs are classified under supervised learning. In supervised learning, each learning example consists of an input vector and a corresponding output value. i.e. during training, the training data set and corresponding targets are presented to the model. This starts with the initialisation of the network weights and biases. The weights and biases are then updated in order to minimize the mean square error MSE. The MSE is a measure of the average squared difference between the estimated values and what is estimated. This can be achieved using the gradient of the MSE otherwise known as the gradient descent algorithm. The gradient descent algorithm is a first-order iterative optimization algorithm used to find the minimum of a function, usually implemented using a technique known as backpropagation [27].

Most of the neural networks used in practical applications are multi-layer neural networks consisting of one or more hidden layers. Typically, the network consists of an input layer of source neurons, at least one hidden layer of computational neurons, and an output layer of computational neurons [28]. The training process of a multi-layer NN is accompanied by additional challenges such as selecting the number of hidden layers, and deciding the number of neurons in the hidden layers.

ANNs have been used in a wide range of applications including pattern classification, pattern recognition, optimization, prediction, and automatic control. Their applications in power systems include load forecasting, fault diagnosis/fault location, economic dispatch, and transient stability among others [29]. ANNs are often used as classifiers since they have the capability of learning complex mappings, linear or nonlinear from the input space to the output space [29].

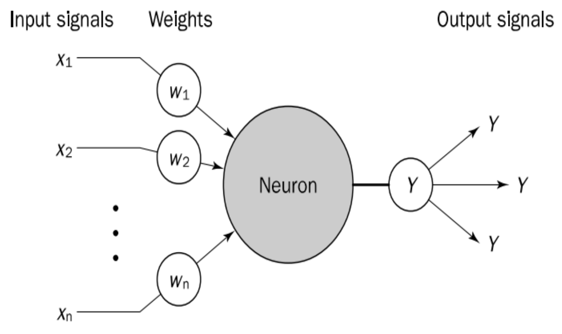

Fig. 1: Architecture of a typical ANN

IV. SYSTEM DESCRIPTION AND DISCUSSION

The single line diagram of the system used in this work is shown in Fig. 2.The system consists of the following:

Utility: 25 kV source at 100 MVA short circuit level
Line: 20 km line represented by its π model
PV solar system: 350 kW
Li-ion battery: 500 Ah
Diesel generator: 50 kVA, 400V
Doubly-fed induction generator (DFIG) wind power system: 1.5 MW
T1: 100 MVA, 25 kV/400 V
T2: 200 kVA, 600 kV/400 V
T3: 400 kVA, 600V/400 V
T4: 2 MVA, 575 kV/400 V
L1: 0.8 MW, L2: 150 kW, L3: 35 kW, L4: 1 MW

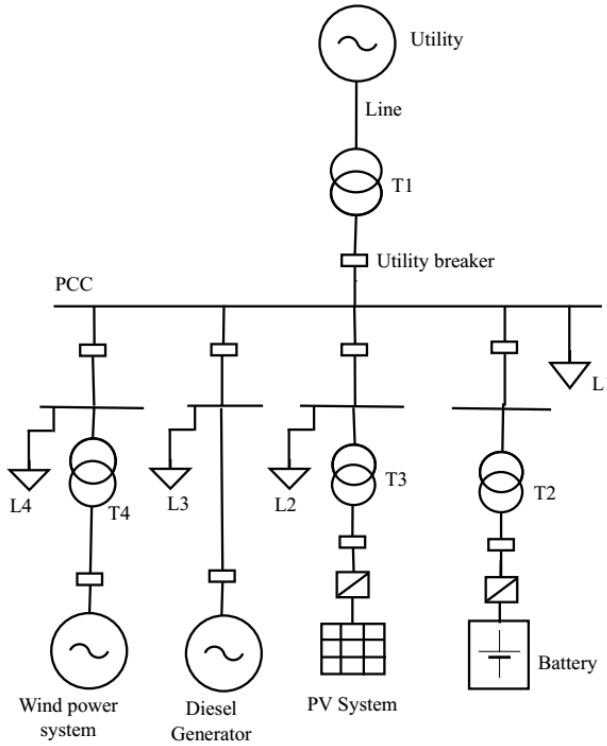

Fig. 2: Grid-connected microgrid

V. PROPOSED ISLANDING DETECTION METHOD

Considering that islanding detection time and NDZ are the most important indices for evaluating the effectiveness of IDMs, this paper proposes a method for islanding detection which has no NDZ. The NDZ is eliminated because islanding conditions are identified by means of the discrete wavelet transform of the transient signals before the opening of the utility circuit breaker. An NDZ is created in other local methods due to a difference in active and reactive power between the load and generation in the microgrid when islanding occurs. Also, as the proposed method detects islanding prior to the opening of the utility circuit breaker, the islanding detection time is shorter since the circuit breaker operation time is eliminated. The method is also independent of the DG type because it is the utility side signals that are considered for islanding detection. It can, therefore, be used in inverter-based, synchronous machine-based or hybrid microgrids and does not introduce power quality problems in the network.

