AN ALTERNATIVE VOLTAGE SAG SOURCE IDENTIFICATION METHOD UTILIZING RADIAL BASIS FUNCTION NETWORK

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ABSTRACT

Power quality monitors (PQM) are required to be installed in a power supply network in order to assess power quality (PQ) disturbances such as voltage sags. However, with few PQMs installation, it is difficult to pinpoint the exact location of voltage sag. This paper proposes a new method for identifying the voltage sag source location by using the artificial neural network (ANN). Radial basis function networks are initially trained to estimate the unmonitored bus voltages during various sags caused by faults. Then voltage deviation of system buses is calculated to pinpoint voltage sag location. The validation of the proposed methodology is demonstrated by using an IEEE 30 Bus test system. The results shows that the proposed method can correctly locate the voltage sag source based on highest voltage deviation obtained through estimated unmonitored bus voltages.

INTRODUCTION

The quality of electric power has been the major concern for both electric utilities and end users of electric power. The reasons for the increased concern are due to the rapid growth in the industrial equipment with microprocessor-based controls and power electronic devices. These devices are more sensitive to power quality variations and any failure may have much more serious consequences in terms of technical and economic losses. Among the power quality problems, the voltage sag is the most significant problem due to its severity and number of occurrences per year. To mitigate it, undoubtedly, the voltage sag source has to be identified first. There are various available methods that have been successfully simulated and tested using extensive simulations, laboratory tests and field testing. Those methods can be categorized into two broad areas which are single power quality monitor (PQM) methods and multi PQM methods.

In single power quality monitoring the aim is to identify the relative location of the voltage sag source. In [1], an energy-based method was proposed that can detect the voltage sag source location during a disturbance event by sensing the change in instantaneous power flow. However it relies on the degree of confidence of both disturbance power and energy. Another method uses distance relay algorithms to figure out the fault location in which its basic idea is to analyse the impedance value during the event [2]. The polarity of the real current component and the slope of system trajectory method was introduced in [3, 4] in which the relationships between the product of voltage magnitude and power factor against current magnitude was determine the sag location relative to the monitoring point. Another alternative way introduced in [5] can determines the sag source location without using line-fitting method but applying the same concept as slope of system trajectory method. There is another method that is very effective in detecting sources of asymmetrical voltage sags as in [6]. It uses Clarke's transformation and new generalized current-based concept.

The proposed method in [7] is capable to locate a sag source when the current measurement is not available because it requires two points of voltage value only. The sag source location estimated by this method is mainly focused at the interconnection point of transmission utilities based on voltages sag magnitude at both sides of the transformer that interconnects two grids. With the drastically increasing in energy consumption nowadays, it prompts the utility sectors to expand the power transmission network to other regions. Hence, the bulk power system can hardly be maintained by single PQM methods since those methods are able to detect the sags in upstream or downstream direction relative to the monitoring point.

Thus, multi PQM methods have been introduced to support this drawback. The multi PQM voltage sag source location methods use more than one PQM in the network. The data collected from each PQM in power network are processed to determine the sag source location.

The method proposed in [8] is capable of identifying the voltage sag if it is originated from a bus in the system. It establishes a bus voltage relation coefficient matrix for power system observation. The coefficient matrix was then used to determine the behaviour of change in voltage of a given bus to that of the other buses. Another way to identify the voltage sag source location with limited available voltage measurement devices installed in the transmission network was introduced in [9]. It uses the changing current on each branch to know sag source area. As proposed in [10], the hybrid method hires the multiway principal component analysis (MPCA) as a dimension reduction tool to detect the sag source location in power network by examining and verifying the real data gathered from substations. The result presented certifies the powerfulness of the developed hybrid for locating sags.

This paper aims to estimate of unmonitored bus voltages from the available bus voltage recorded by PQMs is using ANN and identify sag source location by using voltage deviation from the estimated voltages and steady state voltages.

