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Islanding detection for inverter-based DG coupled with using an adaptive neuro-fuzzy inference system

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ABSTRACT

This paper investigates a new integrated diagnostic system for islanding detection by means of a neuro-fuzzy approach for grid-connected inverter-based distributed generation. Islanding is one important concern for grid connected distributed resources due to personnel and equipment safety. Several methods based on passive and active detection scheme have been proposed. While passive schemes have a large non-detection zone (NDZ), concern has been raised on active method due to its degrading power quality effect. Reliably detecting this condition is regarded by many as an ongoing challenge as existing methods are not entirely satisfactory. The main emphasis of the proposed scheme is to reduce the NDZ to as close as possible and to keep the output power quality unchanged. In addition, this technique can also overcome the problem of setting the detection thresholds inherent in the existing techniques. In this study, we propose to use a hybrid intelligent system called ANFIS (the adaptive neuro fuzzy inference system) for islanding detection. The simulations results, carried out by MATLAB/Simulink, shows that the proposed method has a small non-detection zone. Also, this method is capable of detecting islanding accurately within the minimum standard time. Moreover, for those regions which are in need of a better visualization, the proposed approach would serve as an efficient aid such that the mains power disconnection can be better distinguished.

1. Introduction

It is expected that inverter-based distributed generation technologies will be increasingly used in electrical power systems in the near future. The increased expanding of distributed generation (DG) in utility systems has been mainly caused by the liberalization of the electricity markets. Recent advances in energy conversion systems and the environmental drive to promote green energy. These recent advances in energy conversion include the emergence of cheaper and more efficient power generation systems using renewable and hybrid power schemes. The attractions of 'green energy' have been and will continue to be a powerful force in the expansion of distributed generation. Distributed generation (DG) may be defined as generating resources, other than central generating stations, that is placed close to load being served, usually at a customer site. In fact, many utilities around the world already have significant penetration of DGs in their system. When the distributed generation systems are operated in parallel with utility power systems, especially with reverse power flow, the power quality problems become significant. Power quality problems include frequency deviation, voltage fluctuation, harmonics and reliability of the power system. In addition, one of the technical issues created by DG interconnection is inadvertent islanding [1–6]. Islanding condition causes abnormal operation in the power system and also causes negative impacts on protection, operation, and management of distribution systems. Therefore, it is necessary to effectively detect the islanding conditions and swiftly disconnect DG from the network. Fig. 1 depicts a scenario of islanding, where the load of interest is severed off from the grid but the system continues to operate because of connected distributed generators.

Under this situation, a so-called island is formed, resulting in unexpected consequences that may include an increased complexity of orderly restoration (out of phase switching of re-closers leading to damage of the DG, neighboring loads, and utility equipment), a degraded stability of system voltage and worst of all, a raised risk to related maintenance personnel. In other words, under the scenario of islanding, line crew members may misjudge the load-side of the line as inactive where distributed generations are indeed feeding power to loads; hence jeopardizing the life of operators and meanwhile illuminating the importance of a reliable forewarning mechanism to such events. Therefore, during the interruptions of utility power, the connected DG must detect the loss of utility power and disconnect itself from the power grid as soon as possible [7].

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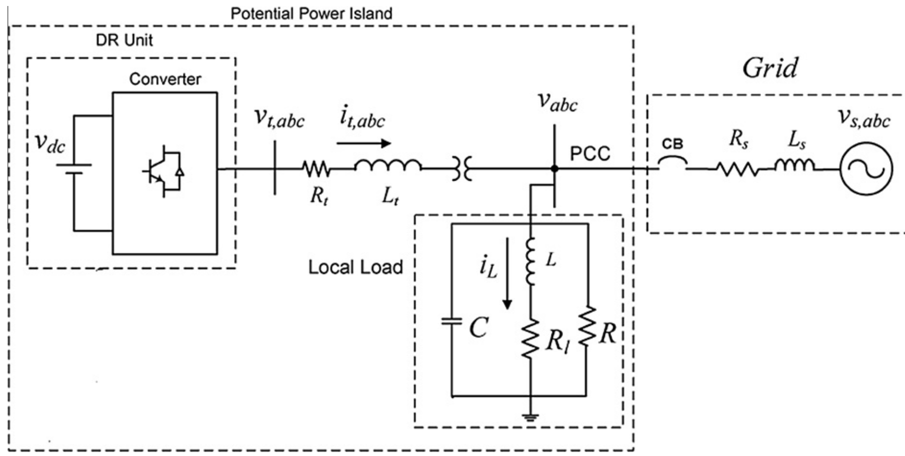

Fig. 1. Schematic diagram of a grid-interfaced DG unit.

There are many proposed techniques for detection of an island [8–18]. Before defining these methods for islanding detection, it is important to highlight two key features in order to understand the islanding phenomenon. The first one is associated with the so-called "non-detection zone" (NDZ). The NDZ can be defined as the range (in terms of the power difference between the DG inverter and the load or load parameters) in which an islanding detection scheme under test fails to detect this condition [10]. The second feature is associated with the type of loads (potential loads inside island), which can be modeled as a parallel *RLC* circuit. This circuit is primarily used because it raises more difficulties for islanding detection techniques than others. Generally, nonlinear loads that produce current harmonics, or constant power loads, do not represent significant problems for islanding detection [11]. Most islanding detection methods suffer from large NDZs [19] and/or have a run-on time between half a second to two seconds [20], and thus cannot be used for uninterruptible autonomous operation of an island. These techniques can be broadly classified into remote and local techniques. Local techniques can be further classified into active and passive techniques. Remote techniques for detection of islands are based on communication between the utility and the DGs. Although these techniques may have better reliability than local techniques, they are expensive to implement and hence uneconomical. These schemes include power line signaling and transfer trip [21,22]. Local techniques rely on the information and data at the DG site. Passive methods depend on measuring certain system parameters and do not interfere with the DG operation. Over/under voltage and frequency is one of the simplest passive methods used in islanding detection. Unfortunately, if the load and the generation on the island are closely matched, the change in voltage and frequency might be very small and within the thresholds, thus leading to an undetected islanding situation. Other passive techniques have been proposed based on monitoring rate of change of frequency (ROCOF), phase angle displacement, rate of change of generator power output, impedance monitoring, the THD technique and the wavelet transform function [23]. These offer superior sensitivity as their settings allow detection to take place within statutory limits, but their settings must be carefully selected to avoid mal-operation during network faults. The trade-off between the two performance criteria is especially difficult for these methods. If the threshold for permissible disturbance in these quantities is set to a low value, then nuisance tripping becomes an issue, and if the threshold is set too high, islanding may not be detected. In active methods, the main theme exists in the design of control circuits such that the required variations can be produced at the outputs of distributed generators. Then, once the loss of grid takes place, this designated bias will accordingly enlarge sufficiently to trip the connected relays, notifying the occurrence of the event. On the contrary, when the utility supply is normally operated, the amount of variations will be insufficient to trip the relays, ensuring that there is no event misidentified. The main advantage of active techniques over passive techniques is their small NDZ. Some important active techniques are impedance measurement, frequency shift and active frequency drift, current injection, sandia frequency shift and sandia voltage shift, and negative phase sequence current injection. Under several circumstances, this active method has won the confirmation. However, the complicated control circuit for the generation of designated bias may offset its merits [24–26]. Generally, if there are large changes in loading for DG after loss of the main power supply, then islanding conditions are easily detected by monitoring several parameters: voltage magnitude, phase displacement, and frequency change. However, in case of small changes in loading for DG, the conventional methods have some difficulty in detecting such a particular islanding condition.

