World Essays Journal / 7 (1): 87-99, 2019


# ANFIS Islanding Detection Based on Wind Turbine Simulator

**Cheng-shu Zhang**
Anhui Finance &Trade Vocational College.

**Abstract**
This paper presents a passive islanding detection method based on means of a neuro-fuzzy approach for wind turbines. 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 proposed method is based on voltage measurements and processing of the hybrid intelligent system called ANFIS -the adaptive neuro fuzzy inference system- for islanding detection. This new method based on passive methods will help to reduce the NDZ without any perturbation that deteriorates the output power quality opposite active methods. This method detects the islanding conditions with the analysis of these signals. The studies reported in this paper are based on an experimental system (wind turbine simulator). The results showed that the ANFIS-based algorithm detects islanding situation accurate than other islanding detection algorithms. 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.
**Keywords:** Distributed generation- islanding detection- non detection zone- adaptive neuro fuzzy inference system,-fuzzy subtractive clustering

## I. INTRODUCTION

The increase of distributed resources in the electric utility systems is indicated due to recent and ongoing technological, social, economical and environmental aspects. Distributed Generation (DG) units have become more competitive against the conventional centralised system by successfully integrating newgeneration technologies and power electronics. Hence, it attracts many customers from industrial, commercial, and residential sectors. DGs generally refer to Distributed Energy Resources (DERs), including photovoltaic, fuel cells, micro turbines, and small wind turbines, and additional equipment [1].
The total global installed wind capacity at the end of 2010 was 430 TWh annually, which is 2.5% of the total global demand. Based on the current growth rates, World Wide Energy Association (WWEA) predicts that, in 2015, a global capacity of 600 GW is possible. By the end of the year 2020, at least 1500 GW can be expected to be installed globally [2]. However, connecting wind turbines to distribution networks produces some problems, such as islanding.
Islanding when occurred, that DG and its local load become electrically isolated from the utility grid [3]. However the wind turbine produces electrical energy and supplies the local load. Islanding creates many problems in system and cause the existing standards do not permit DGs to be utilized in islanding mode [4]. Some of these reasons are:

- Create safety hazard for personals
- Power quality problems for customers load
- overload condition of wind turbine generator
- Out of phase recloser connection [5,6].

Thus, islanding conditions should be detected and interrupted. This application should be done in less than 2 seconds [5].
Originally, the methods of islanding detections are divided to two methods. a) Communication methods. b) Local methods. Local methods have been classified as active and passive techniques [4]. Active techniques are based on directly interact with the on-going power system operation, such as impedance measurement [7], frequency shift, active frequency drift [7], sandia frequency shift [7,9], sandia voltage shift [7,9], phase shift, current injection [8], negative sequence current injection method [10]. Passive techniques are based on measurement and information at the local site, such as under/over frequency [7], under/over voltage [7], voltage phase jump, voltage unbalanced and total harmonic distortion [2], rate of

change of frequency [11], vector surge [11, 13], phase displacement monitoring [13], rate of change of generator power output [7], comparison of rate of change of frequency [11].
In this paper, a new method based on Discrete Wavelet Transform (DWT) has been proposed for islanding detection of wind turbines. The proposed technique, which is suitable for asynchronous DGs, is explained in Section 3. Section 4 explains the simulation and experimentally test system used to verify the effectiveness of the proposed technique. Section 5 explores the effectiveness of the proposed technique applied on simulation and experimentally test system, Section 6 concludes the paper. The simulation test systems were simulated in MATLAB/ SIMULINK using SimPowerSystemBlockSet. Simulation and experimentally results show that the proposed islanding detection technique works well in discriminating between switching and islanding conditions.

## II. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS):

Artificial intelligence, including neural network, fuzzy logic inference [27-28], has been used to solve many nonlinear classification problems. 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 ANN, on the other hand, is the inherent learning capability, which enables the networks to adaptively improve its 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. 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. ANFIS is an adaptive network which permits the usage of neural network topology together with fuzzy logic. It not only includes the characteristics of both methods, but also eliminates some disadvantages of their lonely-used case. Basically a fuzzy inference system is composed of five functional blocks (Fig.1).