In the proposed method, the negative sequence components of voltage V_n and current I_n at the utility circuit breaker are acquired. Negative sequence components are usually considered for disturbance analysis because they reflect the information contained in disturbance conditions. Also, this will reduce computational burden as it will be required that only two signals be analysed. The negative sequence components of voltage and current are expressed in symmetrical component analysis as:

$$V_n = \frac{1}{3}(V_a + \alpha^2 V_b + \alpha V_c) \tag{5}$$

$$I_n = \frac{1}{3}(I_a + \alpha^2 I_b + \alpha I_c) \tag{6}$$

where V_a, V_b, and V_c are three-phase voltages, and I_a, I_b, and I_c are three-phase currents, and $\alpha = e^{j120°}$ is the complex operator. The negative sequence components of the voltage and current are then processed using the DWT to extract useful information (features) that will be used to distinguish between islanding and other conditions. In this paper, the Daubechies mother wavelet (db4) has been used to extract the energy content and standard deviation of the detail coefficients of the negative sequence voltage and current waveforms. This is because the Daubechies wavelets are very suitable for power system transient analysis as studied in [30]. The negative sequence components of the voltage and current signals have been decomposed for 5 wavelet levels in this paper. This is because it was at level 5 that the difference in amplitude in the signals before and after islanding was most conspicuous. The five details extracted from the wavelet decomposition of each signal contain information that can help in islanding detection. However, the information is required in a numerical fashion, to form what is called a feature vector. The energy content and standard deviation in the details of each decomposition level are calculated using the detail coefficients in the corresponding level. The energy content (represented by the L2 norm) and standard deviation of detail 5 coefficients have been included in the feature vector in this paper.

For a scalar-valued signal v(t) defined for t≥0, the L2-norm is defined as the square root of the integral of $v(t)^2$,

$$\| v \|_2 = \left(\int_0^\infty v(t)^2 \, dt\right)^{1/2} \tag{7}$$

A physical interpretation of the L2 norm is that if v(t) represents a voltage or a current, then $\| v \|_2^2$ is proportional to the total energy associated with the signal.

The standard deviation SD, on the other hand, can be considered as a measure of the energy for a distorted signal with zero mean given as

$$SD = \frac{1}{N-1}\sum_{i=1}^{N}(v_i - \mu)^2 \tag{8}$$

where v_i is the amplitude of the i^{th} sample of the DWT of the signal at d5, N is the number of samples and μ is the mean of the DWT of the signal at d5.

Loading has also been considered as a feature since the effect of islanding on the microgrid greatly depends on its load. The feature vector thus consists of the energy content and SD of detail 5 coefficients for both voltage and current, and the loading of the microgrid. The proposed feature vector has been evaluated for two different sets of data corresponding to islanding and non-islanding conditions. The non-islanding conditions include normal operation i.e. grid-connected

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microgrid without any disturbances, and temporal faults in the utility grid (L-G, LL, LL-G, LLL and LLL-G faults) while the islanding condition is the outage of power in the utility grid.

An ANN is used to classify the events into islanding and non-islanding events. This is because the determination of a threshold for features extracted by the DWT is difficult, complex and different from network to network and it may even be unreliable [31]. The input to the ANN is the feature vector and the output is either a high (1) to indicate an islanding event or a low (0) to indicate a non-islanding event. The ANN used in this paper is a two-layer feedforward network with 7 sigmoid hidden neurons and one softmax output neuron. The ANN was trained using the scaled conjugate gradient backpropagation algorithm. 175 random events were generated at different loading conditions of the microgrid for both the islanding and non-islanding events. For each of these events, the feature vector was computed. 123 feature vectors were used to train the network, 26 feature vectors were used to validate the training strategy, and the last 26 feature vectors were used to test the performance of the training strategy.

VI. SIMULATION RESULTS AND DISCUSSION

The test system was modelled using Simulink/Matlab. The sample time used to solve the electric circuit was 5 μs. The sampling frequency was chosen to be 5 KHz, so as to resemble that of a typical digital relay [32]. The maximum frequency that can be captured using this arrangement is 2.5 KHz according to the Nyquist-Shannon theorem. Five decomposition levels were chosen. This is because it was in detail 5 (d5) that the difference between islanding and non-islanding conditions was most conspicuous. The two classes of data (islanding and non-islanding) were simulated at different loading conditions of the microgrid (from 1.032 to 1.8 MW).