RADIAL BASIS FUNCTION NETWORK (RBFN)

Radial basis Function offer several advantages compared to Multilayer Perceptron (MLP) ANN. Firstly, they can be trained using fast two stages training algorithm without the need for time consuming non-linear optimization techniques. Secondly, the RBFN possesses the property of best approximation [12]. The architecture of the RBFN as depicted in Fig. 1 has been utilized in this project under MATLAB platform. The network consists of three layers: an input layer, a hidden layer and an output layer. The output of the RBFN network simply sums the weighted basis function without using any activation function.

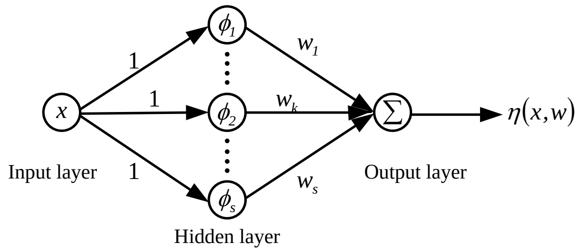

Fig. 1. Simple RBFN.

SAG SOURCE IDENTIFICATION USING RBFN

This research is carried out by modelling and simulating the power systems, creating sag databases, training and testing ANN to pinpoint the sag location using voltage deviation index. The stages of the methodology are explained next.

Creating sag database

In the research work, the IEEE 30 Bus test system is constructed and simulated using Digsilent software to identify the RMS voltage value at every single bus during both the steady state and fault period. In this system, Bus 1 is the slack bus, Bus 2 is the voltage controlled bus, Buses 5, 8, 11 and 13 are synchronous condenser buses and the remaining buses are the 24 load buses. This test system has three different voltage levels, that is, Buses 11 and 13 are at 11kV, Buses 1 to 9 and 28 are at 132kV and the remaining buses are at 33kV level. The PQMs are assumed to be installed at Buses 10, 18, 25 and 29 as marked in red in Fig. 2. PQM installed at Bus 10, it is connected to Buses 6, 9, 11, 17, 19, 21 and 22. PQM at Bus 18 is connected to Bus 15 and Bus 19 and PQM at Bus 25 is connected to Buses 24, 26 and 27. Furthermore, Monitor at Bus 29 is connected to Bus 27 and Bus 30.

After modelling the bus test system, different types of fault are simulated at each bus which incleuds single phase to ground fault at phase A, two phase to ground fault at phase B and C and three phase short circuit at every bus respectively for a short duration of time For all cases, the simulations are repeated with fault resistance 0.0 Ω, 0.1Ω, 0.3Ω, 0.5Ω… to 1.3Ω. Theoretically, during short circuits, bus voltages throughout the network will be depressed and the severities of which are dependent of the distance from each bus to the point where the short circuit occurs. In each simulation, the minimum per unit RMS voltage value stored as sag data. Finally, three different sag databases are created for single phase to ground fault, two phase to ground fault and three phase short circuit respectively.

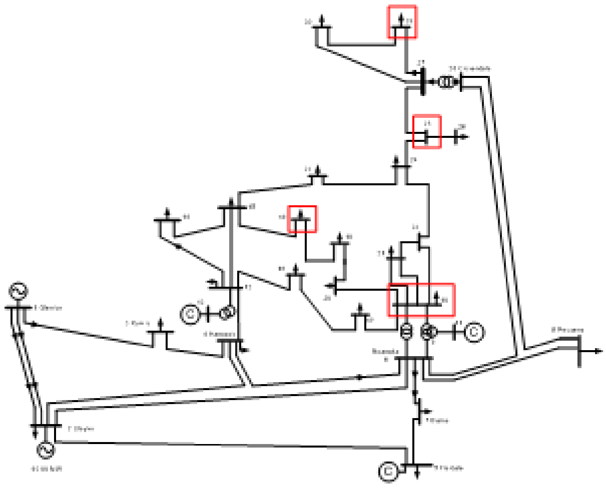

Fig. 2. IEEE 30 Bus test system

Creating and pre-processing the input and target

After the simulation data has been fully collected, the second step is to create the training and testing data for RBFN. The sag databases of different fault types are then mapped into the range between -1 to 1. Next, they are divided into two main parts which are target data (T) and input data (D). In the IEEE 30 Bus test system, the PQMs are assumed to be installed at Buses 10, 18, 25 and 29. Hence, those buses are considered as the input data (D) for developing ANN network. On the other hand, those Buses without PQMs are taken as the target data (T).

