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Radial Basis Neural Network Based Islanding Detection in Distributed Generation

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ABSTRACT

This paper investigates a new integrated diagnostic system for islanding detection by means of a neural network approach for distributed generation. Islanding is an 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 as an ongoing challenges in existing methods are not totaly 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 radial basis neural network for islanding detection.The proposed algorithm is compared with the widely used rate of change of frequency relays (ROCOF) and was found to work effectively in situations where ROCOF fails. This approach utilizes rate of change of frequency at the target distributed generation location and was fed to the radial basis neural network for intelligent islanding detection. Hence a better reliability is provided. This approach utilizes the artificial neural network (ANN) as a machine learning technology for processing and analyzing the large data sets provided from network simulations using MATLAB software. To validate the feasibility of this approach, the method has been validated through several conditions and different loadings, switching operations, and network conditions. Simulation studies showed that the RBNN-based algorithm detects islanding situation more accurately than other islanding detection algorithms.

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1. INTRODUCTION

With deregulation of the electric utility industry, and rising consciousness of environmental protection as well as the availability of fossil fuels, the installation of distributed generation systems has shed new light as alternative resources in energy supply. 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 with the conventional centralized systems by successfully integrating new generation 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, small wind turbines, and additional equipment [1]. DG may be defined as generating resources, other than central generating stations, that is placed close to load being served, usually at customer site. In fact, many utilities around the world already have a significant penetration of DG in their systems. 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, themost important problem is an islanding protection [1-6].Islanding condition causes abnormal operation in the power system and the distributed generation unit, and also causes safety problem.

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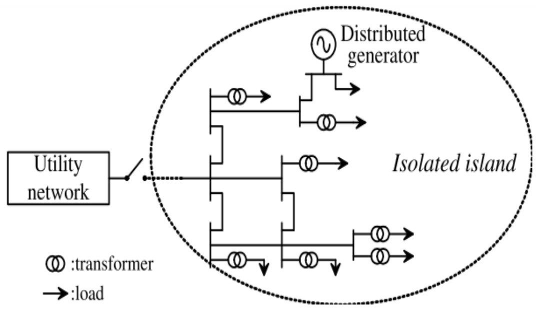


Figure 1. Scenario of islanding operation

Figure 1 depicts a scenario of islanding, where the load-of-interest isseveredoff 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 the other words, under the scenario of islanding, line crew members may misjudge the load-side of the line as inactive, where DGs are indeed feeding power to loads; hence jeopardizing the life of operators and mean while illuminating the importance of a reliable forewarning mechanism to such events. For these reasons, islanding protection is essential for distributed generators connected to the power systems. In the islanding operation mode, all of the distributed generator must be disconnected from the power system immediately [7].

There are many proposed techniques for detection of an island [8-17]. The two main criteria for comparison of the existing islanding detection methods are: 1) speed of detection or run-on time which is defined as the time interval between the actual islanding instant and the islanding detection instant and 2) non detection zone (NDZ) which is a region (or space) specified by the system parameters, in which islanding detection fails [18]. 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 is lands 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[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. Several passive techniques have been proposed which are based on monitoring voltage magnitude, 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]. If the threshold for permissible disturbance in these quantities is set to alow 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. 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 [8, 24]. 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 [8–10].Since no islanding detection scheme can serve all DG source types equally, the method will normally be selected according to its nature in order to maximize its efficiency and reliability.

The widely used ROCOF relays estimate the ROCOF within a measurement window to detect islanding condition. However, the ROCOF relays may become ineffective if the active power imbalance in the islanded system is less than 15%, resulting in a high risk of false detection. During islanding if the active power imbalance (power mismatch) is high, then frequency drift will have higher amplitude and ROCOF works satisfactorily based on a set threshold.However, when the active power imbalance is below 15%, then ROCOF fails and thus unables to provide effective protection measure to DG interfaced to grid, during islanding. Also it is difficult to provide an absolute threshold for detecting islanding detection using ROCOF as the magnitude of ROCOF vary largely with active power imbalance. If a threshold of 0.5 is set (for example), then it cannot detect islanding with 0%imbalance. Even at a threshold of 0.2, ROCOF is unable to detect islanding at nearly 0% active power imbalance. Thus, ROCOF fails to detect islanding events when active power imbalance falls below 15%.Thus, ROCOF fails in the afore mentioned situations [25]. This paper introduces a new intelligent-based approach for islanding detecting that can detect islanding at nearly 0% active power imbalance and use it for all DG types. The proposed technique uses the artificial neural network (ANN) 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 rate of change of frequency at the target distributed generation location and is fed to the radial basis neural network for intelligent islanding detection. The comparison of radial basis neural network with ROCOF relay with threshold value 0.2 at different DG locations during islanding event with power imbalance of nearly 0% shows that the proposed method works effectively for islanding detection.

