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Voltage State Estimation By ANNs with Reduction of PMUs

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Abstract. In this paper the estate estimation of voltage and phase of voltage has been presented. In this paper the PMU has been used to observe some part of power system and ANN (Artificial Neural Network) has been used to estimation. In this paper it is assumed that the power system is partly observable by PMUs and the network is not full observable. This method has been implemented on IEEE 14-Bus. The results show that this estimation is impossible and the error of estimation is negligible.

Key words

State Estimation, PMU, Incomplete Observability, Artificial Neural Network.

1. Introduction

Due to progress on Global Positioning System (GPS), the PMUs (Phasor Measurement Unit) become available and can be used to get data from different points of a power system. This data is necessary for the supervisory control applications or on-line states assessment of a large scale power system. PMUs are able to take the online phasor measurements. This simultaneous measurement is achieved with voltage and current waveforms sampled by GPS signals. The ability of simultaneous measurement of PMUs, improve the monitoring, control and in turn the security level of power networks [1].

In this paper, it is assumed that the power system is not fully observable. This situation may happen due to PMU failure or construction limits. In these states some buses are unobservable. In this paper the ANN has been used to estimate the voltage magnitude and voltage phase of unobservable buses. It is shown in [2] that the voltage magnitude and phase are the best parameters to the voltage stability assessment, so these parameters can be used to the voltage stability assessment. This method has been implemented on IEEE 14-Bus. The results show negligible error.

2. Estimation by ANN

In this paper, the ANN has been used to estimate the voltages of unobservable buses. The power network has been simulated by DIgSILENT software and the ANN has been carried out in MATLAB software. As it is mentioned before, this idea can be used when there is complete observability but one of PMUs or its communication system has failed.

The ANN should be trained by the results of the load flow analysis. The scenarios have been randomly selected for different load or generation levels, which are generated by using Mont-Carlo method. In this method, a random number (N) between 1 and N_b (the number of buses) is generated. This number determines the number of buses, which their parameters should be changed. If a bus is a PQ or PV bus, then in order to change its parameters, scenario 1 or 2 should be selected, respectively.

In the scenario 1, the load active power is randomly selected in the prespecified margin, as follows:

$$P_{L,i}^{PQ} \in \left[P_{L,i}^{\min} \quad P_{L,i}^{\max} \right] \tag{1}$$

In the scenario 2, one of the following three cases, is selected with equal probability, (i.e., 1/3):

Case 1: Only the load active power should be changed, as follows:

$$P_{L,i}^{PV} \in \left[P_{L,i}^{\min} \quad P_{L,i}^{\max} \right] \tag{2}$$

Case 2: Only the active power generation should be changed, as follows:

$$P_{G,i}^{PV} \in \left[P_{G,i}^{\min} \quad P_{G,i}^{\max} \right] \tag{3}$$

Case 3: Both, the bus load and generation should be changed by using the following constraints:

$$\begin{gathered} P_{L,i}^{PV} \in \left[P_{L,i}^{\min} \quad P_{L,i}^{\max} \right] \\ and \\ P_{G,i}^{PV} \in \left[P_{G,i}^{\min} \quad P_{G,i}^{\max} \right] \end{gathered} \tag{4}$$

The ANN used in this paper has 13 nodes on the input and one hidden layer with 20 nodes. The Levenberg–Marquart back-propagation algorithm has been used to identify ANN parameters.

In this step, 1000 different load flow scenarios have been simulated by DIgSILENT. 900 of them have been selected to train the ANN, and 100 scenarios