Neural Network Relaying to Distance Protection of Transmission Lines

Abhijit A Dutta
Assistant Prof
DBACER, Nagpur

Mr. Pankaj Shinde
Deputy (EE)
ALDC Nagpur

Abstract: *A distance relay for the protection of transmission lines is usually designed on the basis of fixed settings The reach of such relays is therefore affected by the changing network conditions The implementation of a pattern recognizer for power system diagnosis can provide great advances m the protection field This paper demonstrates the use of an Artificial Neural Network as a pattern classifier for a distance relay operation. The scheme utilizes the magnitudes of three phase voltage and current phasors as inputs. An improved performance with the use of an Artificial Neural Network approach is experienced once the relay can operate correctly, keeping the reach when faced with different fault conditions as well as network configuration changes*

Keywords: Distance Protection, Relaying, Power Systems, Artificial Neural Networks

I. INTRODUCTION

Distance relaying techniques have attracted considerable attention for the protection of transmission lines. The principle of these techniques measures the impedance at a fundamental frequency between the relay location and the fault point, thus determining whether a fault is internal or external to a protection zone. Voltage and current data are used for this purpose and they generally contain the fundamental frequency signal added with harmonics and the DC offset. With digital technology being ever increasingly adopted in power substations, more particularly in the protection field, distance relays have experienced some improvements, As a consequence, shorter decision time has been achieved. The trip/no trip decision has been improved, compared to electromechanical/solid state relays. However, the digital distance protection is usually designed on the basis of fixed relay settings. The reach accuracy of a distance relay can therefore be affected by the different fault conditions (particularly in the presence of the DC offset in the current waveforms) as well as network configuration changes. In order to face such a problem in conventional settings, a safety margin is necessary so as to avoid overreaching. The potential of **ANNs** has attracted power system researchers to look at it recently as a way to solve problems related to different fields. Pattern recognition approach to distance relaying as well as a fault direction discriminator for transmission lines should be mentioned. Indeed, it gives very encouraging results

The Artificial Neural Network (ANN) approach works as a pattern classifier, being able to recognize the changing power system conditions and consequently improve the performance of ordinary relays using the digital principle. The capability of the relay based on ANN theory to keep the reach accuracy when subjected to different fault conditions as well as
network configuration changes is shown.

I1 . ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANNs) are inspired by biological nervous systems and they were first introduced as early as 1960, Nowadays, studies of ANNs are growing rapidly for many reasons:

- ANNs work with pattern recognition at large.
- ANNs have a high degree of robustness and ability to learn.
- ANNs are prepared to work with incomplete and unforeseen input data.

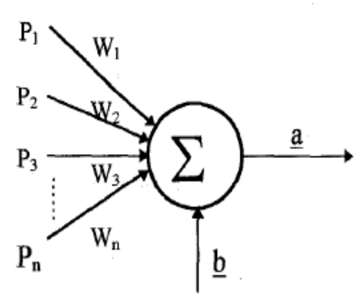

Figure. 1- Perceptron representation

Once trained, a network response can be, to a degree, insensitive to minor variations in its input. This ability to see through noise and distortion to the pattern that lies within is vital to pattern recognition. The neuron is the nervous cell and is represented in the ANN universe as a perceptron. Figure. 1 shows a simple model of a neuron characterized by a number of inputs P_n, P_2, ..., P_N, the weights W_I, W_2, ...$\mathbf{W}_n$, the bias adjust **b** and an output **a.** The neuron uses the input, as well as the information on its current activation state to determine the output a, given as

$$a = \sum_{k=1}^{n} W_k P_k + b$$

The neurons are normally connected to each other in a specified fashion to form the ANNs. These arrangements of interconnections could form a network which is composed of a single layer or several layers. As mentioned before, the ANN models must be trained to work properly. The desired response is a special input signal used to train the neuron. A special algorithm adjusts weights so that the output response to the input patterns will be as close as possible to the respective desired response. In other words, the ANNs must have a mechanism for learning. Learning alters the weights associated with the various interconnections and thus leads to a modification in their strength