For each event, the negative sequence voltage and current signals were extracted using a three-phase sequence analyser, loaded in the wavelet analyser toolbox, and the energy and SD for detail 5 coefficients calculated. The following waveforms; Fig.3-4, and Fig.5-6 are simulated results for both normal operation and islanding respectively. The test loading used in the waveforms was 1.8 MW and the islanding instant was 0.3 s (in Fig.5 and 6). The total simulation time was 0.5 s. Tables 1 and 2 show sample values of the feature vectors used in training, testing and validating the ANN for islanding and non-islanding conditions respectively. SD5 and E5 are the standard deviation and energy of detail 5 coefficients. The performance of the ANN is shown by the graph in Fig.7 and the confusion matrix in Fig.8.

Table 1. Sample feature vector during normal operation

Feature Vector					Label
Loading (MW)	Voltage (detail 5)		Current (detail 5)		
	SD5	E5	SD5	E5	
1.032	0.001196777	0.009910682	0.017379617	0.143557438	0
1.064	0.001193284	0.009882275	0.017360063	0.143393126	0
1.096	0.001189770	0.009853641	0.017340497	0.143229342	0
1.032	0.001186252	0.009824856	0.017321021	0.143067315	0

Table 2. Sample feature vector during islanding

Feature Vector					Label
Loading (MW)	Voltage (detail 5)		Current (detail 5)		
	SD5	E5	SD5	E5	
1.032	0.048367640	0.399695699	0.035141357	0.289785974	1
1.064	0.043468939	0.359158557	0.034905225	0.287836659	1
1.096	0.040782325	0.336936572	0.034683876	0.286010714	1
1.032	0.039179174	0.324106217	0.034477928	0.284312522	1

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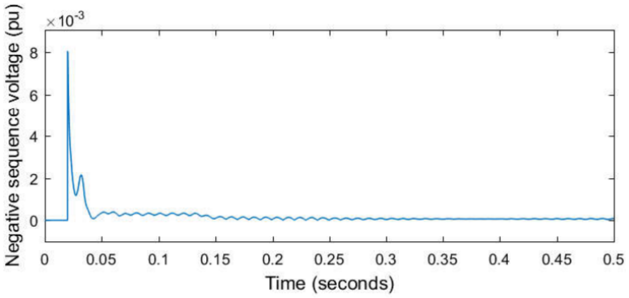
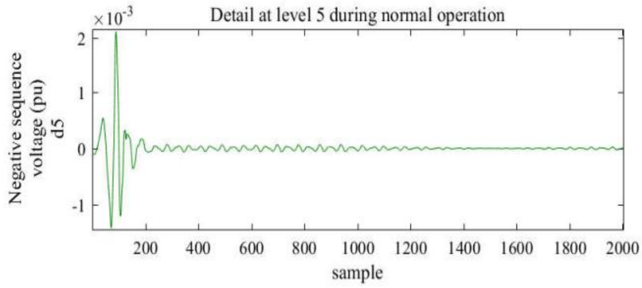
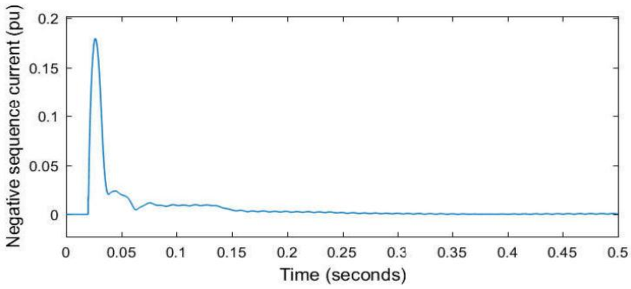


(a)



(b)

Fig. 3. (a) Negative sequence component of voltage during normal operation, (b) DWT at level 5



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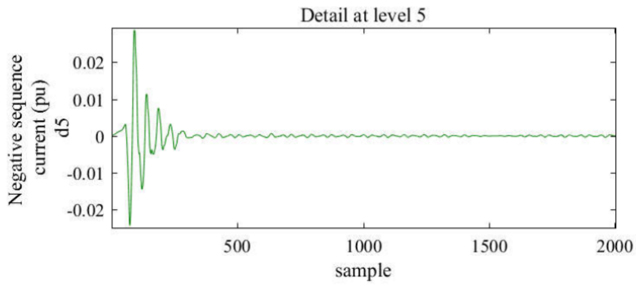
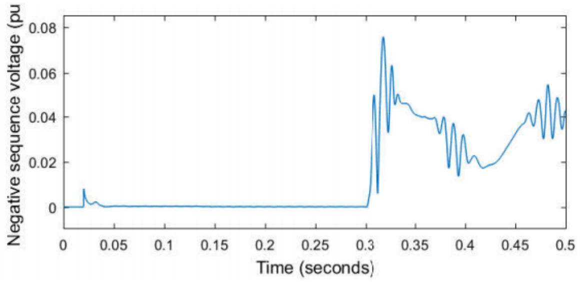