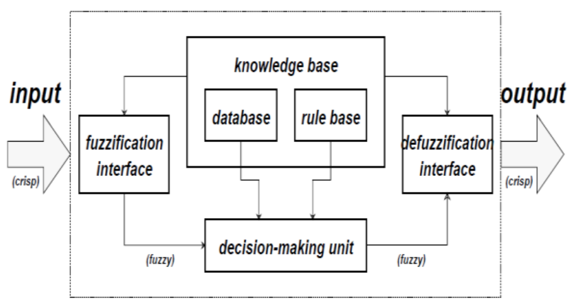


**Fig.1 fuzzy inference system**

Operation of ANFIS looks like feed-forward back propagation 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. The ANFIS approach learns the rules and membership functions from data. The objective of ANFIS is to adjust the parameters of a fuzzy system by applying a learning procedure using input-output training data.
The basic structure of the type of fuzzy inference system is a model that maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output.
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. A typical fuzzy in a Sugeno fuzzy model has the format:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z = f(x, y)$$

Where A and B are fuzzy sets in the antecedent; $z=f(x,y)$ is a crisp function in the consequent. Usually $f(x, y)$ is a polynomial in the input variable x and y, but it can be any other functions that can appropriately describe the output of the system within the fuzzy region specified by the antecedent of the rule. When $f(x, y)$ is a first-order polynomial, this first order sugeno fuzzy model is proposed in sugeno (1998).When f is a constant, then the zero order Sugeno fuzzy model, which is functionally equivalent to a radial basis function network under certain minor constraints. The architecture of ANFIS 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.

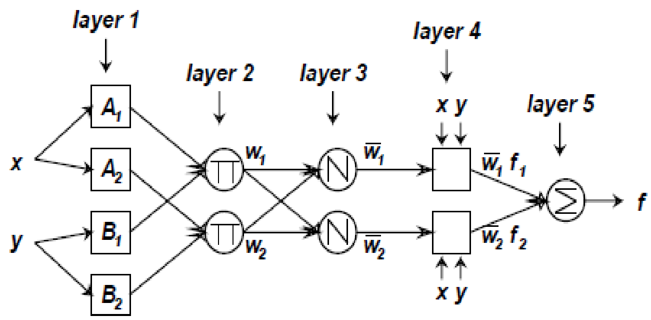


**Fig. 2 ANFIS architecture**

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

Rule 1: If X is Al and Y is B1, then f1 =P1x+q1y+r1,

Rule 2: If X is A2 and Y is B 2 then f2 =P2x+q2y+r2,

Where, P1, P2, q1, q2, r1, r2 are linear parameters and A1, A2, B1, B2 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

$$O_i^1 = \mu_{A_l}(x), \quad O_{i+2}^1 = \mu_{B_l}(y) \quad i = 1,2 \tag{1}$$

Where x is the input to $i_{th}$ node, $O_i^l$ is the membership grade of x in the fuzzy set Ai. Generalized bell membership function is popular method for specifying fuzzy sets because of their smoothness and concise notation, and defined as

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

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. The parameters in this layer are called premise parameters. This layer forms the antecedents of the fuzzy rules (IF part).

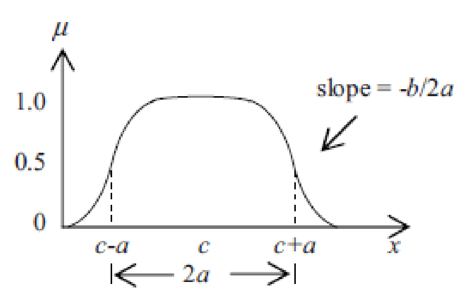


**Fig.3. Generalized bell function**

Layer 2 is 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.

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

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

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \qquad (4)$$

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

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad (5)$$

Here $w_i$ is the output of Layer 3 and the parameters { $p_i, q_i, r_i$) are called as consequent parameters. Layer 5 is summation layer and consists of single fixed node which calculates the overall output as the summation of all incoming signals as

$$O_i^5 = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (6)$$

## III. ROPOSED DETECTION ALGORITHM

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.

