Fault Bus Identification in Kurdistan Power Systems using Artificial Neural Network

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ABSTRACT:

High voltage transmission lines are utilized to transmit electrical energy from the source to the substations. If any fault and disturbance are generated in the transmission lines and not detected, located and eliminated quickly, it may cause instability in the system. This paper presents fault location recognition in Kurdistan Regional power transmission system using artificial neural network (ANN). Load flow and short circuit calculations were performed with Power World Simulator (PWS) software. All Kurdistan region power system has been divided into 40 buses. The calculated results of the currents and the voltages at both line ends were used to train the ANN in Matlab to obtain correct fault location. The training testing and evaluation of the intelligent locator is done based on a multilayer perceptron feed forward artificial neural network with back propagation algorithm. The ANN used to locate the fault have been trained with different available sets of data from the selected power system model. Several algorithms have been carried out in order to train the network such that it locates the fault based on the input data provided. Proposed algorithm was developed by injecting the data randomly and massively to in rich the trained network. None-trained data has been used to validate the network and the network was able to locate the faults exactly.

KEYWORDS: Fault Location, Kurdistan power system Transmission Line, Artificial Neural Network.

INTRODUCTION:

One of the main components in any electric power system is the overhead transmission line which is experience a high rate of fault because it is directly exposed to the nature. Consequently, the most common fault in such transmission lines are Line faults.

These faults could be exposed by a lightning strokes, salt spray on the lines insulator could cause to reduce strength of the insulators, tree falls on the lines, or accumulating of snow and ice on the insulator which causes mechanical failure for the insulators. To optimize the quality of the power delivery, it is necessary to retain the transmission lines from such faults to restore the power as soon as possible by repairing the faulty lines.

As a result, it is necessary to indicate location of the fault in order to remove it. In addition, transient fault maybe possible when the insulators are marginally contaminated or from growing trees under the transmission lines (Lian 1994).

The protective relays mounted over transmission lines uses voltage and current as input signals in order to classify and locate the faults in any protected line. Occurring a fault on any line will trigger the relay to send a trip signal to activate the circuit breakers to amount the line with the fault. This will help the rest of the power system to function correctly and normally (Tekli 2013).

Algorithms to detect the faults have been developed vastly during the last decades. Algorithms like; the differential equation method, the steady-state method, and travelling wave approach (Lian 1994) for one-end algorithm (Zhang 1999) or for two-ended algorithm (Sheng 1998). Moreover, two sampling techniques were developed for the latter approach, which are;
synchronized (Kezunovic1994) and non-synchronized (Novosel1996) methods. However, the protection relays may fail to detect the faults due to its high impedance and the DC offset in the short circuit current. In addition, travelling wave Algorithm may also force problems to detect fault location especially if it's close to a substation or the fault inception is close to zero.

Artificial Neural Networks (ANN) is powerful to mimic systems such as pattern recognition and classification. ANN have been recently involved in power system protection (Beale 2010). ANN is a useful tool in the application of power systems due to its ability to be trained with existing data (i.e. offline training) (Dash2000, Lin2007, Hagh2007, Jain2009).

This paper presents the application of ANN with high training speed to locate faults on the whole power system of Kurdistan transmission line. A feed-forward neural network with the approach of back propagation learning algorithm has been used to realize location of the fault. The current approach is based on generating as many data as possible from the conventional system and use it to train the ANN. Data has been developed by creating manual faults at all the different buses of the power system under consideration. The data has been re-sampled in to larger size and the new sampled data are used for training. Simulation results have been compared with regular algorithm by using only the provided samples and approximately exact match has been obtained compared with the actual fault locations.

1. POWERSYSTEMMODEL

The Power Systems model considered in this article is located in Kurdistan of Iraq. Kurdistan Region is an autonomous region in the north part of Iraq. It is bordered by Iran, Turkey, Kirkuk and Mosel. It consists of three provinces: Duhok, Erbil and Sulaimani. The voltage levels of Kurdistan power system are (11, 13.8, 15, 33, 132 and 400) kV for transmitting power and the main substation is usually consist of (132/33 kV) two winding transformers and (132/33/11 kV) three winding transformers. There are several (33/11 kV) substations connected to each (132 kV) main substation via (33 kV) network. Medium voltage distribution is at (11 kV), which reduces to (400 V) through step down transformer at the distribution networks. Later, the power is distributed to individual consumers via 400 V low voltage distribution networks.

Due to complexity of the power system model under consideration and it's hard to deal with it manually, PowerWorld Simulator software will be used for modeling. Power system model of the region consists of 170 buses in total (UNDP-ENRP 2016-2017). None-active buses have been removed from the power system model and it has been reduced to only 40 buses. Due to the large size of the model to fit in this document, the whole model was divided into two parts, as shown in Fig.1.