111. THE BACKPROPAGATION METHOD

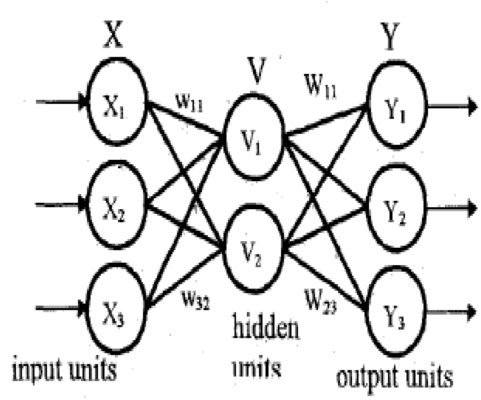

Figure. 2 – Three Layer Artificial Neural Network

The backpropagation algorithm learning of neural network is a closely related approach was proposed by Le Chun (1985). The backpropagation method works very well by adjusting the weights which are connected in successive layers of multi-layer perceptrons The algorithm gives a prescription for changing the weights in any feed-forward network to learn a training set of input output pairs. The use of the bias adjust in the ANNs is optional, but the results may be enhanced by it. A multilayer network with one hidden layer is shown in Figure. 2. The network consists of a set of N input units **(X_i,** $i = 1$,… **N),** a set of n output units (Y_i, $i = 1$,… n) and a set of J hidden units (V_j , $j = 1$,… J**) .** Thus, the hidden unit V_j receives a net input and produces the output:

$$V_j = F\left[\sum_{k=1}^{N} W_{jk}\, X_k\right] \; Where\; j = 1, \dots \dots . . J$$

The final output is then produced as

$$Y_i = F\left[\sum_{m=1}^{J} W_{im}\, V_m\right] \; Where\; i = 1, \dots \dots . . n$$

The above function F[.] is a non-linear transfer function which can be of various forms. Backpropagation networks often use the logistic sigmoid as the activation transfer function. The logistic sigmoid transfer function maps the neuron input from the interval *(-∞,+∞)* into the interval (0,+1). The logistic sigmoid, shown in the equation below is applied to each element of the proposed ANN.

$$F[.] \approx \log sig(n, b) = \frac{1}{1 + e^{-(n+b)}}$$

Where n is the summation of output, bias adjust

In 1986, Rumelhart, Hinton and Williams presented a rule capable of adjusting behavior of a feed forward neural network with hidden layers. Generally speaking, a feed forward neural net (FNN) contains an input layer, an output layer and possibly many hidden layers. Each layer can have one or many processing nodes (neurons). The node receives its inputs through a set of weighted links. These inputs may come from other nodes or from outside sources. Sum of all weighted inputs represents the node activation. The node output is determined by an output function, which responds to this activation. Frequently the so called sigmoid output function is used It should be noted, that FNN processing nodes are connected only in forward direction by links of variable weights. The operation of a neural net consists of the presentation of a set of input signals (input patterns) and subsequent propagation of this inputs through the net. If activation and output functions are chosen, a neural net is completely described by its weights and node thresholds. Finding weights and thresholds for the network may be regarded as being equivalent to finding the unknown input/output relationship. Thus, neural networks are appropriate and especially powerful when they are used to find such relationships that are difficult to describe explicitly. The next section describes a training process of feed forward neural networks.

IV Training

In order for a neural net to learn certain relationship, data sets describing that relationship must be presented. These data sets consist of input vectors and associated target (output) vectors. A training set describes the full range of expected inputs and desired outputs. The neural nets used in this study are trained by the Back Propagation Learning Algorithm Calculating the individual pattern error E_m of pattern m

$$E_m = \frac{1}{2}\sum_z (t_{mz} - o_{mz})^2$$

Where t_{mz} is the desired output of pattern m and o_{mz} is the actual net output. We get the error E for all patterns as a sum of all individual pattern errors as

$$E = \sum E_m = E\ (w)$$

Minimization of Error E is the task of a gradient search. The weight updating process follows the direction of negative gradient;

We can calculate recursively the weight changes "backwards" from the output layer toward the input layer. Once all weight changes are calculated the weights are updated. The entire training process is repeated as long as the error E exceeds a specified threshold.