This paper introduces a new intelligent-based approach for islanding detecting that reduce the NDZ to as close as possible and to keep the output power quality unchanged. The proposed technique uses the adaptive neuro fuzzy inference system (ANFIS) as machine learning method to extract information from the data sets of these parameters after they are obtained via massive event analyses using network simulations. This approach measures the rate of change of active power at the target distributed generation location and feeds it to the ANFIS for intelligent islanding detection without determining any threshold.

This paper is organized as follows. Section 2 introduces the adaptive neuro-fuzzy inference system. Section 3 introduces the mathematical model of islanded system. The effect of the interface control on the NDZ of OVP/UVP and OFP/UFP is discussed in Section 4. Section 5 presents the methodology of the proposed Technique. Section 6 covers the architecture of the proposed algorithm. Section 7 explains the simulation results to verify the effectiveness of the proposed technique and in the last section of this paper the conclusion will be presented.

2. Adaptive neuro-fuzzy inference system (ANFIS)

Artificial intelligence, including neural network, fuzzy logic inference, genetic algorithm and expert systems, has been used to solve many nonlinear classification problems [27,28]. The main advantages of a fuzzy logic system (FLS) are the capability to express nonlinear input–output relationships by a set of qualitative if–then rules. The main advantage of an artificial neural network (ANN), on the other hand, is the inherent learning capability, which enables the networks to adaptively improve their performance. The key properties of neuro-fuzzy network are the accurate learning and adaptive capabilities of the neural networks, together with the generalization and fast learning capabilities of fuzzy logic systems. A neuro-fuzzy (ANFIS) system is a combination of neural network and fuzzy systems in such a way that neural network is used to determine the parameters of fuzzy system. A neural network is used to automatically tune the system parameters.

The ANFIS is a very powerful approach for modeling nonlinear and complex systems with less input and output training data with quicker learning and high precision. The neuro fuzzy system with the learning capability of neural network and with the advantages of the rule-base fuzzy system can improve the performance significantly and can provide a mechanism to incorporate past observations into the classification process. In neural network the training essentially builds the system. However, using a neuro fuzzy scheme, the system is built by fuzzy logic definitions and is then refined using neural network training algorithms.

2.1. ANFIS architecture

The modeling approach used by ANFIS is similar to many system identification techniques. First, a parameterized model structure (relating inputs to membership functions to rules to outputs to membership functions, and so on) is hypothesized. Next, input/output data is collected in a form that will be usable by ANFIS for training. ANFIS can then be used to train the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion. Operation of ANFIS looks like feed-forward backpropagation network. Consequent parameters are calculated forward while premise parameters are calculated backward. There are two learning methods in neural section of the system: Hybrid learning method and back-propagation learning method. In fuzzy section, only zero or first order Sugeno inference system or Tsukamoto inference system can be used. This section introduces the basics of ANFIS network architecture and its hybrid learning rule. The Sugeno fuzzy model was proposed by Takagi, Sugeno, and Kang in an effort to formalize a systematic approach to generating fuzzy rules from an input–output dataset. To present the ANFIS architecture, with two inputs, one output and two rules is given in Fig. 2. In this connected structure, the input and output nodes represent the training values and the predicted values, respectively, and in the hidden layers, there are nodes functioning as membership functions (MFs) and rules. This architecture has the benefit that it eliminates the disadvantage of a normal feed forward multilayer network, where it is difficult for an observer to understand or modify the network. Here x, y are inputs, f is output, the circles represent fixed node functions and squares represent adaptive node functions.

Consider a first order Sugeno fuzzy inference system which contains two rules:

$$\begin{aligned} &\text{Rule 1}: \text{ If } X \text{ is } A_1 \text{ and } Y \text{ is } B_1, \text{then } f_1 = p_1x + q_1y + r_1 \\ &\text{Rule 2}: \text{ If } X \text{ is } A_2 \text{ and } Y \text{ is } B_2, \text{then } f_2 = p_2x + q_2y + r_2 \end{aligned}$$

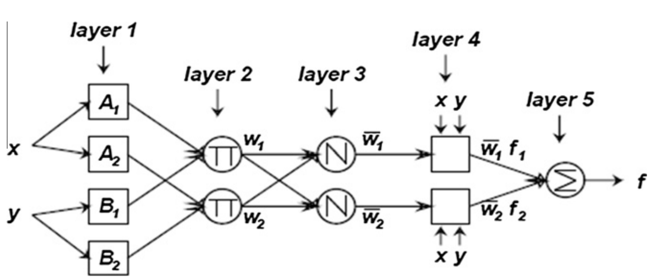

Fig. 2. ANFIS architecture.

where $p_1, p_2, q_1, q_2, r_1, r_2$ are linear parameters and A_1, A_2, B_1, B_2 are nonlinear parameter. ANFIS is an implementation of a fuzzy logic inference system with the architecture of a five-layer feed-forward network. The system architecture consists of five layers, namely, fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer. With this way ANFIS uses the advantages of learning capability of neural networks and inference mechanism similar to human brain provided by fuzzy logic. The operation of each layer is as follows: Here the output node i in layer l is denoted as O_i^l.

Layer 1 is fuzzification layer. Every node i in this layer is an adaptive node with node function

$$\begin{aligned} O_{1,i} &= \mu A_i(x), \quad \text{for } i = 1,2 \\ O_{1,i} &= \mu B_i(x), \quad \text{for } i = 3,4 \end{aligned} \tag{1}$$

where x is the input to ith node, O_i^l is the membership grade of x in the fuzzy set A_i. Generalized bell membership function is popular method for specifying fuzzy sets because of their smoothness and concise notation, and defined as

$$\mu_{A_i}(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{2}$$

Here $\{a_i, b_i, c_i\}$ is the parameter set of the membership function. The center and width of the membership function is varied by adjusting c_i and a_i. The parameter b_i is used to control the slopes at the crossover points. Fig. 3 shows the physical meaning of each parameter in a generalized bell function. This layer forms the antecedents of the fuzzy rules (*IF* part).

Layer 2 is the rules layer. Every node in this layer is a fixed node and contains one fuzzy rule. The output is the product of all incoming signals and represents the firing strength of each rule.

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \tag{3}$$

Layer 3 is normalization layer. Every node in this layer is a fixed node and the ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths. Outputs of this layer are called normalized firing strengths computed as:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{4}$$

Layer 4 is consequent layer. Every node in this layer is an adaptive node and computes the values of rule consequent (*THEN* part) as:

$$O_i^4 = \overline{w_i}f_i = \overline{w_i}(p_ix + q_iy + r_i) \tag{5}$$

Layer 5 is summation layer and consists of single fixed node which calculates the overall output as the summation of all incoming signals as:

$$O_i^5 = \sum_i \overline{w_i}f_i = \frac{\sum_i w_if_i}{\sum_i w_i} \tag{6}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input membership functions. These parameters

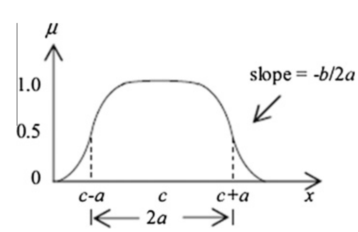

Fig. 3. Generalized bell function.

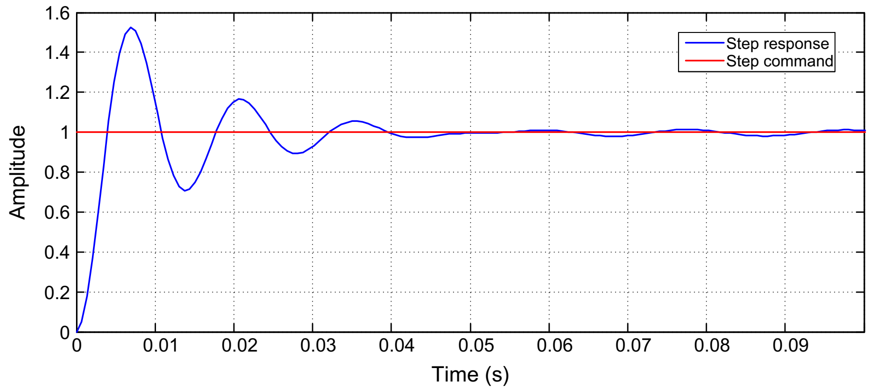

Fig. 4. Shows the step response of system in the islanding mode. Study system.

are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first order polynomial. These parameters are the so-called consequent parameters [29,30].