2. RADIAL BASIS NEURAL NETWORK

In this section, the proposed neural network structure and methodology for islanding protection is presented [26-32]. Radial basis functions neural network has its origins in techniques for performing exact interpolation of a set of data points. For classification purpose, RBFN models the class distributions by local basis functions while multi-layer perceptron (MLP) separates the classes using hidden units, which form hyper-planes in input space. RBFN and MLP play very similar roles in that they both provide techniques for approximating arbitrary non-linear functional mappings between multidimensional spaces. Radial Basis Function Neural Network (RBFNN) is embedded into a two layers feed forward neural network. RBFNN ischaracterized by a set of inputs and a set of outputs, between the inputs and outputs there is a layer of processing units called hidden unit. Each of them implements a radial basis function. Typical structure of RBFNN is shown in Figure2.

RBFNN is a scheme that represents a function of interests using members of a family of compactly (or locally) supported basis functions to perform curve fitting or function approximation. For the purpose of approximating time series function, the network input represents data samples with only single signal output. The activation function at hidden layer use Gaussian function and between hidden layer to output layer uses linear function.

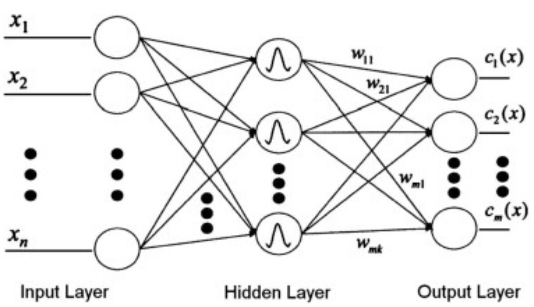


Figure2. Typical structure of RBFNN

By building up several basis functions with Euclidean distance between the input and the center, the mapping relationship between inputs and outputs can be obtained. Denote the input pattern as $X = (x_1, x_2, ..., x_d)^T$ the output of RBFN can be computed by:

$$y(X) = g(\sum_{j=1}^{l} w_j h_j(x) + w_0), \qquad g(a) = \frac{1}{1+\exp(-a)} \tag{1}$$

where *w*is connecting weight, $h_j(0),\ j = 1,2,...,l$ are the Activation Functions (AFs) of the hidden units, they were taken to be Gaussians:

$$h_j(x) = \exp(-\frac{\left\| x - \mu_j \right\|^2}{2\sigma_j^2}), \qquad j = 1,2,..., l \tag{2}$$

The Gaussian AFs are characterized by their centers μ_j and variances σ_j. The centers μ_j can then be regarded as prototypes of the input vectors. In our problem, x is rate of change of frequency vector. Therefore, x is fed into the network.

Let the mean vector of rate of change of frequency be $\overline{R}_{ate}$, the eigenvectors as $\phi_i, i = 1,2,...,d$, corresponding to eigen values sorted in decreasing order. The features in the subspace of m (m<d) dimension can be obtained by:

$$z_i = (X - \overline{R}_{ate})^T \phi_i, \qquad i = 1,2,..., m \tag{3}$$

The features are the projections of the input pattern onto the subspace spanned by m eigenvectors while the information in the complement space is omitted. The distance of the input pattern from the feature subspace (DFFS) provides useful information for discrimination:

$$D_f = \left\| X - \overline{R}_{ate} \right\|^2 - \sum_{i=1}^{m} z_i^2 \tag{4}$$

