Islanding Detection in Grid Connected Wind Plant Using AI Technique

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Abstract.

This paper introduces an ingenious scheme of island detection in a dispersed generation. The discovery of Islanding in distribution generation is one of the most important aspects of a defensive aspect. Islanding is insensible for security of the system as it may cause damage to personnel and equipment in the system due to the improper islanding in the distributed generation system. Islanding detection is needed whenever there is a sudden disconnection of wind power plant and fault. The system operates through the current control mode, in normal or stable mode. The system switches to the power control mode after sitting down. In the proposed work has made using the MATLAB / Simulink software**.**

Keywords. Wind turbine (PV) System, Artificial Neural Network Method (ANN), Voltage, Current, islanding, Levenberg–Marquardt (LM) algorithm and DWT–ANN.

1. INTRODUCTION

Modern day use of distribution production increases distribution production and worse with benefits. Islanding is one such problem. The termination of a local distributed generation (DG) system is termed as an islanding, unintended termination is termed as an unplanned islanding. Islanding can be an error in the main distribution system, due to power disturbance for a short period of time DG is cut off from the main grid.

There are many ways to find an island in a distributed generation system. Local and remote routes practical and idle local routes. In terms of power generation and frequency it is supplied to the PCC and compared to the threshold value while effectively the external interference is injected into the PCC. The reversal of the operating path is an invisible surface. It has low power quality.

Unintended islanding cause main problems which include:

a) Voltage & frequency within tolerable limits.

b) By supplying loads in DG system will risks to monitor staff safety, and

c) The closure of the DG system is out of phase which results in a rapid re-closure. Therefore, in the most important energy system to find the occurrence of an islanding condition.

The means of finding an island are broadly divided into 2 types namely remote and local. Auxiliary local methods, distinguishing between active and passive:

1) Passive routes have a lot of undiscovered area (NDZ) and depend on the unattainable condition to identify the island's population.

2) Effective methods have low NDZ, apart from that it will create a harmonic issue in current.

In this paper a systematic literature review has been carried out thereby considering previous research articles to understand the technical challenges. A recurrent neural network-based islanding protection scheme by using generator speed change has been reported [1]. A review of various islanding detection schemes for renewable based DG system has reported in [2-4]. New ANN-based technique for islanding detection of DG based power network was illustrated in [5] and Deep learning based hybrid scheme for islanding detection in DG system is demonstrated in [6]. Islanding detection based on ANN and novel S-transform for DG system has been explicated in [7] and an Islanding detection method for Inverter-Based DG in Microgrid network has been reported in [8]. In view of the above literature it has been concluded that the importance of identification of islanding condition in a distributed power system network is very significant where grid-connected wind power generation makes system more complex.

2. SYSTEM DESCRIPTION

In this paper, authors have taken the islanding inaction and the mistakes of non-existing on the islanding situation as a research interest. A classification of islanding and non-islanding conditions for islanding acquisition was made. Island and faults are given in a grid connected wind plant at different parameters. The 3-phase voltage and current signals are recorded from the side of the grid and PCC by changing the different parameters. The data sets are simulated from the grid side on the PCC are supplied as an input to ANN after reducing the undesirable noise from the signals. The algorithm used to study the training process by ANN is the Levenberg Marquardt (LM) algorithm.

3. FAULT IN GRID-CONNECTED WIND PLANT

The short circuit fault has been applied at the grid side with a total of 50 fault cases and recorded voltage & current signals on the grid bus (B120) and (wind plant). Fig.1-2 illustrations the voltages and current signals at bus B120 and B25 respectively.

The L-G fault, which is applied phase-A to ground, as shown in Fig.1. The three phases of instantaneous voltage and current signals at the wind turbine bus (B25) are changed, with the amplitude of voltage signals decreasing and the magnitude of current signals increasing, as shown in Fig.2.

