A Novel Application of Neural Networks to Locate Fault Distance in a Double End Fed Transmission Line

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Abstract: Distance relays are used for protection of transmission lines. These relays have been reported to have problems of under-reach, over-reach and mal-operation due to the high impedance fault (HIF). Different system faults on a protected transmission line should be located correctly. This paper presents a novel application of neural network to locate the fault in a double end fed transmission line using only one end data within one cycle after the inception of fault. The proposed Artificial Neural Network (ANN) based Fault Locator uses fundamental components of current and voltage signals to learn the hidden relationship in the input patterns. An improved performance is obtained once the neural network is trained sufficiently and suitably, thus performing correctly when faced with different system parameters and conditions e.g. 0-100Ω fault resistance (Rf), ±45 degrees initial power flow angle δ, different fault incidence angles φ etc.

Key words: Artificial Neural Network · Fault Location · Fault resistance (Rf) · Fault inception angle (φi) and Transmission Line Protection.

INTRODUCTION

FAULT location estimation is a desirable feature in any protection scheme. By accurately locating a fault, the amount of time spent by line repair crews in searching for the fault can be kept at a minimum. Locating the fault on the transmission line accelerates line restoration and maintains system stability. Fault location based on reactance measurement is a well known technique that has been used to estimate the fault location. The technique is based on the linear relation between the reactance, estimated from the voltage and current of the fault and fault location. Most of the reactance-based schemes require the pre-fault load measurements or remote end information. These are required to minimize the error due to the remote end injection and load flow variations. The introduction of long EHV/UHV transmission lines was associated with some phenomena such as high charging current, weakly damped DC component and low frequency transients. These phenomena degraded the performance of reactance-based fault location schemes. It also directed the attention to another family of algorithms that are travelling waves-based schemes. These schemes are based on determining the time needed for a wave to travel between the local end and fault location. However, travelling waves schemes have problems with faults close to the bus and faults with close-to-zero incidence angle.

One of the new tools recently introduced into power system protection is Artificial Neural Networks (ANN). ANN is powerful in pattern recognition, classification and generalization. Consequently, various ANN-based algorithms have been investigated and implemented in power systems in recent years [1]. Neural Networks are used to estimate the fault location. Most of the reactance-based schemes impedance information as the basis of information rather require the pre-fault load measurements or remote end injection and load flow variations. These are required to minimize the error due to the remote end injection and load flow variations. The introduction of long EHV/UHV transmission lines was associated with some phenomena such as high charging current, weakly damped DC component and low frequency transients. These phenomena degraded the performance of reactance-based fault location schemes. It also directed the attention to another family of algorithms that are travelling waves-based schemes. These schemes are based on determining the time needed for a wave to travel between the local end and fault location. However, travelling waves schemes have problems with faults close to the bus and faults with close-to-zero incidence angle.

One of the new tools recently introduced into power system protection is Artificial Neural Networks (ANN). ANN is powerful in pattern recognition, classification and generalization. Consequently, various ANN-based algorithms have been investigated and implemented in power systems in recent years [1]. Neural Networks are useful for power system applications because they can be trained with off-line data. The specialty of ANN based distance protection is that it does not explicitly use the impedance information as the basis of information rather it learns from the examples presented to it during training. ANNs possess excellent features such as generalization capability, noise immunity, robustness and fault tolerance. Therefore, the decision made by an ANN-based relay will not be seriously affected by variations in system parameters. ANN-based techniques have been used in power system protection and promising results are obtained as a basic relaying tool and as an alternative to existing schemes [2-7].

In this paper, we present an extension to fault location methods reported by Tahar Bouthiba in [2]. Other types of fault like phase to phase, double phase to ground
and three phase fault for a double end fed transmission line that were previously ignored, are modelled in this paper using a single neural network architecture for locating all ten types of shunt faults. MATLAB® software is used for offline simulation of the various power system network conditions. A feedforward neural network based on the Bayesian regularization algorithm was used to implement the ANN based fault locator. The neural network based fault distance locator was trained and tested with a number of simulation cases by considering various fault conditions (fault types, fault locations, fault resistances and fault inception angles, initial power flow angle $\delta_0$) for a selected power system network model.

**Power System Network Simulation:** A 220 kV power system is simulated using MATLAB® Simulink and SimPowerSystem toolbox for various types of faults with different system conditions and parameters. The single-line diagram of the system under study is shown in Fig. 1. Short circuit capacity of the equivalent Thevenin sources on two sides of the line is considered to be 1.25 GVA. Source to line impedance ratio, $Z_0/Z_1$ is 0.5 and $X/R$ is 10. The transmission line is simulated using pi model.