2.2. Learning algorithm of ANFIS

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, to make the ANFIS output match the training data. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be written as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{7}$$

Substituting Eq. (4) into Eq. (7) yields:

$$f = \overline{w_1} f_1 + \overline{w_2} f_2 \tag{8}$$

Substituting the fuzzy if–then rules into Eq. (8), it becomes:

$$f = \overline{w_1}(p_1 x + q_1 y + r_1) + \overline{w_2}(p_2 x + q_2 y + r_2) \tag{9}$$

After rearrangement, the output can be expressed as:

$$f = (\overline{w_1}x)p_1 + (\overline{w_1}y)q_1 + (\overline{w_1})r_1 + (\overline{w_2}x)p_2 + (\overline{w_2}y)q_2 + (\overline{w_2})r_2 \tag{10}$$

Which is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backpropagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [28,31].

3. Mathematical model of islanded system

This section provides a state-space mathematical model for the islanded system, Fig. 1. It is assumed that the DG unit and the local load are balanced three-phase subsystems within the island. The state-space model of the islanded system of Fig. 1 is presented in [32]. The state space equations of the potential island of Fig. 1 in the standard state space form are

$$\begin{aligned} \dot{X}(t) &= AX(t) + Bu(t) \\ y(t) &= CX(t) \\ u(t) &= v_{td} \end{aligned} \tag{11}$$

where

$$A = \begin{bmatrix} -\frac{R_t}{L_t} & \omega_0 & 0 & -\frac{1}{L_t} \\ \omega_0 & -\frac{R_l}{L} & -2\omega_0 & \left(\frac{R_l C \omega_0}{L} - \frac{\omega_0}{R}\right) \\ 0 & \omega_0 & -\frac{R_l}{L} & \left(\frac{1}{L} - \omega_0^2 C\right) \\ \frac{1}{C} & 0 & -\frac{1}{C} & -\frac{1}{RC} \end{bmatrix}$$

$$B^T = \begin{bmatrix} \frac{1}{L_t} & 0 & 0 & 0 \end{bmatrix}$$

$$C = [0 \quad 0 \quad 0 \quad 1]$$

$$D = [0]$$

$$X^T = [i_{td} \quad i_{tq} \quad i_{Ld} \quad v_d]$$

Fig. 4 shows the step response of system in the islanding mode. The response time constant of the island system is selected as the analyzing time of ANFIS system output.

DG systems are connected to the distribution system through an inverter as shown in Fig. 1. The system under study consists of one 80 kW inverter based DG connected to an *RLC* load having a quality factor of 1.8 and a grid as illustrated in Fig. 1. The system, controller, and load parameters are given in [6]. The performance of the DG under normal and islanded operating conditions was studied and simulated on MATLAB/Simulink. The inverter performs two main functions:

(A) Controlling the active power output of the DG and, in some cases, injecting a suitable amount of reactive power to mitigate a power quality problem.
(B) According to the IEEE Standard 1547, the DG should be equipped with an anti-islanding detection algorithm, which could be performed using the inverter interface control.

The DG interface control is designed to supply constant current output as shown in [6]. For this interface control, both I_d and I_q components of the DG output current are controlled to be equal to a preset value (I_{dref} and I_{qref}). The DG was operated at unity power factor by setting I_{qref} to zero. In particular, parallel *RLC* loads with a high *Q* factor often present problems for island detection. The quality factor *Q* is defined by

$$Q_f = R\sqrt{\frac{C}{L}} \tag{12}$$

And is the ratio of the amount of energy stored in the load's reactive elements to the amount of energy dissipated in the load's resistance (for example, for $Q = 2$, there is twice as much energy stored in the *L* and *C* of the load as is being dissipated in *R*). Loads that are near resonance at ω_0 and have a high *Q*-factor are the ones that cause difficulty in islanding detection. Unfortunately, the level of real or reactive power mismatch is not uniquely determined by load parameters. Specifically, the reactive power consumption of the load is given by

$$Q_{Load} = V_{rms}^2[(\omega L)^{-1} - (\omega C)] = \Delta Q \tag{13}$$

Eq. (3) clearly shows that there are infinitely many combinations of *L* and *C* that will yield the same ΔQ.

4. Non-detection zone (NDZ)

One of the important characteristics to determine the effectiveness of an islanding detection method is the non-detection zone (NDZ). NDZ is the operating region where islanding conditions cannot be detected in a timely manner. It can either be represented in terms of power mismatch or in terms of the *R*, *L*, and *C* of the load. In [6,33], an approximate representation of the NDZ for OVP/UVP was derived. An exact and accurate representation of the NDZ is presented in this part of paper. The paper examines the NDZ of an OVP/UVP and OFP/UVP islanding scheme when implemented for constant current controlled inverters. In order to determine the amount of mismatch for which the OVP/UVP and OFP/UFP will fail to detect islanding, the amount of active power mismatch in terms of load resistance can be expressed as follows:

$$\Delta P = 3V \times I - 3(V + \Delta V) \times I = -3V \times \Delta V \times I \tag{14}$$

Which *V* and *I* indicate the rated current and voltage, respectively. In distribution network, voltage values between 0.88 pu and 1.1 pu are in acceptable range for voltage relays. These voltage levels are equivalent to $\Delta V = -0.12$ and $\Delta V = 0.1$, respectively. The calculated imbalance amount by Eq. (14) for our test network (the inverter rated output power is 80 kW), are 9.6 kW and −8 kW, respectively. Frequency and voltage of an *RLC* load has the active and reactive power as follows:

$$P_L = \frac{V_L^2}{R_L} \tag{15}$$

$$Q_L = V_L^2\left(\frac{1}{\omega L} - \omega C\right) \tag{16}$$

where *V*, ω, *P* and *Q* are the load voltage, frequency, active power and reactive power, respectively. In normal operating conditions, a common coupling point voltage is determined by the power grid, and distributed generation system has no control over voltage and until it is connected to the network the voltage is fixed at nominal value of 1 pu. Once the island is occurred, distribution system cannot control the voltage and the amount of active power imbalance determines the voltage deviation from the nominal values. Since the output power of the inverter is in unity power factor, before islanding reactive power of load is supplied just by network and after islanding the amount of reactive power imbalance is equal to the consumed load before islanding, hence we have:

$$\Delta Q = 3\frac{V^2}{\omega_n L}(1 - \omega^2 LC) = 3\frac{V^2}{\omega_n L}\left(1 - \frac{\omega_n^2}{\omega_r^2}\right) \tag{17}$$

where ω_n and ω_r are system frequency and resonance frequency of load, respectively. Reactive power imbalance leads to the resonance frequency, then the frequency changes after the islanding occurrence is equal to the difference between network frequency and load resonance frequency.

$$\omega_r = \omega_n \pm \Delta\omega, \omega_r = \frac{1}{\sqrt{LC}} \tag{18}$$

Thus, the reactive power imbalance needed for certain changes in frequency can be obtained by,

$$\Delta Q = 3\frac{V^2}{\omega_n L}\left(1 - \frac{f_n^2}{(f_n \pm \Delta f)^2}\right) \tag{19}$$

In distribution network of Iran, the acceptable frequency range is between 49.7 and 50.3 Hz which are equal to $\Delta f = -0.3$ and $\Delta f = 0.3$ Hz. In this paper test system, the amounts of reactive power imbalances are 5.137 and 5.132 kV A, respectively. Fig. 5 shows the NDZ for the constant current interface controls for the inverter rated output power that study in this paper.