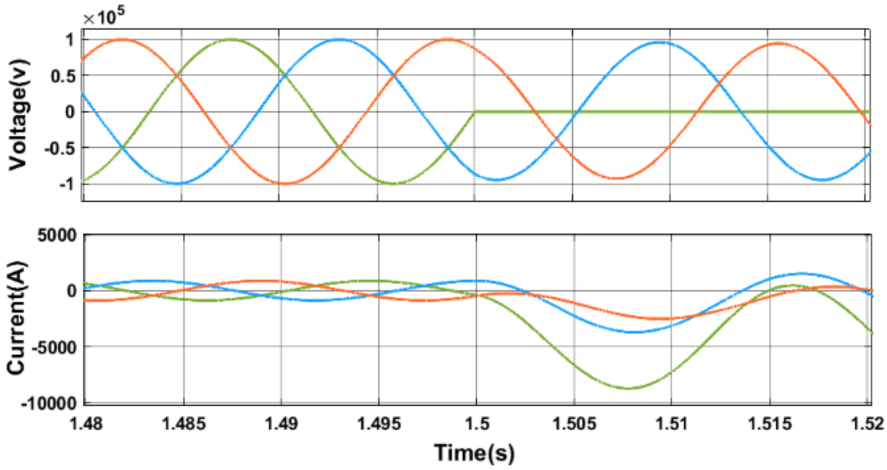


Figure 1 3-phase signals at fault inception time 1.5s at Grid bus (B120):

(a) voltage waveform (b) current waveform,

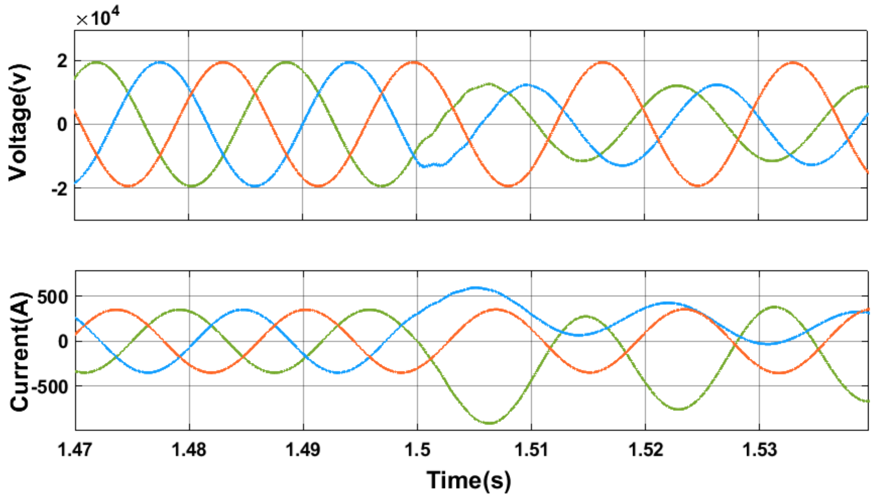


Figure 2 3-phase signals at fault inception time-1.25s at Wind turbine bus (B25): (a) voltage waveform (b) current waveform,

4. Islanding Condition In a Grid-Connected Wind Plant

Grid disconnection is provided using a breaker and a total of 50 cases of Islanding conditions are recorded on the grid bus and wind plant bus. Measure the voltage and current signals on the side of the grid and at the wind plant. Fig.3-4 demonstrations the voltage/current signals of the side grid B120 and wind plant bus B25 respectively.

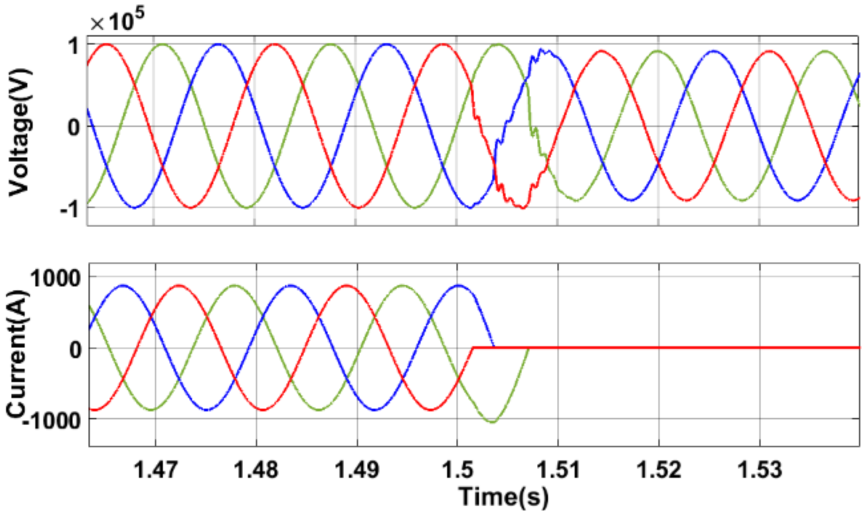


Figure 3 3-phase signals at islanding inception time-1.5s at Grid bus (B120): (a) voltage waveform (b) current waveform