It is expected that the object patterns have small distance from feature subspace and non-object patterns have large distance. Hence, we incorporate the DFFS into RBFN with the hope to further improve the classification performance:

$$y(x) = g(\sum_{j=1}^{l} w_j h_j(z) + w^D D_f + w_0) \tag{5}$$

The RBFN is trained by supervised learning on a set of islanding and non-islanding samples with theaim to minimize the empirical loss of mean square error:

$$E = \frac{1}{2}\left(\sum_{n=1}^{N_s} \left[y(x^n) - t^n \right]^2 + \lambda \sum w_i^2 \right) = \sum_{n=1}^{N_s} E^n \tag{6}$$

where N_x is the total number of training samples, t^n is the target output of sample X^n, which takes value 1 for islanding condition samples and 0 for non-islanding condition samples. λ is the coefficient of weight decay to restrict the size of connecting weights (excluding the bias). The weight decay is helpful to improve the generalization performance of neural networks. The weights w are initialized randomly while the Gaussian centers μ_j were initialized by k-means clustering algorithm on face and non-face samples. On an input pattern $Z^n = Z(x^n)$, the connecting weights and Gaussian centers are updated by gradient descent method:

$$w(n+1) = w(n) - \eta \frac{\partial E^n}{\partial w} \tag{7}$$

$$\mu_j(n+1) = \mu_j(n) - \frac{\partial E^n}{\partial \mu_j} \tag{8}$$

where η is the learning rate, which is small enough and decreases progressively.

3. PROPOSED ALGORITHM

This proposed algorithm utilizes rate of change of frequency at the target distributed generation location and is fed to the radial basis neural network for intelligent islanding detection. Also, this approach utilizes the ANN as a machine learning technology for processing and analyzing the large data sets provided from network simulations. The network structure has one input node, hidden layers neurons, and single output node. The input of the network is rate of change of frequency derived at the target distributed generation and the output is the trip signal representing the islanding situation. The simulation results, which are the parameters indices at the target point under each event, are stored in a matrix. These results are transferred to ANN algorithm in Nero Solution environment. For training and testing around 0.1 sec length window data of rate of change of frequency representing different operating cases, loading and utility conditions are used.This data is produced using MATLAB/SIMULINK software which is widely used for power system simulations. Figure 3 shows a training result with radial basis neural network in MATLAB environment. Rate of change of frequency data window which has 0.1 sec of time length is used as neural network input. During parallel operation, the RBF neural network output is assumed around 0 or less than 1.0, and in the islanding condition the output of 1.0 is assumed. The architecture of the proposed intelligent-based islanding relay is shown in Figure 4. It consists of three main modules, namely the input module, neural network system, and the output module.

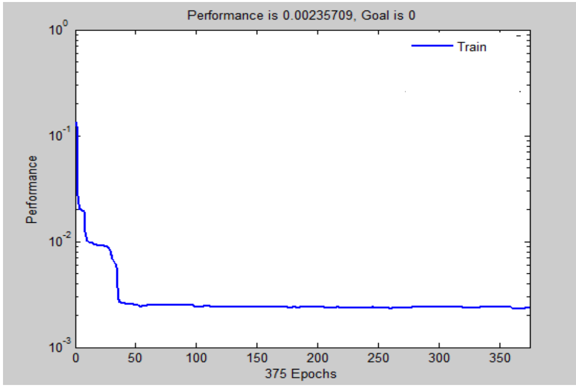


Figure3. Training result with radial basis neural network

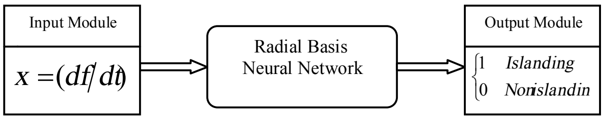


Figure 4. Architecture of the proposed islanding detection relay

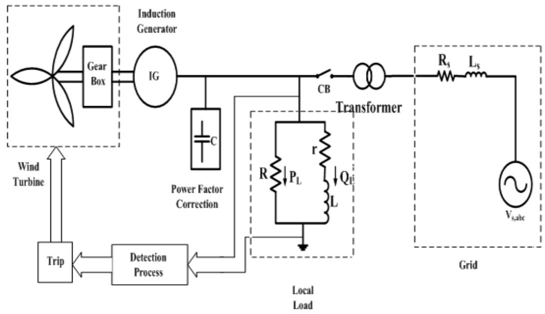


Figure5. Study system

4. STUDY SYSTEM

Single line diagram of the system studied in this paper is shown in Figure 5. As depicted in this figure, the DG has been shown by a wind turbine, a gearbox and a self excited induction generator. A capacitor bank is located at the end of induction generator in order to correct the power factor. A step-up transformer is located between the DG unit with its local loads and the utility grid. The utility grid is simulated with an ideal source and a resistance Rs and an inductance Ls. Connection between the utility grid and the DG is done with a Circuit Breaker (CB). The local load is a three-phase parallel RL before the circuit breaker (CB). 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 is connected to a Point of Common Coupling (PCC) with a step-up transformer. The system parameters are given in Table1.