Structure of the proposed RBFN

In this work, RBFN with one hidden layer and one output layer has been chosen. The proposed method is elaborated by designing an appropriate RBFN to estimate the voltage value for unmonitored buses in the IEEE 30 Bus test system for each type of fault. Therefore 3 similar independent networks are created for three phase, double line to ground and single line to ground faults.

The input data (D) for developed ANN contains those PQM buses RMS voltage value (V10, V18, V25 and V29) during faults and the target/output parameter, (T) which are RMS voltage value for unmonitored buses during faults. This is considered as 4 inputs and 26 outputs. Therefore the networks have four input neurons and twenty six output neurons. Fig. 3 shows the structure of the network.

Network training and testing

The training of the RBF ANN consists of choosing proper spread value so that the weights and biases in connections between the layers are such that it produces performance between output values over the set of training input-output vector pairs. Hence, the training process is repeated by changing the spread value systematically to find the most suitable spread constant for the network. Table 1 shows the mean average error (MAE), sum of square error (SSE) and mean square error (MSE) results obtained for various spread constants that is used in training the IEEE 30 Bus system for single phase to ground fault. Therefore, the spread constant 1 is considered as the most suitable value for this network.

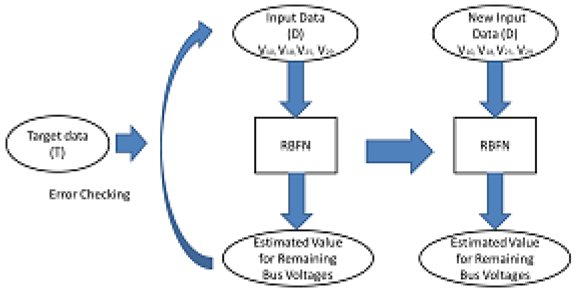

Fig. 3. The structure of the training and testing network

Table 1.The MAE,MSE and SSE calculation results for various spread constants

SPREAD	MAE	MSE	SSE
25	0.0642	0.0145	22.5343
15	0.0374	0.005	7.77428
10	0.0312	0.0038	5.9528
5	0.0172	0.0014	2.2114
2	0.0066	1.90E-04	0.2907
1	0.0017	2.21E-05	0.0339

Voltage Deviation Calculation

After the network is trained network, a new set of data is created by performing short circuit test using different faults resistances that are not used in training phase. Then, the voltage deviations for each bus are calculated using steady state RMS voltages and during sag RMS voltage obtained from ANN. The voltage deviation can be expressed as:

$$\%V_{deviation} = \frac{V_{steadystate} - V_{estimated-during-sag}}{V_{steadystate}} \times 100\% \quad (1)$$

After calculating the voltage deviation, it is rescaled into 0 to 1 range. One shows the highest deviation and 0 indicates the smallest deviation from the steady state. The rescaled outputs are plotted in mesh graph with the aid of colour map. The graphs can clearly show the sag source location by having the highest peak marked dark red colour in graphs. The highest voltage deviation determines the sag source location. In the testing stage, the network can almost instantaneously calculate output for a given an input testing data. The time taken for a network to produce output samples is 0.2694 second.

The implementation procedures in the fault identification are presented as follows:

Step 1: Obtain sag databases from the simulation.

Step 2: Assemble and pre-process the training data for the RBFN.

Step 3: Create the network object and train the network.

Step 4: Test and network performance analysis.

Step 5: Stored the trained network.

Steps (1–5) are offline processes. Next, the network is ready to test with the new input, which is an online process.

Step 6: The new input is pre-processed before presented to the trained RBFN.

RESULT AND ANALYSIS

The voltage deviation is calculated by using estimated voltages from ANN for all three faults and they are rescaled into 0 to 1 range. The highest deviation determines the sag source location.