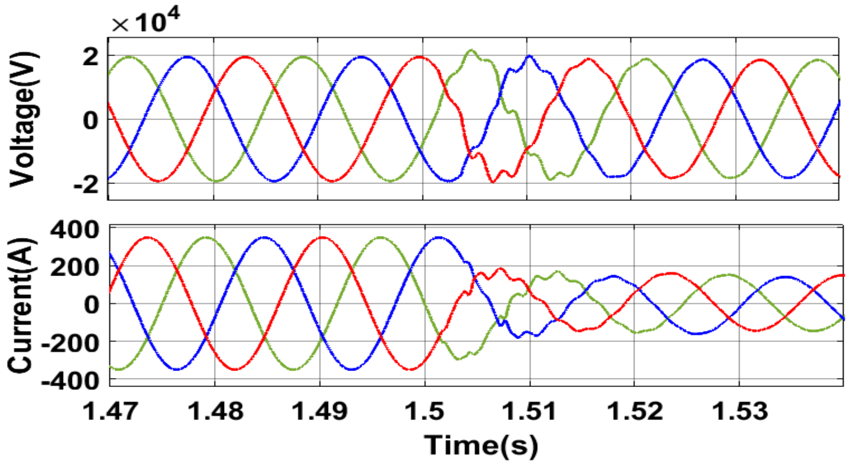


Figure 4 3-phase signals at islanding inception time-1.5s at PV bus (B25): (a) voltage waveform (b) current waveform

5. PROPOSED METHODOLOGY

The proposed MATLAB/Simulink model consists of a wind plant, grid and existing power plants with different loads connected and a transmission cable. Fig.5 shows a single line diagram of the connected wind plant when voltage and currents are measured at PCC.

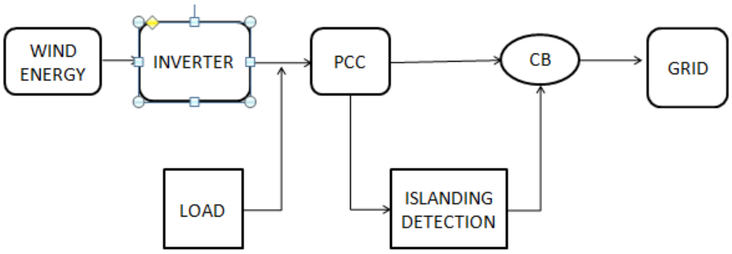


Figure 5 Single line diagram of Grid-connected wind plant

It must be separated the electrical signals from the wind plant and the grid on the PCC, and in the event of any deviation, they should be returned to ANN, and identify the islanding status and issues a trip signal to the breaker to isolate the wind plant to avoid damage with local loads caused by disturbance.

6. ANN For Grid-Connected Wind Plant

A multi-layered neural network is used for the island wind turbine detection. The multi-layered neural network contains output, input and encryption layers that require algorithm training to minimalize the error using the LM-algorithm. Discrete wavelet transform is employed to eliminate noise. These databases are then processed through a DWT-ANN processor to remove noise from the current 3-phase and voltage signals to read the model as quickly and accurately as possible. Then, from all the voltage and current signal on the Wind turbine bus and the Grid bus, we must take samples of two cycle data (single-cycle or pre-islanding data, and one single-cycle data- fault or post-landing).

Finally, the standard deviation of the two-cycle data of current and voltage signals on the grid bus and wind plant bus during fault, as well as islanding situation are used to design input data set to train DWT-ANN. module, and provide the target output at '0 'if incorrect, and '1' when connected to the ANN feed network to the ANN feed supply provided 70 percent training, 15 percent testing, and 10 percent verification -15. Typical data diversion of two three-phase current and voltage signals on bus120 and bus25 with error modes and single-line circuit islands used to design a data set input training DWT-ANN module. Various parameters have been used to generate input / output data set for training and testing as noted in Table.1.