TABLE 1. Test system parameters

Value	Parameter
(660KVA)	Turbine rated power
(1 Ω)	Rs
(1mH)	Ls
(0.4 KV)	Rated voltage of local load
(20 KV)	Nominal grid voltage
(0.4/20 KV)	Transformer voltage power
(660 KVA)	Transformer rated power
(50 HZ)	Frequency
Value	Parameter
(660KVA)	Turbine rated power
(1 Ω)	Rs
(1mH)	Ls
(0.4 KV)	Rated voltage of local load

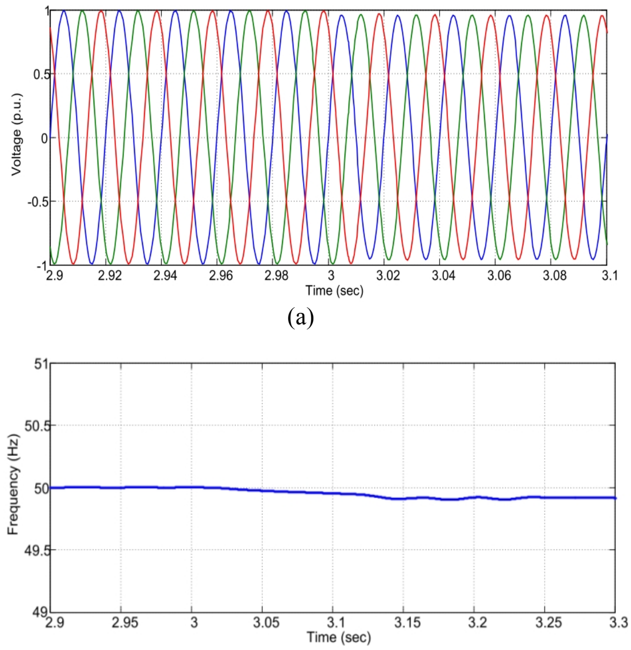
When the circuit breaker (CB) is closed, the DG with local load is connected to power grid. When the CB is opened, islanding state occurs in this mode, and the DG with a local load constitutes an islanding state together which creates an independent power grid in which just the DG supplies loads demand. In this condition, islanding state should be identified and power production should entirely be disconnected from the power grid and is started again to produce power after reconnection to the network.

5. NUMERICAL SIMULATION

To validate the effectiveness of the method, the proposed method has been applied to examine different conditions.

5. 1. Match Power Condition In this test, the active and reactive power of local load is 150 kW and 230KVAR, respectively. The distributed generator is assumed to beseparated from the grid, where the event is assumed to take place at 3 s. In Figures6a and b, the waveforms of three phase voltage and frequency of DGs are individually depicted. Immediately following this loss of utility, rate of change of frequency is increased but its value dose not increase todetermined threshold. Thus, ROCOF relay fails to detect islanding condition. Figure 7 shows the rate of change of frequency at match power condition. But neural network output has reached to "1" value which leads to islanding detection. So the radial basis neural network based protection algorithm produces the trip signal and sends to DG. The neural network response to this condition is shown in Figure 8.

5. 2. Mismatch Power Condition In this test, the active and reactive power of local load is 180 kW and 280Kvar, respectively. The DG is assumed to be separated from the grid, where the event is assumed to take place at 3 s. In Figures 9a and b, the waveforms of three phase voltage and frequency of DGs are individually depicted. Immediately following this loss of utility, rate of change of frequency is increased.