V Application of Back Propagation Method in Distance Protection

Power simulation program (PSCAD) instead of mathematical functions to generate faults, thus realistic training data was obtained. They used backpropagation ANN as a pattern classifier for a distance relay of 100 km with two sources at both ends. The protected zone was 80% of the line within which the network was trained to classify fault pattern i.e. to avoid overreaching. One type of fault, phase a to ground fault, was simulated with varying the fault distance, fault resistance, fault inception angles, source impedance, source capacities, and power transfer angle, the total of 2,144 different faulted cases were gathered. The ANN took six inputs namely normalised $|V_a|$, $|V_b|$, $|V_c|$, $|I_a|$, $|I_b|$, and $|I_c|$. The ANN had 6 nodes in the input layer, 6 nodes in the first hidden layer, 2 nodes in the second hidden layer and 1 node in the output layer. The log sigmoid functions were used as the output functions. The ANN was successfully trained to detect fault in protection zone only with inaccuracy at 78-82 % of the protection zone. The ANN relay has the ability to learn aspects related to the fault condition as well as network configuration.

The hidden layer consisted of 6 nodes with tansig transfer function. The output layer had one node with linear function. This is mapping of inputs to a number in linear manner, thus the output ranges from 0 to any number instead of from 0 to 1 as in log sigmoid function. The network was trained for inputs with varying fault types, fault distances, and fault resistance values. After applying various improvement techniques, the method chosen for network training was backpropagation method. This technique requires more computing memory, but has faster learning rate compare to traditional gradient descent algorithm. The training resulted in average error in locating a fault of 0.12% to 0.7%. The average error could be reduced with longer training time.

VI ANN Based Relay

The ANN relay in this project is based on a distance relay with two identical three-phase power sources at both ends. The length of the transmission line (TL) is 100 km. The line model is shown in the figure 3

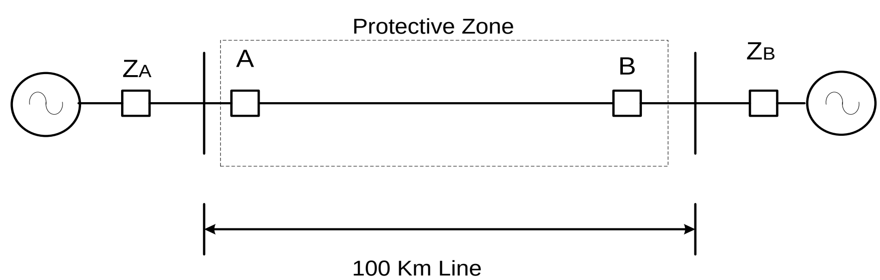

Figure3: Distance Relay Model

The relay is intended to protect the protection zone along the 100 km line. The ANN relay was trained to see faults from one side (A) only, i.e. the impedance measured is the one facing the relay. The relay on the other side (B) can use similar relay.

The distance relay above is modelled using PSCAD to get the data for network training and testing. The rms positive sequence current, voltage, and impedance is shown in figure 4

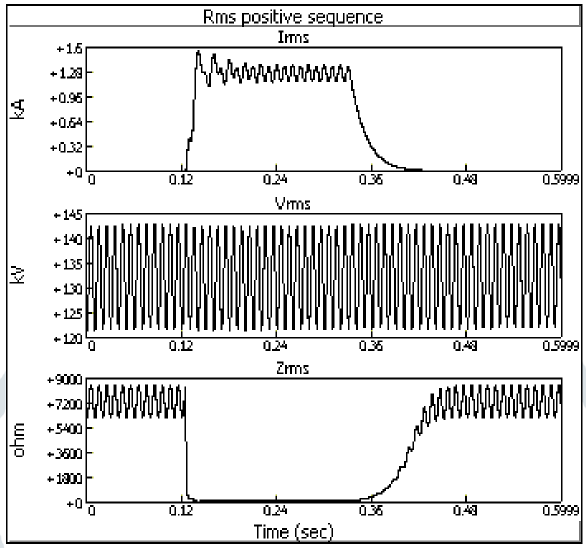

Figure 4: Rms Value of The Positive Sequence Current, Voltage, and Impedance

For each fault type and fault inception angle, the location of the fault was varied by varying the length of the transmission lines pairs. Measured from the relay A, the fault distances (in km) simulated were 1, 10, 20, 30, 40, 50, 60, 70, 80, 90, and 99kms. 1,100 fault cases were simulated. Faults generation using PSCAD (4.2) and the network simulation using MATLAB (7.4).