5. Methodology of the proposed technique

The concept of the proposed technique is based on recognizing the patterns of the sensitivities of some indices at a target location to prescribed credible events since every event could have a signature on the patterns of these indices. The following independent variables are defined with respect to this target location. The current and voltage signals are acquired at this location. The behavioral model of the proposed islanding detection technique can be represented within the fuzzy inference system as follows:

$$Data_{in} = \begin{bmatrix} \frac{dP^1}{dt} \\ \frac{dP^2}{dt} \\ \cdots \\ \cdots \\ \cdots \\ \frac{dP^M}{dt} \end{bmatrix}_{M*1} \quad Data_{out} = \begin{bmatrix} Output\left(\frac{dP^1}{dt}\right) \\ Output\left(\frac{dP^2}{dt}\right) \\ \cdots \\ \cdots \\ \cdots \\ Output\left(\frac{dP^M}{dt}\right) \end{bmatrix}_{M*1}$$
$$[y_i] = [Data_{out}] \quad i = 1, 2, \ldots, M$$
$$S = [Data_{in} Data_{out}] \tag{20}$$

That:

$X^i = \Delta P^i/\Delta t$ rate of change of the power (MW/s) under the *i*th event.
M: the number of performed tests.

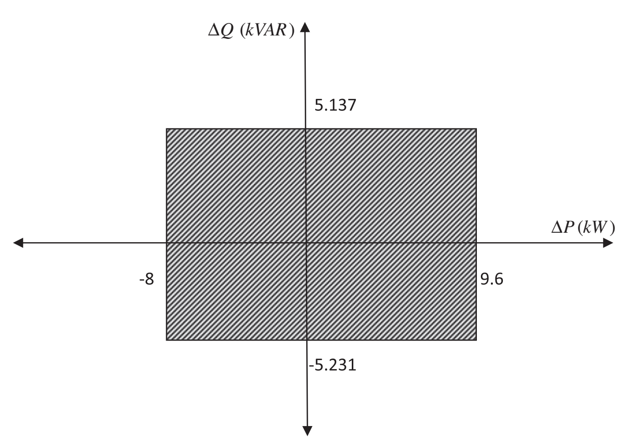

Fig. 5. NDZ for the constant current interface controls for distributed generation.

The possible values of any class variables (y_i) can be given by the binary set {0,1} such that: $y_i = 0$ for non-islanding condition, and $y_i = 1$ for islanding condition. In this study, we propose to use a hybrid intelligent system called ANFIS for islanding detection. We combine the ability of a neural network (NN) to learn with fuzzy logic (FL) to reason in order to form a hybrid intelligent system called ANFIS. The goal of ANFIS is to find a model or mapping that will correctly associate the inputs with the target. The fuzzy inference system (FIS) is a knowledge representation where each fuzzy rule describes a local behavior of the system. The network structure that implements FIS and employs hybrid-learning rules to train is called ANFIS. The proposed methodology involves: (a) working methods which engage various tasks associated with any selected distributed generation (DG) and (b) definition of prescribed events for training the ANFIS. The methodology starts with a target location in which an islanding detection is to be installed.

5.1. Tasks of the methodology

These tasks can be summarized as follows:

(a) Selecting a target distributed generation (DG) location in which an islanding is to be installed for a given distributed generation.
(b) Simulating the prescribed events associated with the selected distributed generation (one event at a time) in the network simulator. These events are prescribed in an event database.
(c) Analyzing the current and voltage signals of the distributed generation that are generated from the simulation in order to determine the values of the independent variables (system parameter indices) of the pattern vector X^i.
(d) Storing the determined pattern vector X^i along with the corresponding class variable y_i in the same pattern distributed generation database.
(e) Repeating steps 2–4 for all N prescribed events.
(f) Compiling the pattern vector X^i and the corresponding class variable y_i to generate the ANFIS [S] for the islanding detection relay at the distributed generation (DG) location.

The output of this methodology is ANFIS for the islanding detection relay at the distributed generation location.

5.2. Prescribed events

In this proposed methodology, extensive prescribed events are simulated off-line in order to capture the essential features of the system behavior that produce the ANFIS. These prescribed events are defined in the event database from which the network simulator executes the required events. The definition of these events are based on three main sources, namely: (a) the operational requirements in the IEEE1547 standards, (b) the testing practices that are recommended by most of the manufacturers of islanding relays and (c) possible operating network topologies. The prescribed events can be categorized into faults and switching actions under different network operating states. The following is a list of some possible events: (a) all possible tripping of circuit breakers that are liable to assume the conditions of islanding formation (under different conditions with various load conditions); (b) opening of any breakers between the power system and DG; (c) abrupt change in the load of distributed generation; (d) loss of any distribution lines of the distribution network; (e) motor starting with various capacity; (f) capacitor bank switching with various capacity; (g) non-linear load switching to network; and (h) three-phase fault on the Gen-Bus.

6. Architecture of the proposed algorithm

The architecture of the proposed Intelligent-based islanding relay is shown in Fig. 6. It is consists of three main modules, namely the input module, fuzzy inference system, and the output module. These modules are described as follows.

6.1. Input module

The input to this module is the rate of change of active power at the target distributed generation.

6.2. Fuzzy inference system (FIS)

This module is the fuzzy inference system software model of the islanding detection relay. This module has already been discussed in Section 2.

6.3. Output module

This is an output unit which is connected to the tripping unit of the circuit breaker of the DG. If the islanding is detected, the output of this unit is 1. Conversely, if the islanding is not detected, the output of this unit is 0.

The proposed approach is based on the passive method of islanding detection considering the data clustering approach. In addition this method includes building a simplified and robust fuzzy classifier initialized by the subtractive clustering and makes a fuzzy interface system (FIS) for islanding detection. As a result of the increasing complexity and dimensionality of classification problems, it becomes necessary to deal with structural issues of the identification of classifier systems. Important aspects are the selection of the relevant features and determination of effective initial partition of the input domain. In this study we want to reach a zero non-detection zone, our dataset are very large thus we used form fuzzy clustering. Clustering of numerical data forms the basis of many classification and system modeling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. Subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. This approach measure rate of change of power, at the target distributed generation location and fed to the ANFIS for training and obtained the fuzzy membership function (MF) without need to determine of type and number of membership function. Thus, with this technique can also overcome the problem of setting the detection thresholds inherent in the existing techniques. In this paper an ANFIS models which takes rate of change of power as inputs and islanding condition as output. If the islanding is detected, the output ANFIS is 1 and if the islanding is not detected, the output ANFIS is 0. The result obtained to indicate that ANFIS is effective method for islanding detection. Firstly, rate of change of active power measurements taken from the distributed generation for provide a dataset of target distributed generation in the all possible condition and selected relevant features from the dataset that this selected data must be contain islanding and non-islanding (normal operation) information. The next step, subtractive clustering dataset and construct a fuzzy inference system (FIS) that could

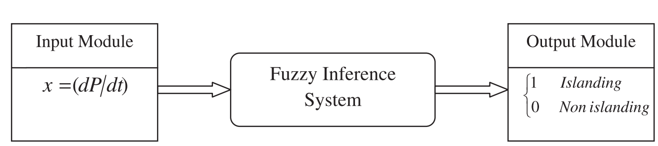

Fig. 6. Architecture of the proposed intelligent-based islanding detection relay.