(b)

Figure6. Match power condition: (a) three phase voltageand (b) frequency

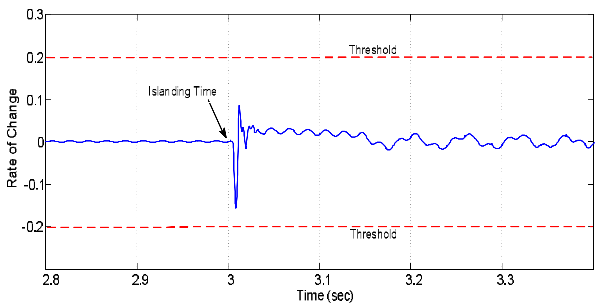


Figure 7. Rate of change of frequency for match power condition

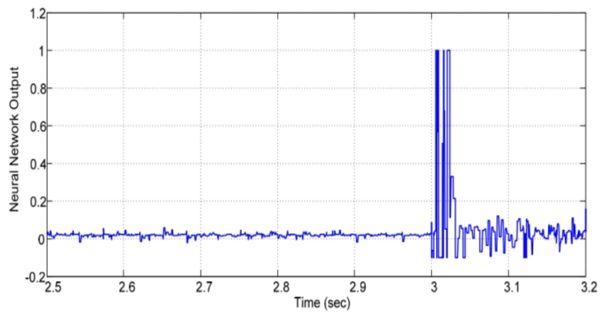
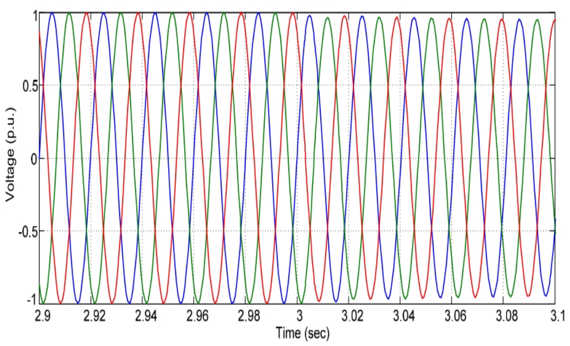


Figure8. Neural network output for match power condition

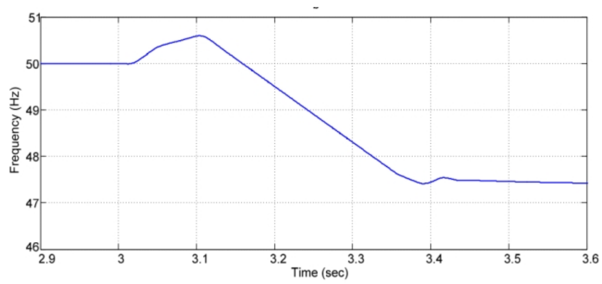
Figure 10 shows the rate of change of frequency at this condition. Neural network output is reached to “1” value which leads to islanding detection. So the radial basis neural network based protection algorithm produces the trip signal and sends to DG. The neural network response to this condition is shown in Figure 11.

5. 3. Motor Starting Condition The starting of large induction motors may cause a malfunction of the islanding detection algorithm. To study the reliability of the proposed algorithm, at t=3 s an induction motor with P=80 kW and Q=60 KVAR is started and connected to the Point of Common Coupling (PCC). In Figures 12a and b, the waveforms of three phase voltage and frequency of DGs are individually depicted.Immediately following motor starting, rate of change of frequency is increased. Figure 13 shows the rate of change of frequency at this condition. The neural network response to this condition is shown in Figure 14. The value of neural network output does not reach to "1" value. Therefore, the proposed method does not send a trip signal to DG and works in a reliable mode.

5. 4. 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=3 s a large 50Kvar capacitor bank was switched at the PCC in the non-islanding case. In Figure 15a and b, the waveforms of three phase voltage and frequency of DGs are individually depicted.Immediately following motor starting, rate of change of frequency is increased. Figure 16 shows the rate of change of frequency at this condition. The neural network response to this condition is shown in Figure 17. The value of neural network output does not reach to 1 value. Therefore, the proposed method does not send a trip signal to DG and works in a reliable mode.