Some fault types have a similar waveform pattern. Given below are the waveform patterns for various fault types with constant fault distance

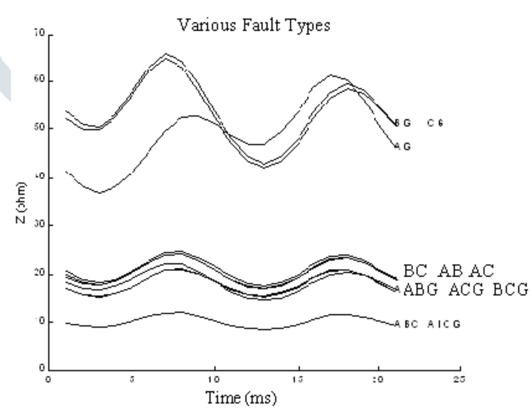

Figure 5: Waveforms of Various Fault Types

The network input layer requires (input, desired output) pair of input data. The desired output data can be generated by setting a pickup value below which a trip (1) signal is generated. The value of Z which is required for setting the relay can also be obtained by training the ANN this is called as goal setting

The training can be done by arbitrarily choosing network architecture as in figure 6 and then trained it using the proposed learning algorithm. As the size of input and output can be specified, only the size of hidden layer was concerned. The training is started with a big network size and then gradually reduced to smaller size if network testing gave satisfactory result. The location of a fault plays important role in the trip decision when it comes to overreaching issue. When overreaching occurs, the relay ignores it altogether, operates a delayed tripping, or communicates to other relay to trip.

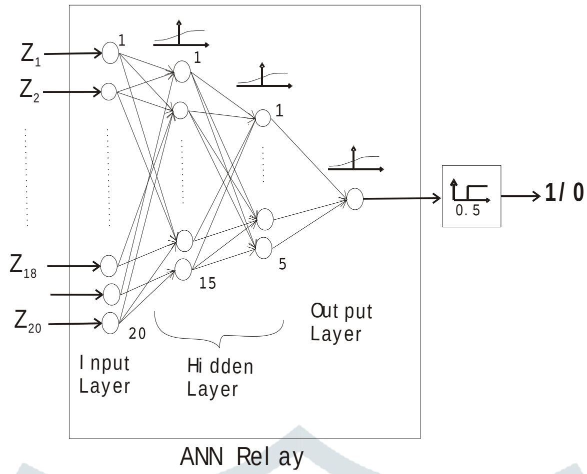

Figure 6: ANN Relay Architecture

VII Conclusion

The use of an ANN as a pattern classifier is used to simulate a distance relay. The results obtained in this scheme are very encouraging. The *ANN* relay can provide a fast and precise operation, keeping its reach accuracy when faced with different fault conditions (even in the presence of the DC offset in the current waveforms) as well as network changes. This is an improvement in performance if compared to conventional distance relays. Thus, the use of ANNs can make it possible to extend the first zone reach of the relays, enhancing system security. The process involving training and testing of different network configurations can be carried out until satisfactory results are achieved. It must however be pointed out that this tool opens a new dimension in relay philosophy which should be widely investigated, allowing one to solve some of the various problems related to the distance protection of transmission lines.

VIII References

[1] Coury, D.V. & Jorge, D.C. 1998, 'Artificial Neural Network Approach to Distance Protection on Transmission Lines', IEEE Transactions on Power Delivery, vol. 13, no. 1, pp. 102–108.

[2] T **S** Sidhu, H Smgh, and M **S** Sachdev, "Design, Implementation and Testing of An Artificial Neural Network Based Fault Direction Discmator for Protecting Transmission Lines", IEEE Transactions onPowerDelivety, Vol 10, no 2, April 1995, pp 647-706

[3] Manitoba HVDC Research Centre, 2005, Electromagnetic Transient Program Manual PSCAD Version 4.2.0.

[4] MATLAB Version 7.4

[5] S.N.Sivanandam, S.Sumathi, S.N.Deepa Introduction to Neural Networks using MATLAB 6.0 TMH