(b)

Fig. 4. (a) Negative sequence component of current during normal operation, (b) DWT at level 5



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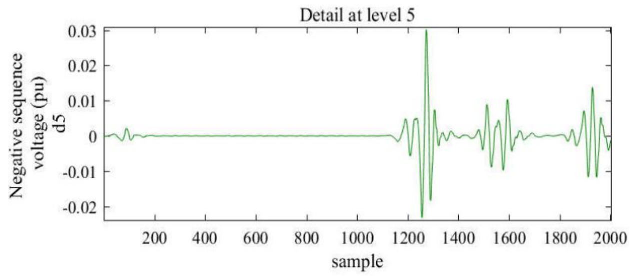
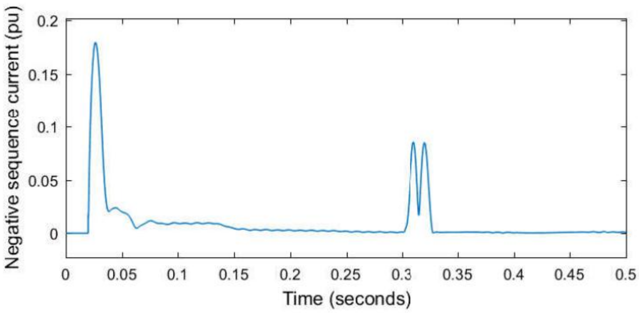
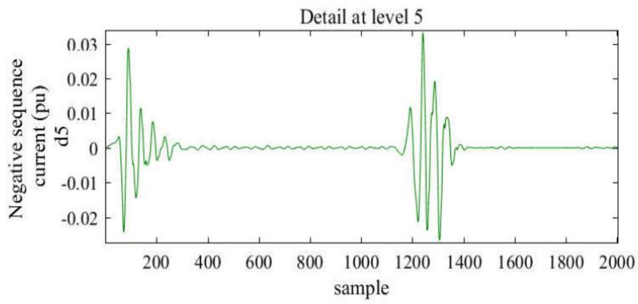


(b)

Fig. 5. (a) Negative sequence component of voltage during islanding condition, (b) DWT at level 5



(a)



(b)

Fig. 6. (a) Negative sequence component of current during islanding condition, (b) DWT at level 5

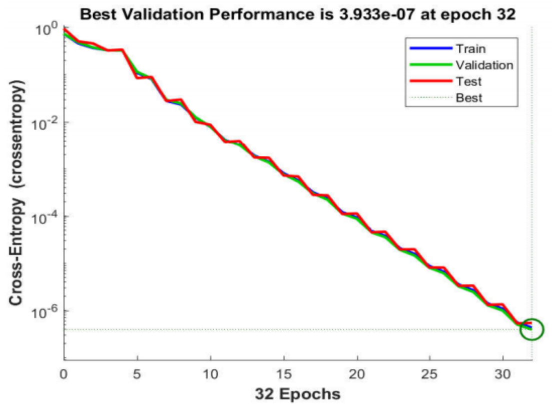


Fig. 7. ANN performance

Fig. 8. Confusion matrix of ANN performance

By comparing Fig.3-4 with Fig.5-6, it is evident that there are differences in the negative sequence components during islanding and non-islanding conditions. These difference are reflected in the DWT indices and an ANN will therefore be able to classify the events with high prediction accuracy. Fig.8 validates the characteristic signature as the classification accuracy is 100%. Hence, the algorithm is reliable and fast.

VII. CONCLUSION

This paper has presented a new method for islanding detection in a microgrid based on the measurement of the negative sequence components of the utility voltage and current flowing through the utility circuit breaker. Islanding can be detected before its occurrence by selecting this point of measurement. The negative sequence component of the utility voltage and current have been processed by the DWT to extract the features used to detect islanding, in this case, the energy content and standard deviation of detail 5 coefficients. These features together with the load of the microgrid constitute a feature vector. Finally, an ANN has then been used as a classifier to differentiate islanding from other disturbances in the network. The results of the simulation show that the proposed method distinguishes between islanding and other disturbances with 100% accuracy. This, therefore, makes it suitable to be implemented in practical systems.

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