(a)



(b)

Figure 9. Mismatch power condition: (a) three phase voltageand (b) frequency

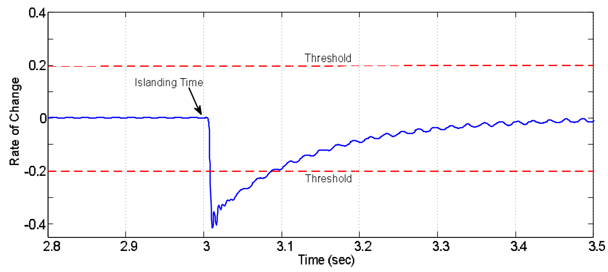


Figure10. Rate of change of frequency for mismatch power condition

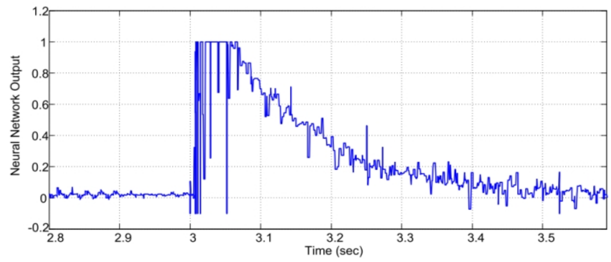
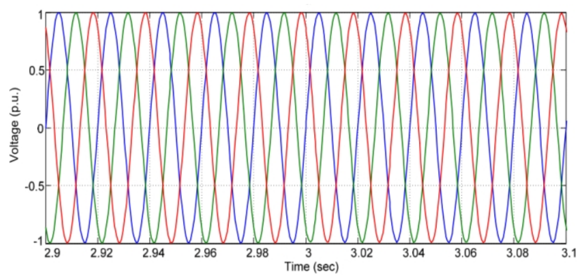
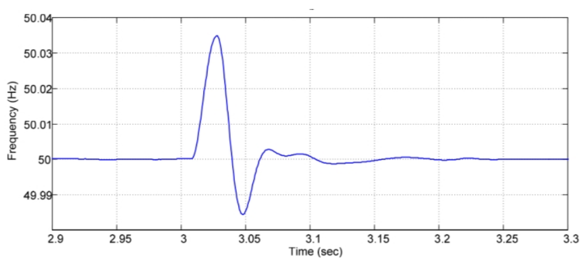


Figure 11. Neural network output for mismatch power condition



(a)



(b)

Figure 12. Motor starting condition: (a) three phase voltage and(b) frequency

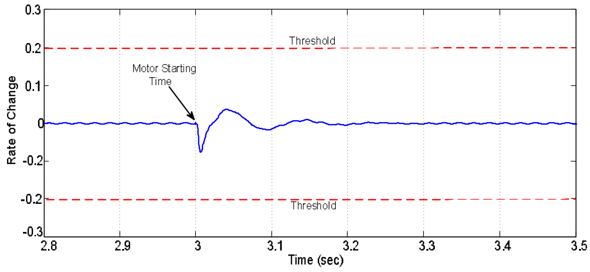


Figure 13. Rate of change of frequency for motor starting

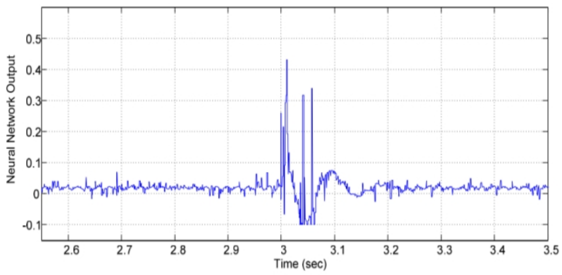
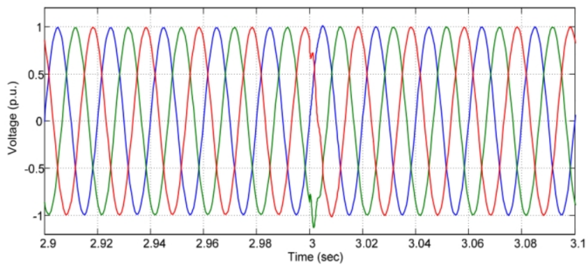
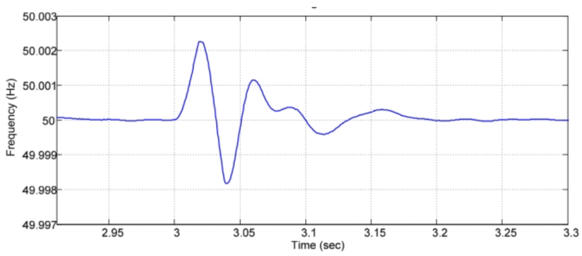