Parameters in particular start time, type of error and islanding method used, number of data sets or cases of island residency, and error Grid bus and wind turbine we used for training and testing using the ANN feed-forward network we have. is done throughout the project to acquire an island Grid-connected wind turbine via ANN.

Table.1 Parameters variation considered to generate the datasets for training & testing

S.no	Condition	Parameter	Training and Testing data
1	Fault	Fault type	AG
		Fault resistance	**0.001**
		Fault inception time	0.9-1.88
		Voltage signal and current signals measured	At grid bus and wind turbine
		Total no.of cases	Training cases -70,testin-30 Total no.of cases 100
2	Inception	Islanding type	Passive
		Islanding resistance	0.01
		Islanding inception time	0.9-1.88
		Voltage and current signals measured	At grid bus and wind turbine
		Total no.of cases	Training cases -70,testing-30 Total no.of cases 100

7. MODELLING & SIMULATION

After that, we constructed the proposed ANN model with feedforward network utilizing the Levenberg–Marquardt (LM) method with DWT-ANN processor to remove noise from the signals, which we did using MATLAB Simulink. The Grid-connected wind turbine system is depicted in Fig.6.

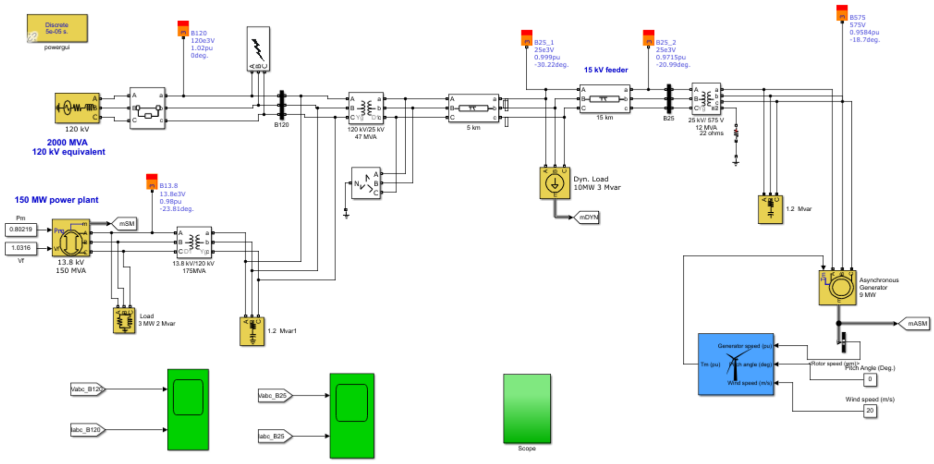


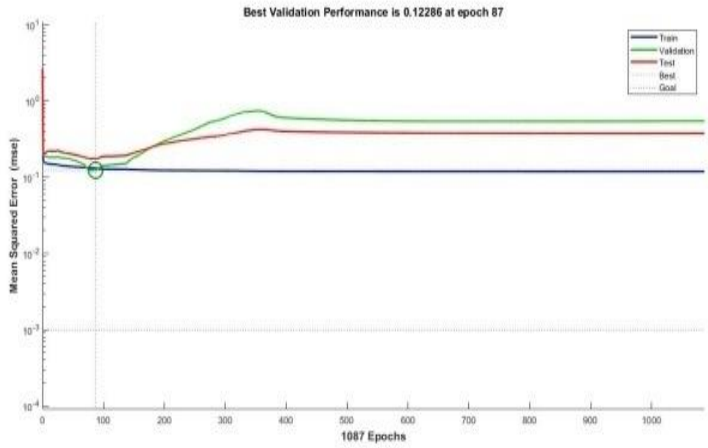
Figure 7. MATLAB Simulink diagram of Grid-connected wind plant

ANN is trained using the MATLAB code, which includes parameters such as performance goal, conversion, verification check, number of layers hidden in the feedforward network, and number of epochs. Provide some parameter values in the code and trained the network, check the MSE performance for each variation where the MSE is the lowest, and then apply those values to the ANN Feed Transfer Network to find the islanding condition to respond quickly and accurately. In the ANN feedforward network, there is a single layer with six neurons, a single outgoing layer with six neurons, and a hidden layer with a different number of neurons that are provided to the feed network in a variety of conditions. ANN network. The ANN Feed-forward network training structure is shown in Table.2, and the curves to ensure their performance during ANN between Epochs and MSE are set out in Fig.7.