ANFIS training algorithm can be efficiently used to build fuzzy rules from correct input-output numerical data pairs. The main motivations for such an investigation are: i) the ANFIS is a well known and successful solution; ii) it can be used directly on the data recorded in the learning stage, and so it can be further considered for a real-time implementation; iii) it stands as a classical algorithm, with trustful implementation as the one included in MATLAB. More specifically, in the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backwards and the premise parameters are updated by gradient descent. We don't necessarily have a predetermined model structure based on characteristics of variables in ours system. There will be some modeling situations in which we can't just look at the data and discern what the membership functions should look like. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input-output data in order to account for these types of variations in the data values. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. Using a given input/output data set, the ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm. This allows our fuzzy systems to learn from the data they are modeling.

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. The purpose of clustering is to identify natural groupings of data 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.

In this paper an ANFIS models which takes voltage signal as inputs and islanding condition as output. Firstly, voltage data taken from the distributed generation for provide a dataset. The next step, construct a fuzzy inference system (FIS) that could best predict the islanding condition or normal condition. ANFIS training can use alternative algorithms to reduce the error of the training. A combination of the gradient descent algorithm and a least squares algorithm is used for an effective search for the optimal parameters. The main benefit of such a hybrid approach is that it converges much faster, since it reduces the search space dimensions of the back propagation method used in neural networks. ANFIS was trained with the first half epochs and the next half epochs were used for validation. The root mean squared error (RMSE) from each of the validating epochs was calculated and averaged to give the RMSE per patient. Averages of RMSE per patient were calculated for all patients to give the average RMSE. Thus before training a fuzzy inference system, the data set has been divided into training set and test sets. The training set is used to train a fuzzy mode, while the test set is used to determine when training should be terminated to prevent over fitting. After training, for verify the model (FIS) we calculate the root mean square error of the system generated by the training data that it is equal 0.1068. To validate the generalize ability of the model; we apply test data to the FIS that it is equal 0.018. Fig.4 shows the membership function obtained only from dataset for all conditional of islanding and normal operation without any setting of threshold for islanding detection parameter. In this paper we can overcome the problem of setting the detection thresholds for islanding detection.

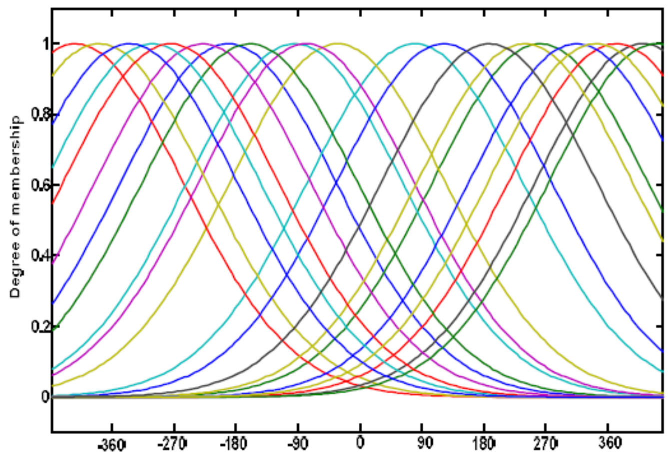


**Fig.4 membership function**

ANFIS models which takes voltage as inputs and islanding condition as output. If the islanding is detected, the output ANFIS is higher than 0.6. Conversely, if the islanding is not detected, the output ANFIS is around 0 or less than 0.5. The result obtained to indicate that ANFIS is effective method for islanding detection.

## IV. CASE STUDY

Fig. 5 shows a schematic diagram of a wind turbine unit. The DG unit is a wind turbine induction generator, and a capacitor bank is used to improve the power factor. The local load is a three-phase parallel RL before the circuit breaker (CB), in which "r" denotes the series resistance inductance and $V_f$ indicates the voltage drop across the parallel load. The parallel RL is conventionally adopted as the local load for the evaluation of islanding detection methods when the load inductance is tuned to the system frequency. This system, as shown in Fig. 5, is connected to a Point of Common Coupling (PCC) with a step-up transformer. To obtain the experimental results, a wind turbine simulator, as shown in Fig. 6, was implemented. Fig. 7 and Fig. 8 show the implemented simulator system. The implemented system parameters are given in Table 1. The parallel load inductance is considered infinite. Thus, the parallel load is only a resistance, and hence the unit of "L" is "inf". Fig. 9 shows the motor saturation curve. In the grid-connected condition, the switches SW1 and SW2 are closed. The islanding condition occurs when SW2 is open.