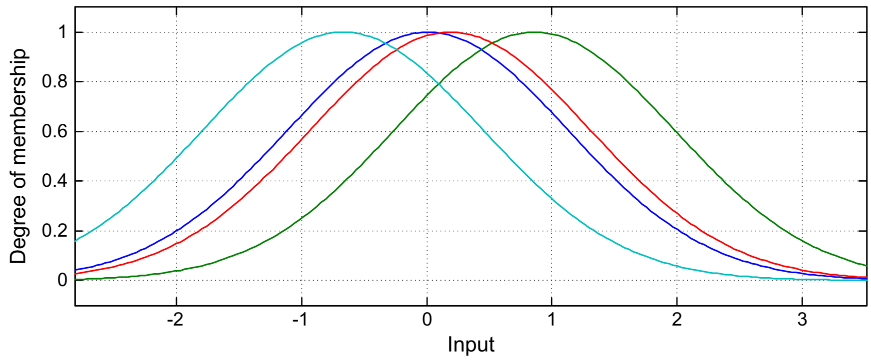

Fig. 7. The fuzzy membership function.

Table 1
System, DG, and load parameters.

DG output power	80 kW
PWM carrier frequency	2000 Hz
Input DC voltage	800 V
$Voltage_{rms}(phase–phase)$	380 V
R_t	1.5 mΩ
L_t	300 μH
Nominal grid frequency	50 Hz
Load quality factor	1.8
R	1.805 Ω
L	3.192 mH
C	3.174 mF
Proportional gain (K_p)	0.4
Integral gain (K_i)	500

Table 2
Various loads for islanding mode test.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Power (kW)	72	75	78	82	85	88
R (Ω)	2.0056	1.925	1.851	1.761	1.698	1.641
L (mH)	3.192	3.192	3.192	3.192	3.192	3.192
C (mF)	3.174	3.174	3.174	3.174	3.174	3.174

best predict the islanding condition or normal condition. ANFIS training can use alternative algorithms to reduce the error of the training. Fig. 7 shows the fuzzy membership function obtained only from dataset for all conditional (islanding and normal operation) without any setting threshold for islanding detection parameters for case study. In this paper we can overcome the problem of setting thresholds for islanding detection parameters. The result obtained to indicate that ANFIS is effective method for islanding detection.

7. Simulation results

In this section, the test system shown in Fig. 1 has been simulated by MATLAB/Simulink. The system, DG, and load parameters are listed in Table 1. The proposed islanding detection method has been also tested for various conditions.

7.1. Islanding mode test

Performance of the proposed method is analyzed in islanding mode for the various loads which are given in Table 2. Design and selection of loads should be such that the imbalance of reactive power is equal to zero resulting in the situation which is more difficult to identify the island mood. Further, the load quality factor is equal to 1.8 which is the maximum recommended amount in standards.

For all examined cases in Table 2 at the time $t = 1.5$ s circuit breaker (CB) opens and distributed generation along with local loads isolated from power grid and islanding mode is occurred. Effective voltage waveform of the common coupling point for each cases reviewed in Table 2 are shown in Fig. 8. Also, the frequency of common coupling point voltage, and rate of change of active power for all cases studied in Table 2 are shown in Figs. 9 and 10 respectively. Immediately following these loss of utility at the time $t = 1.5$ s, rate of change of active power for each condition are increased or decreased. Finally, in Fig. 11 the output of detection method for all studied cases are shown. It is obvious from Fig. 11 that after islanding value of the proposed algorithm has been increased and the output of ANFIS is reach 1. So the ANFIS based

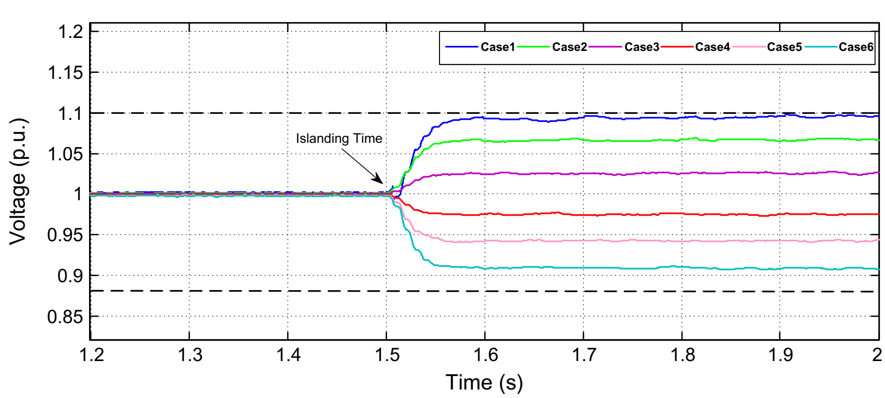

Fig. 8. Effective voltage waveform of the common coupling point for islanding mode.

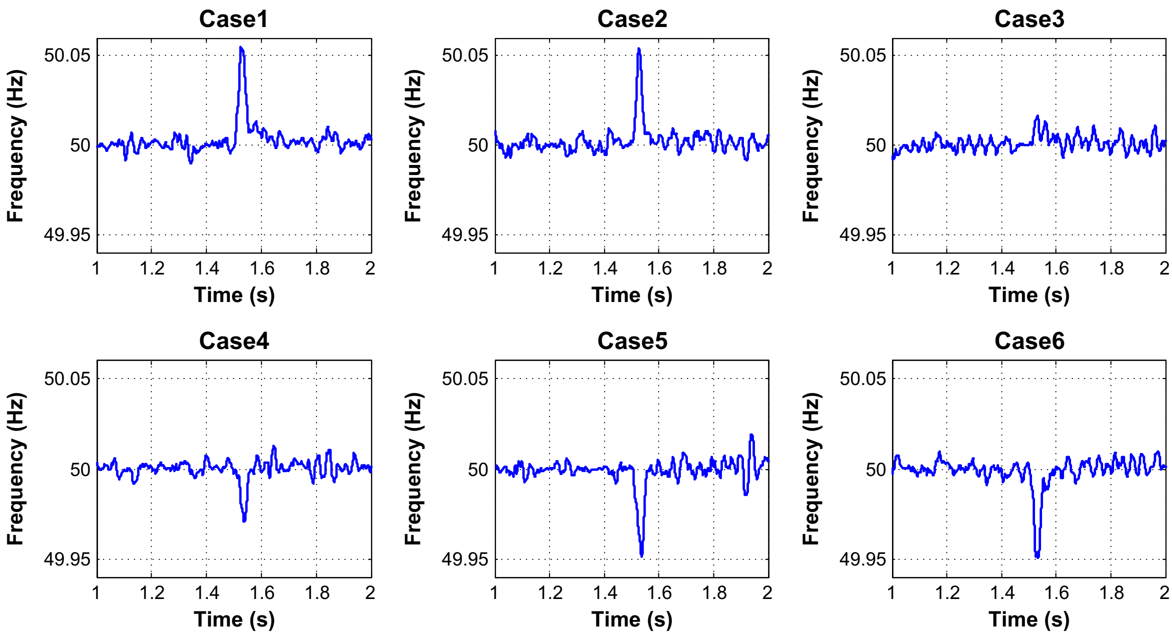

Fig. 9. The frequency of common coupling point voltage for islanding mode.