**Patterns Generation and Preprocessing:** Preprocessing is useful method that significantly reduces the size of the neural network and improves the performance and speed of training process [5 and 6]. Three phase voltage and current input signals extracted from the simulation at the relay location (end S) are processed by simple 2nd-order low-pass Butter worth filter. The filter had a cut-off frequency of 400 Hz. Voltage and Current signals are sampled at 1 kHz (20 samples per one 50 Hz cycle). This sampling rate is compatible with the sampling rates commonly used in digital relays. The one full cycle Discrete Fourier Transform (DFT) block of MATLAB® SimPowerSystem toolbox was utilized to obtain the magnitudes of the signals just after the fault occurrence and only the fundamental frequency component was used. The simulated power system data obtained through MATLAB® 7.0 software simulation are used as the input information to train the proposed neural network. Network training pattern generation process is depicted in Fig. 2. It should be mentioned that the input signals have to be normalized in order to reach the ANN input level (±1). The routine ‘premnx’ of the neural network toolbox of MATLAB® version 7.0 software is used to normalize the input signals.

![Fig. 1: Power System under Study.](image1)

![Fig. 2: Training patterns generation process using Matlab® SimPowerSystem toolbox.](image2)

![Fig. 3: (a) & (b) Fundamental Voltage & Current estimate during a three phase ABC fault respectively at 60 ms, 85 Km, 45 degree ds.](image3)

**Approach to Fault Location Using Ann**

**Design Process:** The design process of the ANN based fault locator goes through the following steps:

- Preparation of a suitable training data set comprising of all possible cases that the ANN needs to learn.
Table 1: Training Patterns Data Generation

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Parameter</th>
<th>Set value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Fault type</td>
<td>LG, LL, LLG, LLL</td>
</tr>
<tr>
<td>2.</td>
<td>Fault location Lf (km)</td>
<td>Different values between 50-100 km</td>
</tr>
<tr>
<td>3.</td>
<td>Fault inception angle (Fi)</td>
<td>0 &amp; 90 deg</td>
</tr>
<tr>
<td>4.</td>
<td>Fault resistance (Rf)</td>
<td>Different values between 0-100 W</td>
</tr>
<tr>
<td>5.</td>
<td>Source angle ds</td>
<td>-45, 0 &amp; 45 Deg</td>
</tr>
</tbody>
</table>

- Selection of a suitable ANN structure for a given application.
- Training the ANN.
- Evaluation/validation of the trained ANN using test patterns to check its correctness in generalization.

The training data set of an ANN contains the necessary information to map the input patterns to corresponding output patterns. Combinations of different fault conditions were considered and training patterns were generated by simulating different kinds of faults on the selected power system as shown in fig. 1. Fault type, fault location, fault resistance and fault inception time (angle), initial power flow angle $\delta_0$ were changed to obtain training patterns covering a wide range of different power system conditions as shown below in Table 1.

**Inputs and Outputs:** The ANN based Fault Locator (FL) uses the magnitudes of the three phase voltages ($|V_a|$, $|V_b|$, $|V_c|$) and phase currents ($|I_a|$, $|I_b|$, $|I_c|$) corresponding to the post-fault fundamental frequency (50 Hz). The output of the ANN fault locator is the estimation of the fault location (in km) in the transmission line.

**Structure and Learning Rule of the Neural Fault Locator:** A three-layer feed-forward neural network (FFNN) was selected to implement the algorithm for fault location. As regards the ANN structure, parameters such as the number of inputs to the network as well as the neurons in the input and hidden layers were selected empirically.

This process involved a trial-and-error procedure with various network configurations which were trained and tested in order to establish the appropriate network with a satisfactory performance. With supervised learning, the ANN was trained with various input patterns (Table 1) corresponding to different types of fault at various locations for different fault conditions and different power system data. The transfer function of the hidden layer was the sigmoid function and that of the output layer neurons was the linear function.

In this paper a single fault locator for all ten types of faults is presented. The structure of each fault locator corresponds to the number of neurons in the input, hidden and output layers. The number of neurons in the input layer corresponds to the number of the input variables to the ANN. There are six neurons in the input layer. The number of neurons in the hidden layer was determined after a series of trials. It was found that thirty neurons in the first hidden layer and fifteen neurons in the second hidden layer lead to the best performance. The output layer consists of one neuron to estimate the fault location. So the ANN structure was 6-30-15-1 for the ANN based FL. The ANN structure of the FL is shown in Fig. 4.