The voltage and frequency of DG should have admissible values in both grid-connected and islanded modes. In the grid-connected mode, the voltage magnitude and frequency of the local load at the PCC are regulated by the grid.

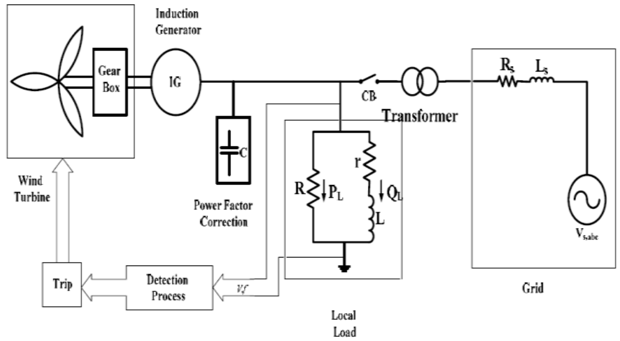


**Fig.5 .Single line diagram of study system**

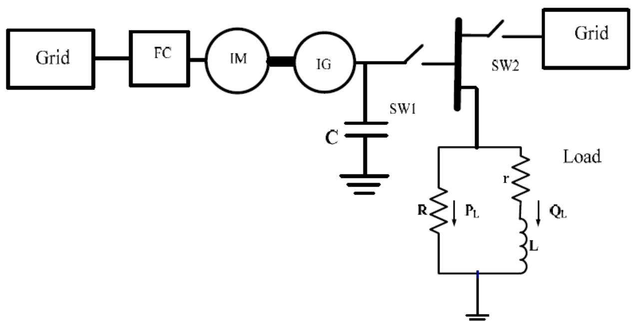


**Fig. 6. Single line diagram of implementation system in order to islanding condition detection**

**Table 1. Parameters of the implemented system**

| Parameters | Value | |
|---|---|---|
| Induction Motors | Sn | 2KVA |
| | Vn | 400V |
| | F | 50HZ |
| | PF | 0.78Lag |
| | Rs, Rr | 2.3541Ω |
| | Lr,Ls | 0.01678H |
| | Lm | 0.275H |
| Local Load | R | 180 Ω |
| | L | Inf |
| Capacitor | C | 36.75μF |