All the connecting buses have a standard Pi model as shown in Figure 2 which connects two cities (namely; KHABAT and SHAQLAWA). It consist of two substations, one at the beginning of each city and one at the end of the transmission line. As shown, the three-phase voltages $V= [V_aV_bV_c]^T$ and currents $I= [I_aI_bI_c]^T$ are measured at KHABAT substation. Utilizing PowerWorld software, all different types for fault simulations (i.e. phase to ground fault, double-phase to ground fault, phase to phase fault, and 3-phase fault) are presented. Only the faults data related to the transmission line under study were took under consideration. For example, when a SLG (or any other type) fault happens at any of the regional buses, the phase voltages and currents at the nominated buses will be affected. These data will be recorded and will be considered in training the NN system.

2. ARTIFICIAL NEURAL NETWORKS

The interconnection between the artificial neurons in an Artificial Neural Network (ANN) gave it the flexibility to adapt and copy any mathematical model (Bashier2007). In the last decades, it's been found that the nonlinear relationship between the inputs and the outputs in any black-box system can be replaced with ANN (Chow 2007). This modeling is depicted as a supervised training procedure. This approach gives the ability for the network to adapt and modify its interconnections based on the error signal. This error helps the ANN output to track the target output. The main aim is to reduce the total error to a predefined and set number which is possible by continuing to adapt the system. The current network performance considered is sum of errors of all training samples. System adaptation will help it to learn the unknown network
architecture and minimize the cost function (Morgan 1990, Chow 2007).

Kurdistan power system model has been modeled using PowerWorld Simulator software due to the large of the system. Manual fault has been injected at each bus of the 40 buses on the whole power system region. The Fault considered at the buses is single-line to ground (SLG). At each bus the fault took place all the 3-pase voltage/currents on each bus have been measured and considered. Total number of the data generated will be 40x40=1600. Few of these data are tabulated in Table 1. To test the proposed neural network 20 of these data will be considered for validation and testing purposes. These data should not be used in the training process in order to check robustness of the trained network. Fault at Bus 1 and Bus 30 has been graphed as shown in Figure 4, where it shows the voltage at phase Va is zero at that bus. Effect of the fault on Bus 1 and Bus 30 voltages and currents have been considered as a sample of data.

The proposed neural network has six inputs based on the Bus voltages and currents. Input are normalized with respect to the pre-fault values of the voltages and currents. The output of the neural network it gives the Bus number which faults happen, which indicates whether the fault has been occurred or not. The developed architecture of the ANN has a total of three layers (1 input, 1 hidden, and 1 output layer). Simulation has been carried out several times with different architectures to choose the best of it. It consist of 6 inputs, N neurons in the hidden layer and single neuron at the output.

Network training was achieved using the method of Levenberg-Marquardt backpropagation (LMBP) due to its fast training process (Chow 2007). This method has the property of approaching to second-order training speed with no computation of the Hessian matrix $H$.

$$ H = J^T J $$

where $J$ is the Jacobian matrix that contains first derivatives of the network error with respect to the weights and biases. The LMBP algorithm uses the following approach to minimize the total error $e$:

$$ x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e $$

One of the problems of training a NN is picking the initial values. It is advantageous to depict a NN that is independent of the initial values and can learn the system correctly regardless of what the initial values were (Lufty 2018, Abdulrahman 2014). Therefore, the proposed NN were trained by two different ways. First way was achieved by including only the samples obtained from PowerWorld simulator, and the second way by repeating the samples to three times randomly.

### 3. Simulation Results

The ANN constructed needs to learn how to predict the fault location through the process of identification of the power system model. Therefore, the power system has to develop enough data to train the NN under consideration. Total number of the points can be obtained are 1600 input-output pair (6 input and 1 output). Using these available data to train the NN will lead the system to fall in local minima and the NN will not learn the system correctly (Chow 2007). An ANN architecture of 6x250x1 (250 hidden neurons) has been used with input data of the same generated data and the results are shown in Fig.5. 20 of the total number of data has not been used for the training purposes and will be used for validating the ANN model. From performance of the NN model the system has been trained enough as low as 0.004 but the system was not robust enough for validation Fig.5 (right). Validation of the NN has been carried out with 20 of data that not been used for training. There is a great difference between the actual fault location and the predicted one with the ANN model. This is due to falling in local minima due to the data are not randomized and have a specific scheme.