The input layer simply transfers the input vector $x$ (which is composed of the magnitudes of the currents and voltages at 50 Hz) to the hidden neurons. The outputs $v^1_j$ and $v^2_j$ of the first and second hidden layers with the sigmoid activation functions were calculated and transferred to the output layer which consisted of only one neuron. The output value of the neuron in the output layer with the linear activation function is calculated which gives the fault location in the transmission line (in km). In the same way, the final weights and biases are adjusted in the training phase. The network considered was trained with Levenberg-Marquardt (Trainlm) training algorithm and Bayesian Regularization training algorithm (Trainbr). Bayesian regularization is modification of the Levenberg-Marquardt training algorithm to produce networks that generalizes well and reduces the difficulty of determining the optimum network architecture. One problem that can occur when training neural networks is that the network can overfit on the training set and not generalize well to new data outside the training set, this can be prevented by training with Bayesian regularization training algorithm.

**Training:** Artificial Neural network fault locator (ANN FL) was trained using the Levenberg-Marquardt training algorithm (Trainlm) and Bayesian Regularization training...
Training with Levenberg-Marquardt Algorithm: Fig. 5 shows the training figure obtained during training of ANN based fault locator with Levenberg-Marquardt algorithm. It has been found that ANN FL with 6 inputs, 30 neurons in first hidden layer, 15 neurons in second hidden layer and 1 neuron in output layer (6-30-15-1) is capable of minimizing the mean square error (mse) to a final value of 0.00099683. Therefore, the possibility of weight changing decreases cycle by cycle until training is stopped. This learning strategy converges quickly. One can see that during learning sum of squared error decreases in 121 cycles to 0.00099683 (instead of first cycle error 3.85992).

Training with Bayesian Regularization Algorithm: Fig. 6 shows the training figure obtained during training of ANN based fault locator with Bayesian Regularization algorithm. ANN FL with 6 inputs, 30 neurons in first hidden layer, 15 neurons in second hidden layer and 1 neuron in output layer (6-30-15-1) is capable of minimizing the sum of squared error (SSE) to a final value of 3.93816. It is clear from fig. 6 that during learning sum of squared error decreases in 156 cycles to 3.93816 (instead of first cycle sum of squared error 25537.9). Learning was done by using a neural network toolbox of Matlab® 7.0.

Performance: The performance of a trained network can be measured to some extent by the errors on the training, test data sets, but it is often useful to investigate the network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets. The routine postreg of Matlab® neural network toolbox is designed to perform this analysis.

Here we pass the network output and the corresponding targets to postreg. It returns three parameters. The first two, m and b, correspond to the slope and the y-intercept of the best linear regression relating targets to network outputs. If we had a perfect fit (outputs exactly equal to targets), the slope would be 1 and the y-intercept would be 0. The third variable returned by postreg is the correlation coefficient (R-value) between the outputs and targets. It is a measure of how well the variation in the output is explained by the targets. If this number is equal to 1, then there is perfect correlation between targets and outputs.

A regression analysis on the network previously trained by Levenberg-Marquardt algorithm (Trainlm) is given below:

$$m = 0.9975$$
$$b = 0.1732$$
$$r = 0.9988$$

Fig. 7 Regression analysis of ANN FL trained with “Trainlm”
A regression analysis on the network previously trained by Bayesian Regularization training algorithm (Trainbr) is given below:

\[ m = 0.9987 \]
\[ b = 0.0971 \]
\[ r = 0.9994 \]

Fig. Nos. 7 and 8 illustrates the graphical output provided by postreg for the neural network based Fault Locator trained with “Trainlm” and “Trainbr” respectively. The network outputs are plotted versus the targets as open circles. The best linear fit is indicated by a dashed line. The perfect fit (output equal to targets) is indicated by the solid line. As shown in Fig. 10 it is difficult to distinguish the best linear fit line from the perfect fit line, because the fit is so good.

From the regression analysis carried out for ANN based fault locator trained by using Levenberg-Marquardt training algorithm (Trainlm) and Bayesian Regularization training algorithm (Trainbr), it is clear that the value of the “y” intercept of network trained with Trainlm is more as compared to the network trained with Trainbr. Also it has been seen that the network trained with Trainbr generalizes well when tested with the unseen patterns with different system and fault conditions as compared to the network trained with Trainlm. Thus in the next section few test result obtained during testing the ANN based FL trained with Trainbr are only presented.

**RESULTS**

After training, the neural network based fault locator was then extensively tested using independent data sets consisting of fault scenarios never used previously in training. For different faults of the validation/test data set, fault type, fault location and fault inception time, power angle \( \delta \) were changed to investigate the effects of these factors on the performance of the proposed FL. Extreme cases like faults near the protection zone boundary including fault resistance were also included in the validation data set. The network was tested by presenting 240 different faults with different fault types, different fault locations, fault inception angles/times, different initial power flow angles etc. All 240 faults are located correctly and precisely after one cycle delay. The reason for the good estimation of fault distance is the extensive body of training patterns.