**Fig. 7. Implementation system in order to islanding condition detection**

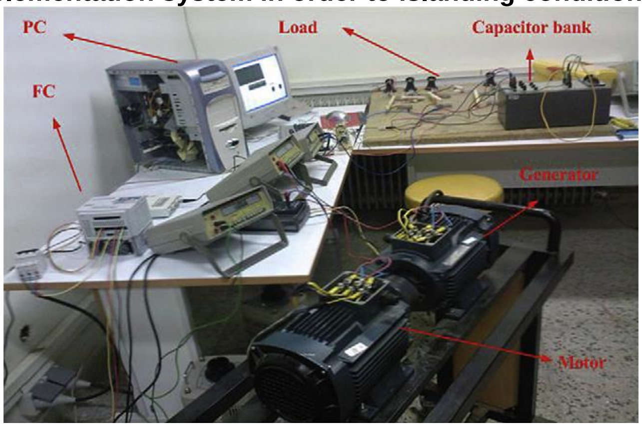


**Fig. 8. Implementation system in order to islanding condition detection**

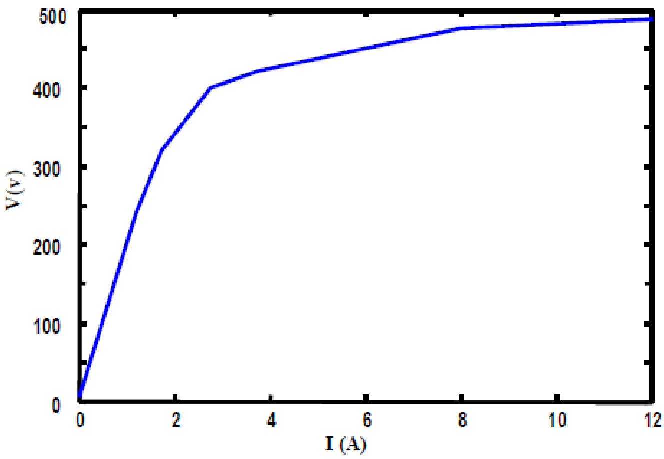


**Fig. 9. Motor and generator saturation curves**

## V. IMPLEMENTATION RESULTS

In this study, the simulation is conducted in four scenarios to illustrate the effectiveness of the proposed method.

### A. Match power condition

In this test, the active and reactive power of local load is 0.8 KW and 0Kvar respectively. The value of capacitor is 36.0μF, the distributed generator is assumed to separate from the grid, where the event is assumed to take place at 2.2 s. In Fig. 10a and b, the waveforms of phase voltage and frequency of DGs are individually depicted. Immediately following this loss of utility, proposed method relay fails to detect islanding condition. Fig.11 shows the output of proposed method algorithm result. ANFIS output is rich to above "0.5" value which leads to islanding detection. So the ANFIS based protection algorithm produced the trip signal and sends to distributed generation (DG).

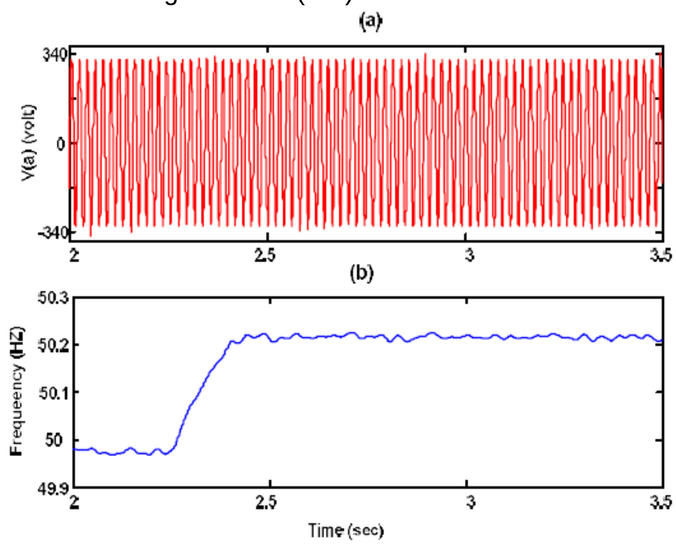


**Fig.10. match power condition: (a) phase voltage; (b) frequency**

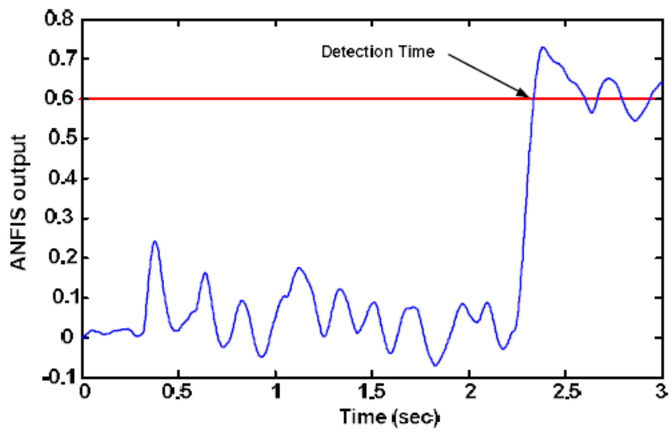


**Fig.11 ANFIS output for match power conditional**

### B. Mismatch power condition

At first, the amount of capacitor bank is lesser than nominal condition. The active power set to 0.66 KW and reactive power set to 0.1Kvar respectively. The distributed generator is assumed to separate from the grid, where the event is assumed to take place at 1.15 s. In Fig. 12a and b, the waveforms of phase voltage and frequency of DGs are individually depicted. Immediately following this loss of utility, frequency is increase and voltage is drop. Fig.13 shows the ANFIS output that is rich to higher than "0.5" value which leads to islanding detection. So the ANFIS based protection algorithm produced the trip signal and sends to distributed generation (DG).