Figure 14. Neural network output for motor starting



(a)



(b)

Figure 15. Capacitor bank switching condition: (a) three phase voltageand (b) frequency

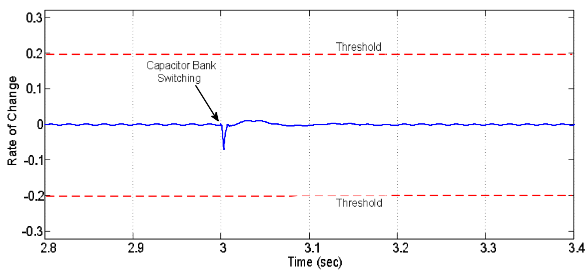


Figure 16. Rate of change of frequency for capacitor bank switching condition

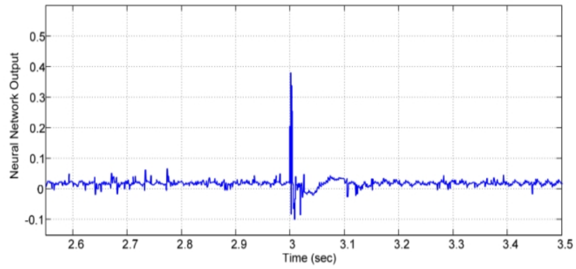


Figure 17. Neural network output for capacitor bank switching condition

6. CONCLUSION

A new technique for islanding detection of DG is proposed based on ANN. Following the increased number and enlarged size of DGunits 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 DG 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. By case studies with numerical simulations, the proposed approach was verified with feasibility, flexibility and robustness.

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Radial Basis Neural Network Based Islanding Detection in Distributed Generation

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چکیده

دراین مقاله یک روش جدید مبتنی بر شبکه عصبی برای تشخیص وضعیت جزیرهای الکتریکی ارائه شده است. یکی از مشکلات تولیدات پراکنده پدیده جزیرهای شدن ناخواسته می باشد .این مسأله باعث ایجاد مشکلاتی از قبیل ایجاد خطر برای تکنسینهای تعمیر خط، آسیب رساندن به وسایل مصرف کنندگان به دلیل عدم ثبات ولتاژ و فرکانس و بروز ناهماهنگی در اتصال مجدد به شبکه سراسری را داشته باشد. روشهای فعال و غیر فعال مختلفی در این زمینه ارائه و پیشنهاد شده است. هر کدام از روشهای موجود معایب و نقایصی دارند. روشهای غیر فعال ناحیه عدم تشخیص بزرگی دارند و همچنین مشکل تعیین مقدار آستانه از معایب اصلی این نوع روش می باشد و روشهای فعال هم مشکل کاهش کیفیت توان را دارند. تاکید اصلی مقاله و روش ارائه شده کاهش ناحیه عدم تشخیص و عدم تاثیر روش تشخیص بر روی کیفیت توان سیستم قدرت می باشد. بعلاوه روش پیشنهادی در این مقاله، معضل و مشکل تعیین مقدار آستانه را برای روش تشخیص به طور کلی مرتفع کرده است. در روش پیشنهادی از شبکه عصبی پایه شعاعی برای تشخیص وضعیت جزیرهای الکتریکی استفاده شده است. روش پیشنهادی با روش تشخیص مبتنی بر نرخ تغییرات فرکانس مقایسه شده است که نتایج شبیه سازی حاکی از دقت و قدرت تشخیص روش پیشنهادی نسبت با این روش پر کاربرد می باشد. در روش پیشنهادی نرخ تغییرات فرکانس تولید پراکنده به ازای وضعیت و شرایط مختلف سیستم جمع آوری شده است و بخشی از این دیتاهای جمع آوری شده به عنوان دیتاهای آموزشی برای تعیین وزنها و با یاس های شبکه عصبی استفاده شده است و بخش دیگر از این دیتاهای به عنوان دادهای تست برای بررسی صحت شبکه عصبی آموزش دیده شده استفاده گردیده است .نتایج شبیه سازی طی وضعیت و شرایط مختلف سیستم، قابلیت اطمینان و قدرت روش پیشنهادی را به نمایش می گذارد.

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