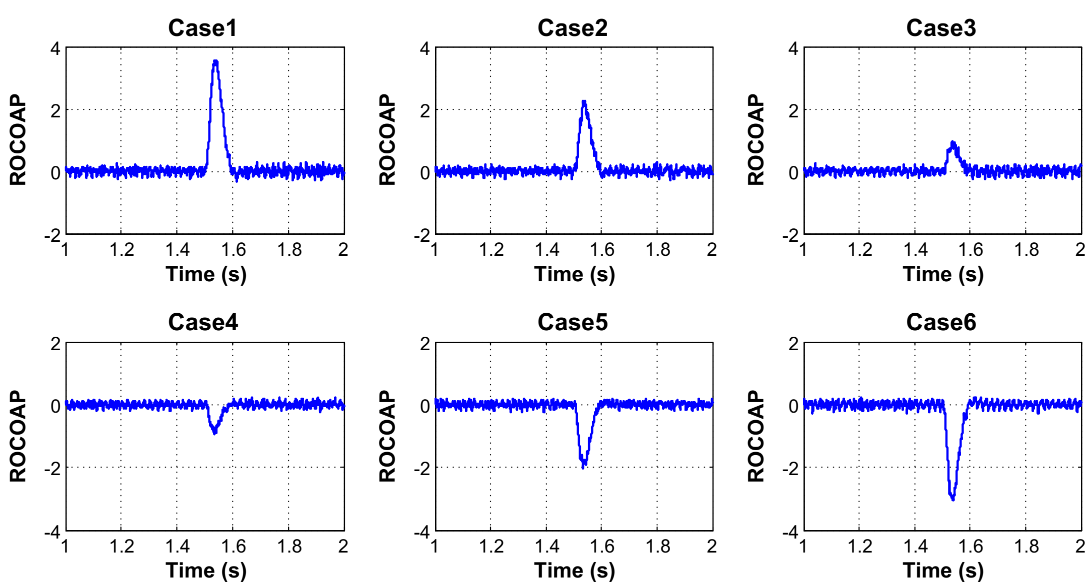

Fig. 10. Rate of change of active power for islanding mode.

protection algorithm produced the trip signal and sends to distributed generation (DG).

7.2. Normal operation

Performance of the proposed method is analyzed in this operation mode for the various loads which are given in Table 3.

For all examined cases in Table 3 at the time $t = 1.5$ s is applied to the system. Effective voltage waveform of the common coupling point for each cases reviewed in Table 3 are shown in Fig. 12. Also, the frequency of common coupling point voltage, and rate of change of active power for all cases studied in Table 3 are shown in Figs. 13 and 14 respectively. Immediately following these change at the time $t = 1.5$ s, rate of change of active power for each condition are increased or decreased. Finally, in Fig. 15 the output of detection method for all studied cases are shown. It is obvious from Fig. 15 that after all studied cases value of the proposed algorithm has not changed and the output of ANFIS is remained 0. Therefore, the proposed method does not send a trip signal to distributed generation and works in a reliable mode.

7.3. Voltage deviation (Voltage Swell, Voltage Sag) in islanding detection method

Voltage deviation in the distribution network, depending on the time period can be divided into three categories: (a) Transient period: the time period for this voltage deviation is in milliseconds. (b) Short-term period: the time period of this state is up to one minute. Voltage Swell and Voltage Sag are of this deviation type. (c) Long term: for this the voltage deviation may be continued more

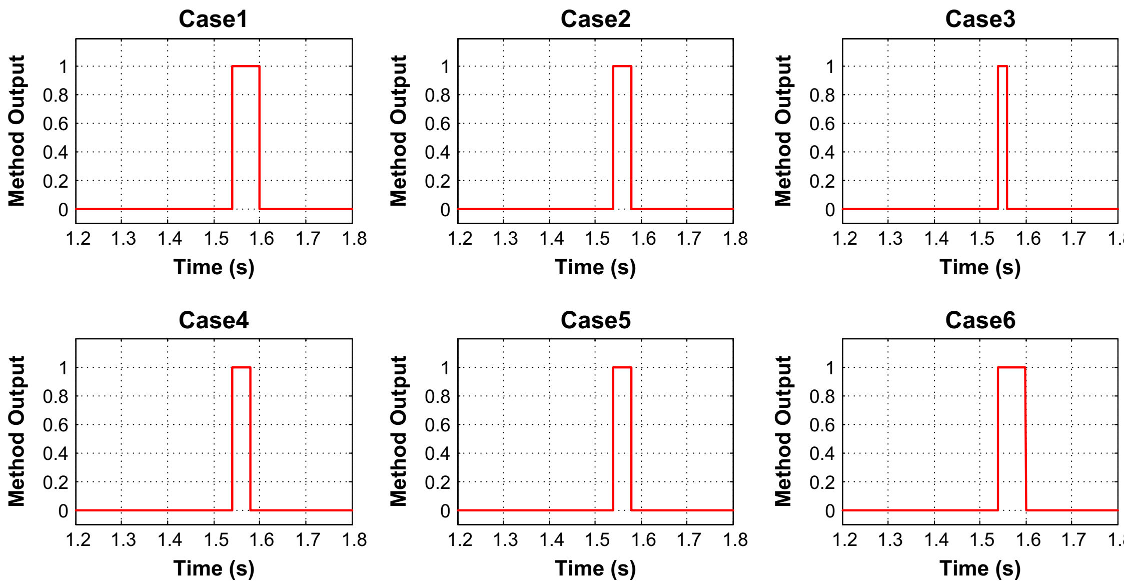

Fig. 11. The output of detection method for islanding mode.

Table 3
Various loads for normal operational test.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Power (kW)	50% N.l. (Out)	20% N.l. (Out)	20% N.l. (In)	40% N.l. (In)	50% N.l. (In)	80% N.l. (In)
R (Ω)	3.61	9.025	7.22	4.5125	3.61	2.226
L (mH)	6.383	20.5	14.37	7.98	6.383	4.488
C (mF)	1.587	0.4937	0.7054	1.27	1.587	2.257

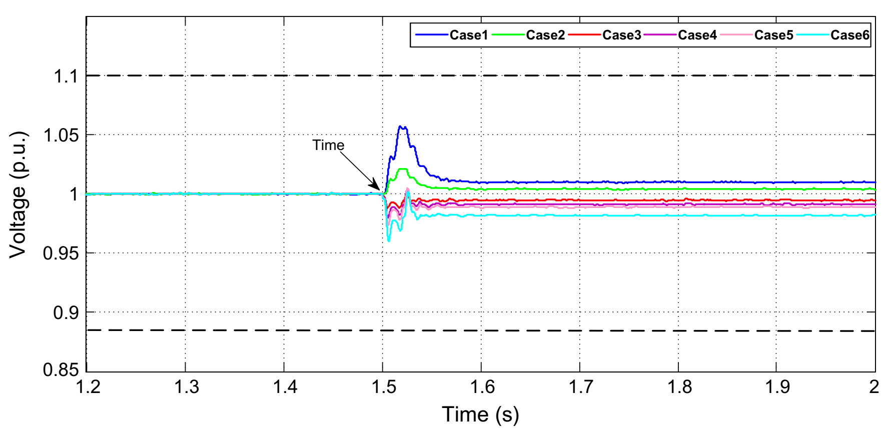

Fig. 12. Effective voltage waveform of the common coupling point for normal operation mode.

than one minute. Islanding detection method should be kept safe from voltage changes. By adding an adaptive system with a delay system, one can keep safe the detection method from the voltage changes. Thus, the inverter output current is monitored continuously and once the difference between this current and the rated current is observed the comparator detects automatically these abnormal conditions. These abnormal conditions can be sign of either: (a) an electrical island, and (b) voltage deviation. Table 4 shows Voltage relay responses when an abnormal condition is observed in the standard distribution network IEEEStd.1547. Simple voltage relays should detect the voltage changes at the appropriate time and then eliminates the distributed generation from the grid.