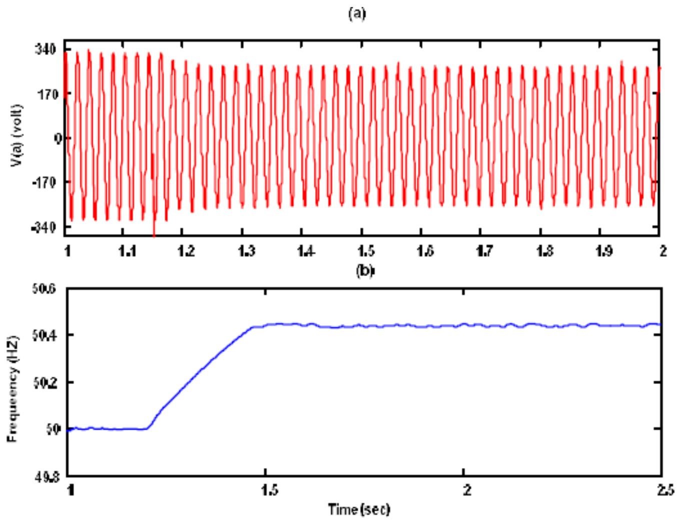


**Fig.12 Mismatch power condition: (a) three phase voltage; (b) frequency**

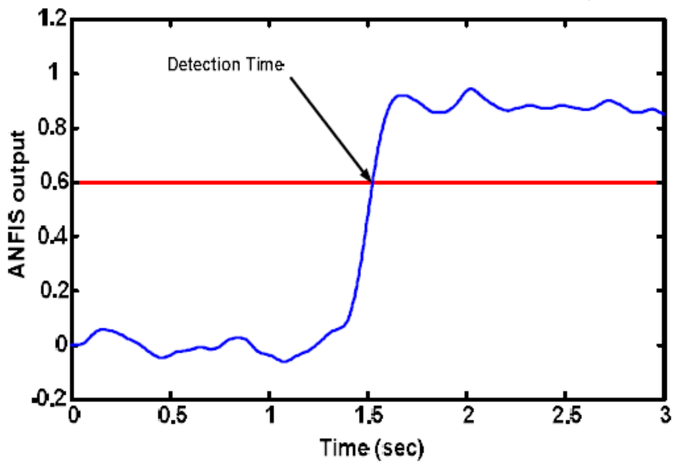


**Fig.13 ANFIS output for Mismatch power condition**

At the next test, the amount of capacitor bank is higher than nominal condition and set to 40 μF. The active power set to 0.66 KW and reactive power set to 0.1Kvar respectively. After islanding event at 2.6 s, figures 14a and b and c that show waveforms of instantaneous phase voltage, RMS phase voltage and frequency of DGs respectively. As can be seen, frequency is drop and voltage is increase. Fig.15 shows the ANFIS output that is rich to higher than “0.5” value which leads to islanding detection. So the ANFIS based protection algorithm produced the trip signal and sends to distributed generation (DG).