The mesh plot shows in Fig. 4 shows the voltage deviation of buses when tested for three phase short circuit. The dark red colour in the graph represents the highest voltage deviation. On the other hand, the dark blue colour represents the lowest voltage deviation from steady state. From the figure it can be noted that the maximum (dark red colour) voltage deviation value appear on the diagonal element which corresponds to the sag location (Y axis) when the fault happens on that Bus (X axis). Hence, it can be concluded that the sag source buses experienced the highest voltage deviation as compared to other buses which are away from sag source. For example, the cursor in the graph shows that the Bus 3 located at the experience the highest voltage deviation which is 1, when the fault take place at location Bus 3.

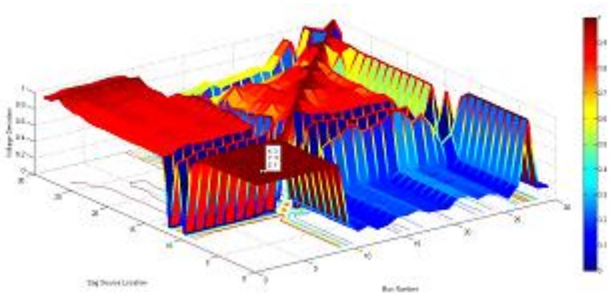

Fig. 4. The mesh graph of the voltage deviation of all buses when tested with three phase short circuit

To further evaluate the performance, Fig. 5 shows the voltage deviation of all buses when tested with two phase to ground fault. However, in this graph, the highest voltage deviation appearance at the diagonal is not very consistent. This is because some buses that experienced highest voltage deviations are different from the sag source buses. For example, the sag source at Bus 21 does not provide highest voltage sag at Bus 21 but the highest voltage sag is experienced at Bus 12. Inaccurate detection generally observed when faults have high impedance resistance.

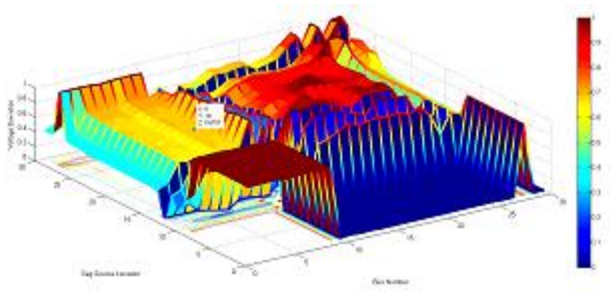

Fig. 5. The mesh graph of the voltage deviation of all buses when tested with two phase to ground fault

Finally similar test were conducted for single phase to ground faults and its results are depicted in Fig. 6. In Fig. 6, the mesh graph of voltage deviation for buses when tested with single phase to ground fault are shown. By looking at the shape of this mesh graph, highest voltage deviations at the diagonal elements can be easily visualized. Hence, it can be concluded that the network had successfully estimate the values for unmonitored buses and locate the voltage sag source. In this case only one misdetection was observed in which Bus 1 is detected as sag source instead of actual fault location which is Bus 3. The cursor in this graph shows this case.

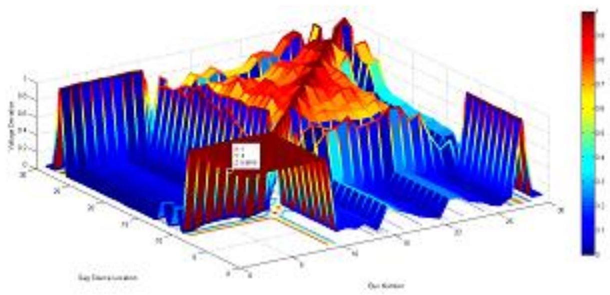

Fig. 6. The mesh graph of the voltage deviation of all buses when tested with single phase to ground fault

CONCLUSION

This paper has presented a sag source location method using ANN. It is implemented by estimating unmonitored bus voltages from bus voltages recorded by PQMs. The estimated voltages were then used to calculate voltage deviation index by comparing the steady state voltages. The highest difference values show the location of the sag source originated. The results show that the proposed method can effectively identify voltage sag source with reasonable accuracy. Furthermore, the proposed method is computationally efficient and does not involve complex calculations.

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