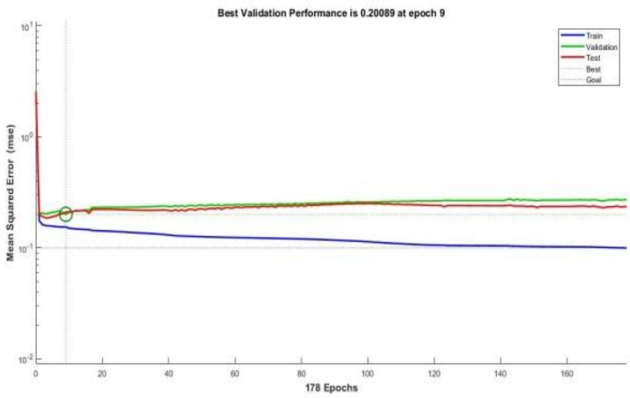
Table.2. Training architecture of different cases of Feed forward ANN

Cases	1	2	3	4
size of input dataset	6×200	6×200	6×200	6×200
Size of architecture	6-20-6	6-20-6	6-30-6	6-35-6
No.of epochs	10,000	11,000	15,000	20,000
Performance goal	10e-51	10e-01	10e-9	10e-11

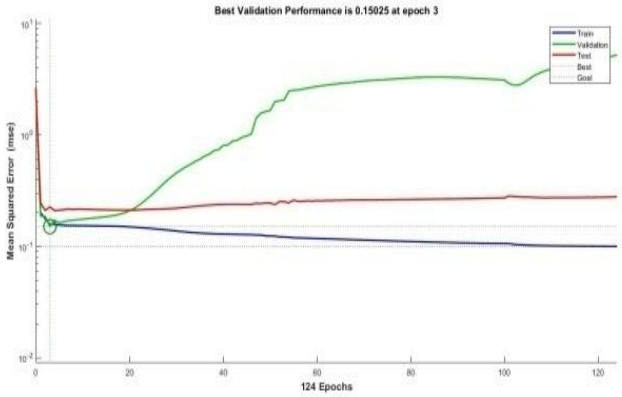
By looking at training curves, tests, and performance confirmation curves, we can determine the best case. Case 2 is advanced because its three curves (training, testing, and validation) will meet in one place that satisfies the island's living conditions whenever a descent is possible in the system.



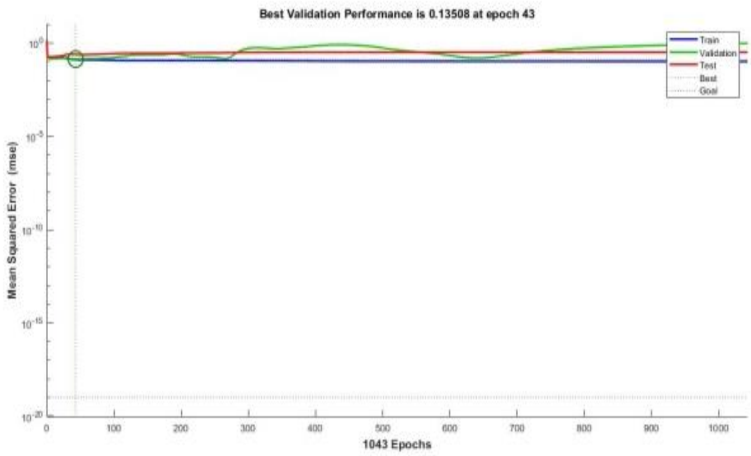
(a)



(b)



(c)



(d)

Figure 7. Performance Validation curves during ANN using different size of architectures: (a) case-1(6-20-6), (b) case-2 (6-25-6) (c) case-3 (6-30-6), (d) case-4 (6-35-6)

8. CONCLUSION

This paper is based on the detection of an islanding of wind plant using the ANN method. Electrical power and current side grid and PCC signals at different inception times are provided as input to the DWT-ANN module and are trained by the Levenberg-Marquardt algorithm with 100 instances of ANN training data sets. Testing / training and verification is done to improve the performance of proposed method.

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