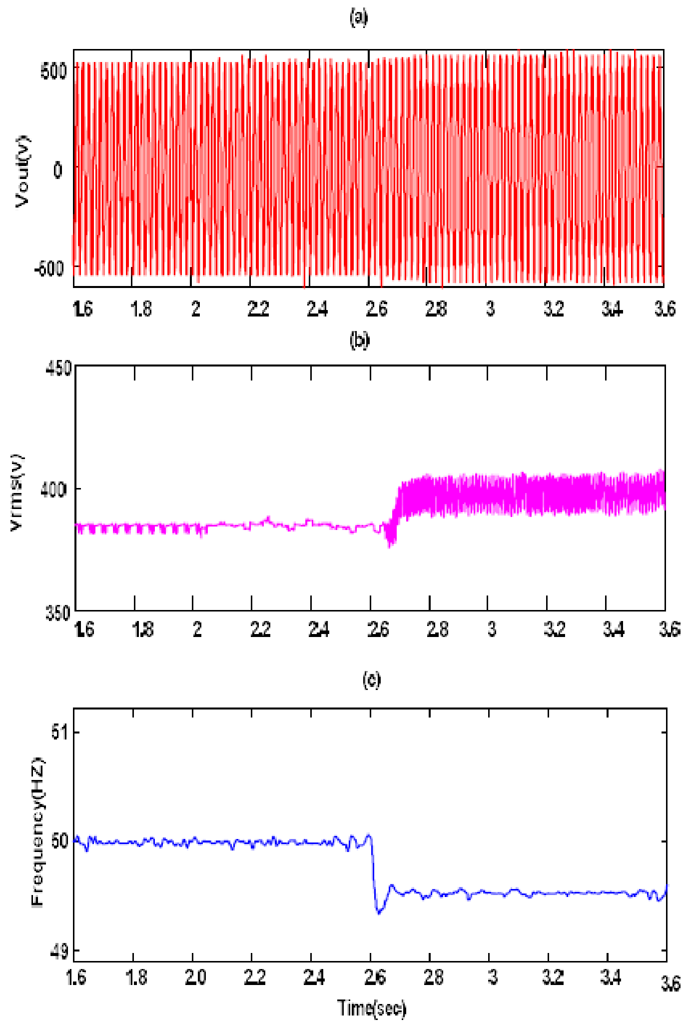


**Fig.14 Mismatch power condition: (a) phase voltage; (b) RMS voltage value (c) frequency**

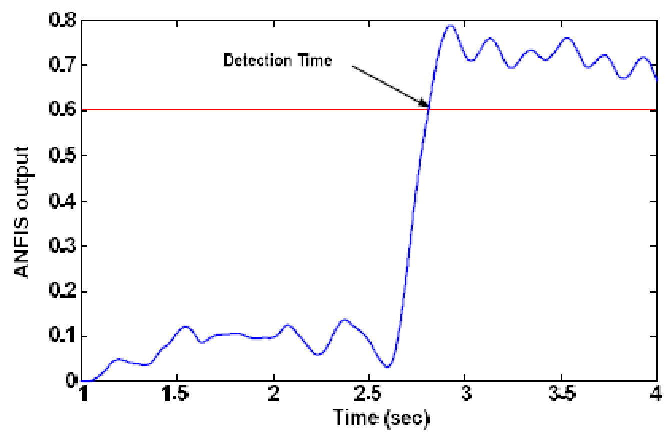


**Fig.15 ANFIS output for Mismatch power condition (2)**

### C. Motor starting condition

The starting of induction motors may cause a malfunction of the islanding detection algorithm. To study the reliability of the proposed algorithm, at t=1.15 s an induction motor with P=1KW and Q=1.1Kvar is starting and connected to the Point of Common Coupling (PCC). In Fig. 16a and b shows the waveforms of phase voltage and frequency of DGs respectively. Fig.17 shows the ANFIS results at this condition. The value of neural network output is not reach to threshold value. Therefore, the proposed method does not send a trip signal to distributed generation and works in a reliable mode.