For example test result for a three phase ABG fault accuracy. Error in the fault location in KM is within ±0.4%.

The ANN based fault locator results for few faults with different system conditions and parameters are presented in Table 2.

For the faults, which involved ground, the relay operation results for 0 and 100 Ohms fault resistance is shown. For the faults, which do not involve ground,
Table 2: Proposed Fault Locator test results

<table>
<thead>
<tr>
<th>Fault type</th>
<th>Fault location (KM)</th>
<th>Inception angle (°)</th>
<th>Power angle (ds)</th>
<th>Fault Resistance 0W (Rf)</th>
<th>Fault Resistance 100W (Rf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AG</td>
<td>57</td>
<td>45</td>
<td>-45</td>
<td>56.986</td>
<td>57.023</td>
</tr>
<tr>
<td>BG</td>
<td>92</td>
<td>90</td>
<td>-45</td>
<td>91.867</td>
<td>92.346</td>
</tr>
<tr>
<td>CG</td>
<td>83</td>
<td>0</td>
<td>-45</td>
<td>82.764</td>
<td>83.022</td>
</tr>
<tr>
<td>ABG</td>
<td>97</td>
<td>45</td>
<td>45</td>
<td>96.873</td>
<td>97.451</td>
</tr>
<tr>
<td>BCG</td>
<td>64</td>
<td>0</td>
<td>-45</td>
<td>63.645</td>
<td>64.78</td>
</tr>
<tr>
<td>ACG</td>
<td>77</td>
<td>90</td>
<td>45</td>
<td>76.675</td>
<td>77.321</td>
</tr>
<tr>
<td>ABC</td>
<td>73</td>
<td>45</td>
<td>0</td>
<td>73.001</td>
<td>-</td>
</tr>
<tr>
<td>ABC</td>
<td>61</td>
<td>135</td>
<td>45</td>
<td>61.12</td>
<td>-</td>
</tr>
<tr>
<td>ABC</td>
<td>88</td>
<td>90</td>
<td>-45</td>
<td>88.001</td>
<td>-</td>
</tr>
<tr>
<td>AB</td>
<td>82</td>
<td>135</td>
<td>0</td>
<td>81.935</td>
<td>-</td>
</tr>
<tr>
<td>BC</td>
<td>69</td>
<td>180</td>
<td>-45</td>
<td>68.993</td>
<td>-</td>
</tr>
<tr>
<td>AC</td>
<td>57</td>
<td>90</td>
<td>45</td>
<td>57.045</td>
<td>-</td>
</tr>
</tbody>
</table>

Fig. 9(a): Test result of ANN based FL for ABG fault at 92 KM from 'S' end with 80° Rf at 60 ms (0 deg fault inception angle Fi), with 45 deg. δs.

Fig. 9(b): Test result of ANN based FL for ABG fault at 92 KM from 'S' end with 80° Rf at 60 ms (0 deg Fi), with 45 deg. δs.

Fault resistance is not a critical factor. Therefore, only the module performance without fault resistance is investigated. As shown in Table 5.3, the proposed module performs quite accurately and reliably. For most of the faults on the line, the module is able to respond with an error less than 1% percent. The module output for a few faults with different power system conditions is presented in this section. The main emphasis is on checking the

Fig. 10: Test result of ANN based Fault Locator for ABC Fault at 82 KM at Fi 135 deg. with 45 deg. δs.

Fig. 11: Test result of ANN based Fault Locator for BC Fault at 88 deg at 88 KM at 70ms
network’s performance under extreme fault cases. In
general, the network performs better for more usual fault
cases.

CONCLUSION

In this paper an accurate fault distance locator have
been proposed. The results demonstrate the ability of
Artificial Neural Networks to generalize and locate
accurately different fault scenarios from the provided
patterns using only one end data and within one cycle
after the inception of fault. The Neural network fault
distance locator uses the magnitudes of the fundamental
frequency (50 Hz) components of the voltage and current
phasors. Performance result obtained in a variety of fault
situations comprising various fault types, fault locations,
fault inception angle, fault resistances and power angle
ϕs, indicate that the proposed fault distance locator is
able to locate the fault distance correctly.

The result presented shows the worst case error.
The largest error is seen to be 1 KM during testing the
network under different fault situations. The best
performance is seen with an error of 1 meter.

It must however be pointed out that, ANN opens a new
dimension in relaying philosophy which should be widely
investigated so as to solve various problems related to
distance protection of transmission lines.

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