To avoid the training process in falling in local minima the data will be re-sampled and randomized (Wong1980). All the 1600 data has been sampled to 15,000 except 20 of the original data has not been included and will be used for testing the network. Training has been done again using only 10 neurons to test the training and the results are shown in Fig.6. As shown from the network performance, Fig.6 (right), testing has been done successively. However, the results are not promising and not usable due to the large difference between the actual fault locations with the predicted one, Fig.6 (left). This is due to the
trained network is not rich enough to hold the massive data used for training.

Number of the hidden neurons will be increased by two ways, first with one hidden layer of 100 neurons and another with two hidden layers with number of neurons equal to 20 for each layer. Both networks have been simulated and the simulation results show there is a difference as most of the tested data have been predicted, Fig.7,8 (left). However, few of the tested data has not been predicted and a large difference is shown, trial 13, 14, and 19 in Fig.7 (left) and trials 4, 7, 13 and 19 in Fig.8 (left).

Increasing number of the hidden neurons has shown promising results. Therefore, the hidden neurons have been increased to 250 neurons on a single layer and the results were the best among all testing has been done previously, Fig.9 As shown from the performance of the trained ANN, it got out the local minima twice, Fig. 9 (right). The trained NN has been used to validate the results and the results were almost identical between the actual and the predicted values, Fig.9 (left).

4. CONCLUSIONS

In this paper, lack of data problem in Power systems has been overcome using the process of randomization. Where, the data obtained using PWS software have been randomized and re-sampled to increase its number. This algorithm reduced the need for large data in order to train any NN. Increasing number of the hidden layer was enough to overcome the problem of local minima as appeared in the results obtained. In addition, simulation results reveal robustness of the proposed model to detect the fault at any Bus of the power system model.

Table (1). Samples of voltage and current when a fault took place

| Bus | Va  | Vb  | Vc  | Ia  | Ib  | Ic  |
|-----|-----|-----|-----|-----|-----|-----|
| 1   | 0.63| 1.08| 0.99| 1.86| 1.1 | 2.5416|
| 1   | 0.89| 0.95| 0.94| 1.90| 1.2 | 2.5785|
| 1   | 0.95| 1.02| 1.02| 2.00| 1.3 | 2.6651|
| 1   | 0.95| 1.02| 1.01| 2.00| 1.3 | 2.6633|
| 2   | 0.04| 1.35| 1.04| 1.46| 1.0 | 2.5506|
| 2   | 0.04| 1.36| 1.08| 1.67| 1.0 | 2.5612|
| 2   | 0.04| 1.35| 1.08| 1.77| 1.0 | 2.5572|
| 2   | 0.94| 1.04| 1.01| 1.92| 1.2 | 2.6023|
| 5   | 0.01| 1.37| 1.09| 1.58| 1.0 | 2.5623|
| 5   | 0.03| 1.37| 1.07| 1.57| 1.0 | 2.5566|
| 5   | 0.02| 1.37| 1.08| 1.57| 1.0 | 2.5612|
| 5   | 0.00| 1.37| 1.09| 1.54| 1.0 | 2.5644|
| 20  | 0.06| 1.32| 1.10| 1.88| 1.1 | 2.6964|
| 20  | 0.22| 1.25| 1.05| 1.93| 1.1 | 2.6876|
| 20  | 0.87| 1.02| 0.94| 1.87| 1.2 | 2.5664|
| 40  | 0.05| 1.28| 1.05| 1.93| 1.2 | 2.7475|
| 40  | 0.05| 1.27| 1.04| 1.93| 1.2 | 2.7474|
| 40  | 0.00| 1.28| 1.05| 1.69| 1.2 | 2.7491|
| 40  | 0.06| 1.26| 1.01| 1.89| 1.2 | 2.7414|
| 40  | 0.06| 1.25| 1.00| 1.84| 1.2 | 2.7398|

Figure 1. PowerWorld Simulator Model for load flow and short circuit calculation
**Figure 2.** Transmission Line between two cities

**Figure 3.** Effect of fault on bus voltages and currents, top-left: 3-phase currents on Bus 1, top-right: 3-phase voltages on Bus 1, down-left: 3-phase currents on Bus 30, down-right: 3-phase voltages on Bus 30.

**Figure 4:** Selected BPNN for fault detection on The power system transmission line.

**Figure 5.** (left) Prediction of fault occurrences, (right) performance of training the ANN.
**Figure 6.** (left) Prediction of fault with 10 hidden neurons, (right) performance of training the ANN

**Figure 7.** (left) Prediction of fault with 100 hidden neurons, (right) performance of training the ANN

**Figure 8.** (left) Prediction of fault with 20x20 hidden neurons, (right) performance of training the ANN

**Figure 9.** (left) Prediction of fault with 250 hidden neurons, (right) performance of training the ANN

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