Performance of the proposed method is analyzed in this mode for the various conditions which are given in Table 5. Three phase voltage waveform of the common coupling point for each cases reviewed in Table 5 are shown in Fig. 16. Also rate of change of active power for all cases studied in Table 5 are shown in Fig. 17. Immediately following these change at the time $t = 1$ s, rate of change of active power for each condition are increased or decreased. Finally, in Fig. 18 the output of detection method for all studied cases are shown. It is obvious from Fig. 18 that after all studied cases value

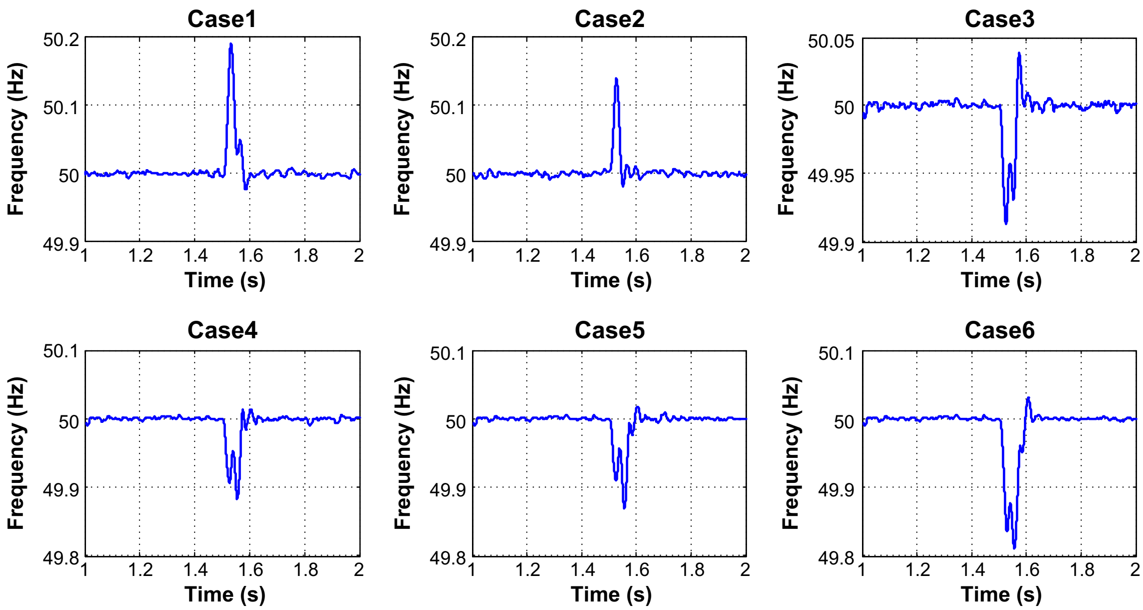

Fig. 13. The frequency of common coupling point voltage for normal operation mode.

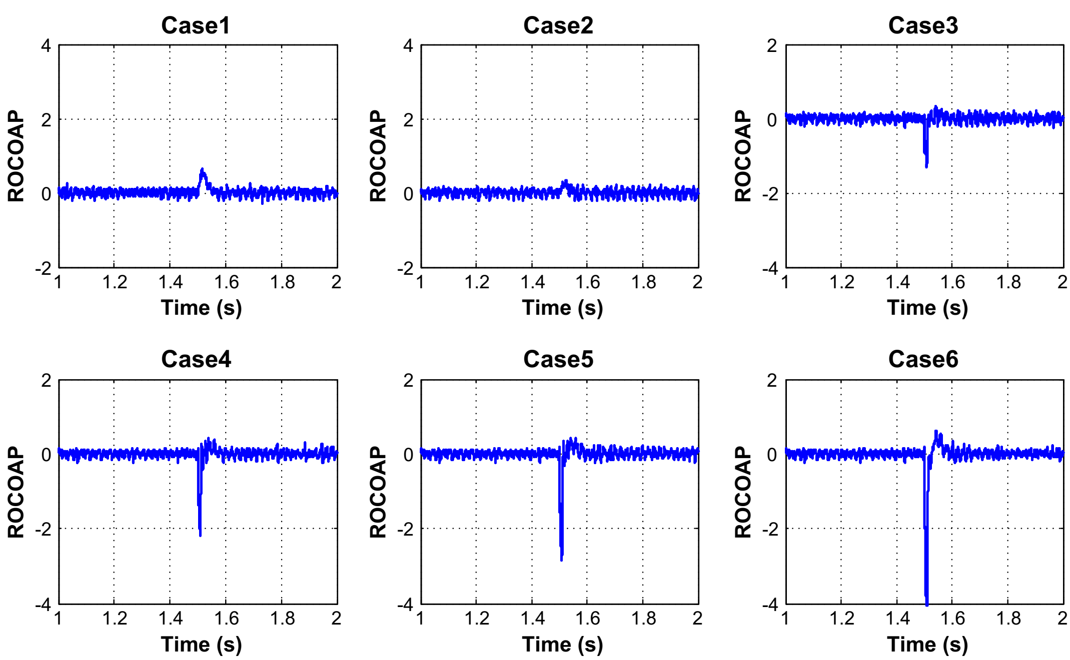

Fig. 14. Rate of change of active power for normal operation mode.

of the proposed algorithm has not changed and the output of ANFIS is remained 0. Therefore, the proposed method does not send a trip signal to distributed generation and works in a reliable mode.

8. Conclusion

A new technique for islanding detection of distributed generation is proposed based on adaptive neuro fuzzy inference system. Following the increased number and enlarged size of distributed generating units installed in a modern power system, the protection against islanding has become extremely challenging nowadays. Islanding detection is also important as islanding operation of distributed system is seen a viable option in the future to improve the reliability and quality of the supply. The islanding situation needs to be prevented with distributed generation due to safety reasons and to maintain quality of power supplied to the customers. The main emphasis of the proposed scheme is to reduce the NDZ to as close as possible and this technique can also overcome the problem of setting the detection thresholds inherent in the existing techniques. In this paper, we propose to use a hybrid intelligent system called ANFIS for islanding detection. By case studies with numerical simulations, the proposed approach was

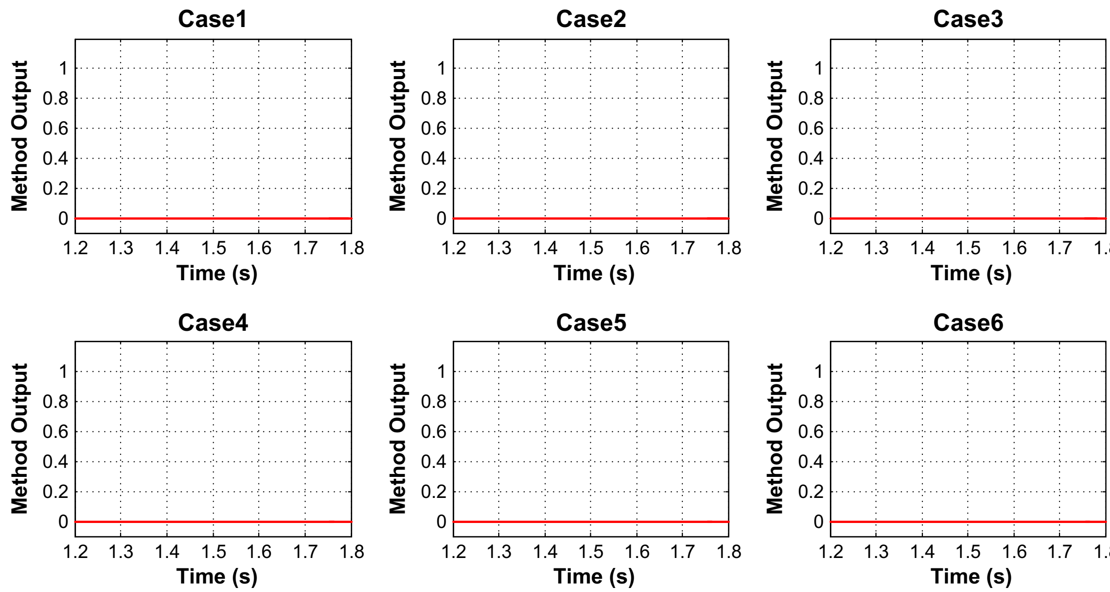

Fig. 15. The output of detection method for normal operation mode.

Table 4
Voltage relay responses.