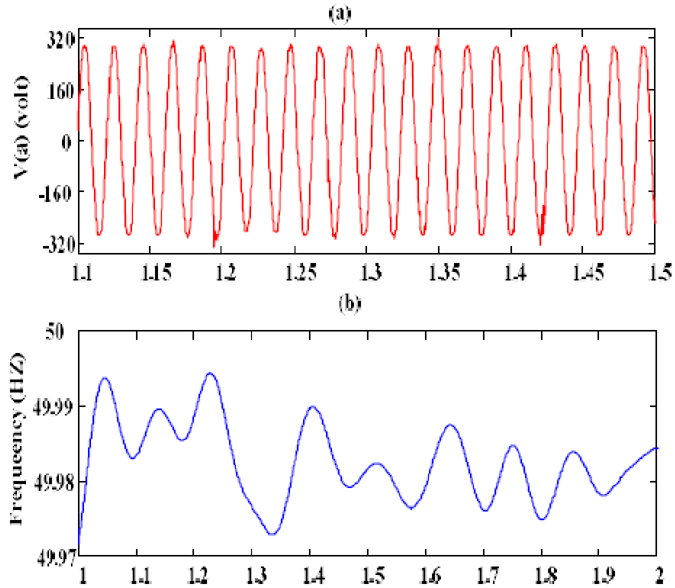


**Fig.16 Motor starting condition: (a) three phase voltage; (b) frequency**

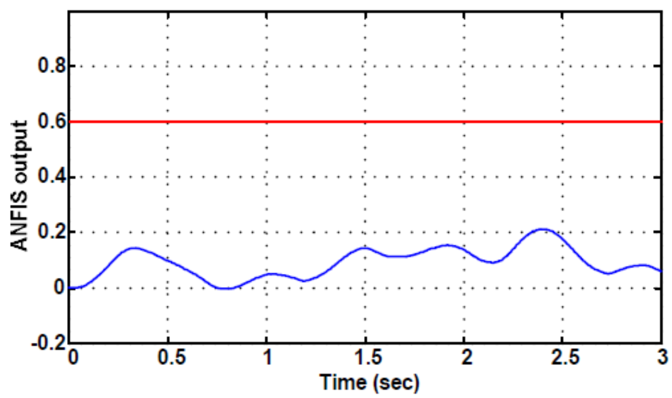


**Fig.17 ANFIS output for motor starting**

### D. Capacitor bank switching condition

Large capacitor bank switching in distribution power systems initiates disturbances. These disturbances are propagated in the distribution system and have some effects on the proposed method. To test the proposed algorithm, at t=2 s a large 30 μF capacitor bank was switched at the PCC in the non-islanding case. In Fig. 18a and b, the waveforms of phase voltage and frequency of DGs are individually depicted. Fig.19 shows the neural network response. The value of neural network output is not reach to threshold value too. Therefore, the system continue to working without any mistaken trip.

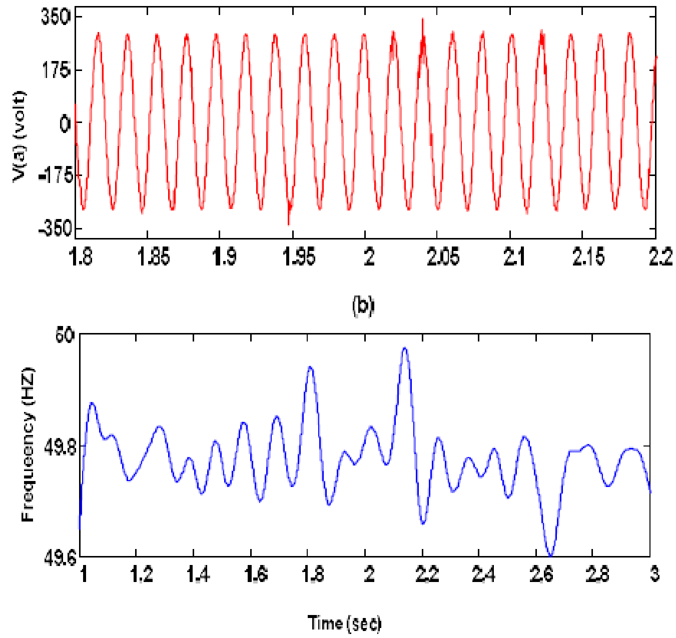


**Fig.18 Capacitor bank switching condition: (a) three phase voltage; (b) frequency**

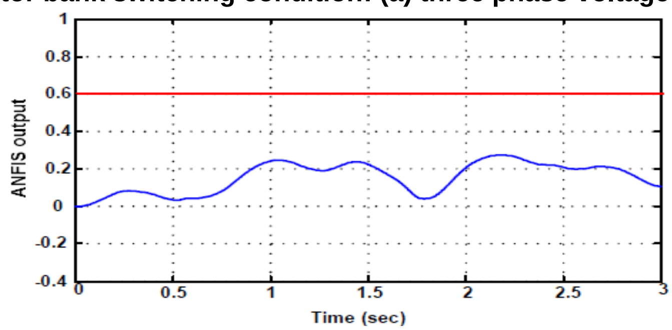


**Fig.19 ANFIS output for motor starting**

## VI. CONCLUTION

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. By case studies with numerical simulations, the proposed approach was verified with feasibility, flexibility and robustness.

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