Voltage range (% of base voltage)	Clearing time (s)
$V < 50$	0.16
$50 < V < 88$	2
$110 < V < 120$	1
$V > 120$	0.16

verified with feasibility, flexibility and robustness. The comparison of ANFIS method with other islanding detection methods at different DG locations during islanding event with power imbalance of nearly 0% shows that the proposed method works effectively for islanding detection while other methods fails to detect islanding.

Table 5
Various condition for voltage deviation test.

	Case 1 One-phase fault	Case 2 Two-phase fault	Case 3 Two-phase fault	Case 4 Three-phase fault	Case 5 Three-phase fault	Case 6 Three-phase fault
Fault resistance (Ω)	1	0.1	1	0.05	0.1	1
Ground resistance (Ω)	0.1	0.1	0.1	0.1	0.1	0.1

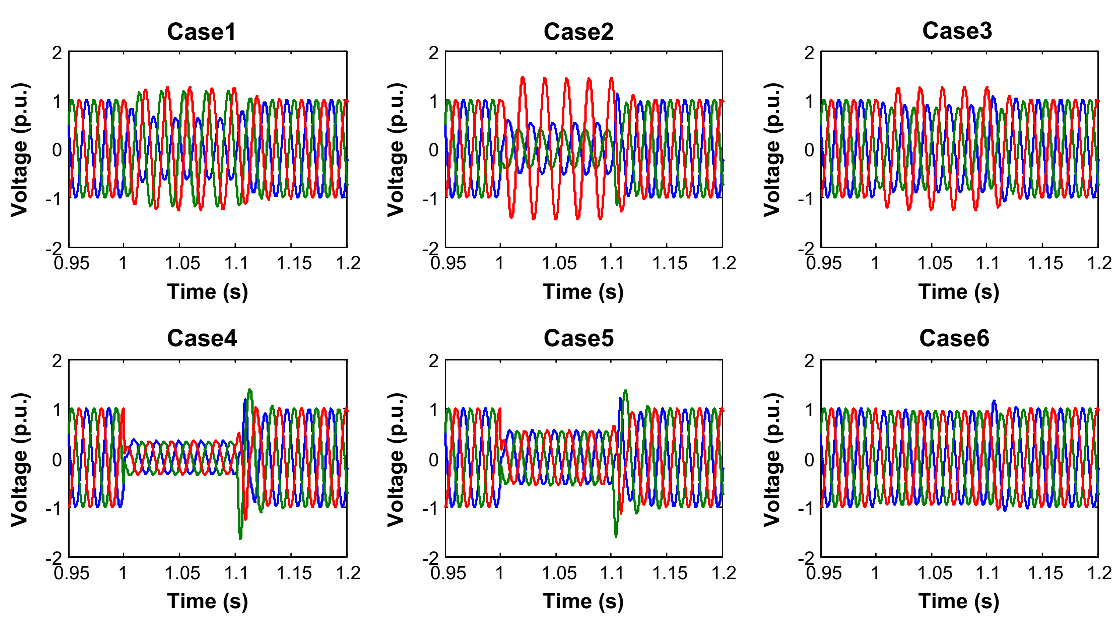

Fig. 16. Three phase voltage waveform of the common coupling point for voltage deviation mode.

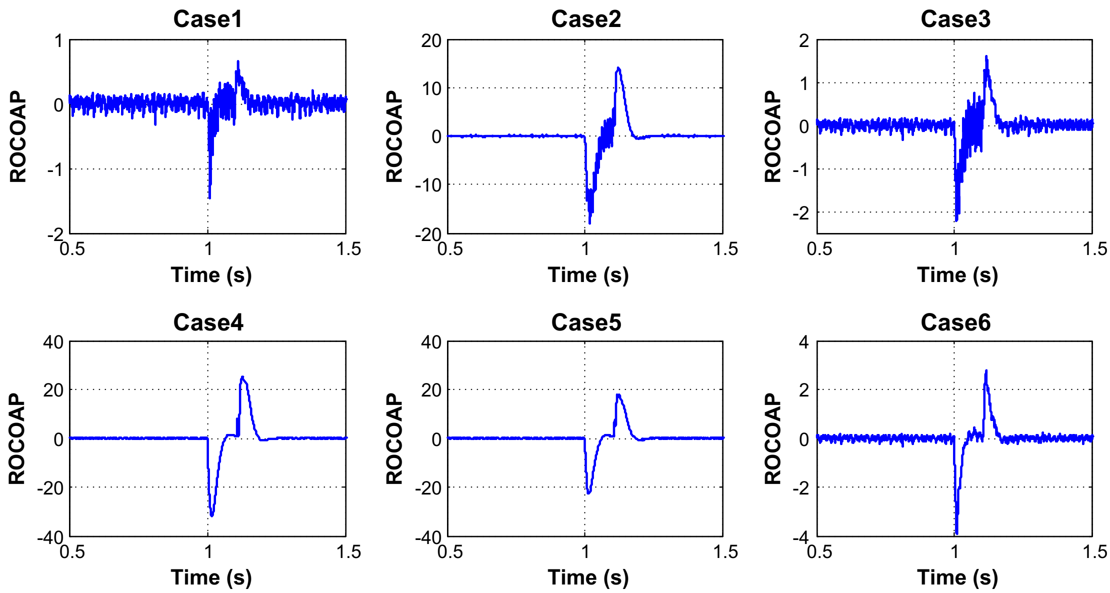

Fig. 17. Rate of change of active power for voltage deviation mode.

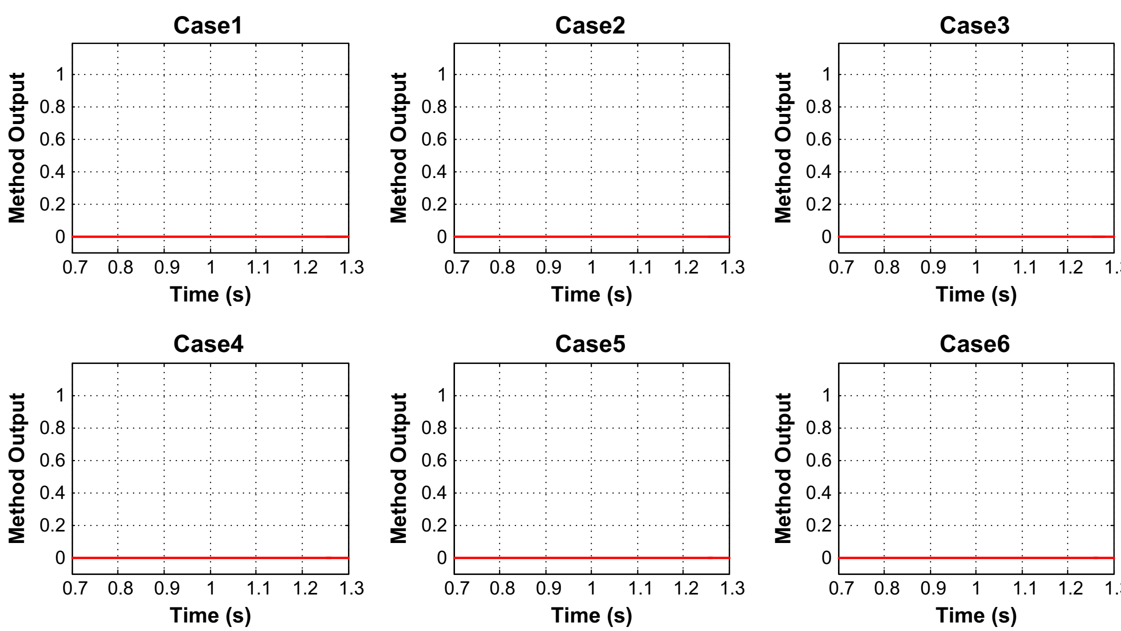

Fig. 18. The output of detection method for voltage deviation mod.

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