Accurate fault location technique for UHV line using one end data

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Received 12 February 2015; accepted 20 March 2016; published 25 March 2016

ABSTRACT
To maintain high reliability and quality in electrical power delivery, it is essential for utilities to accurately locate fault point. The proposed technique implements GA - adaptive neuro-fuzzy inference systems for the purpose of locating fault points and identifying the fault. The two methods such as ANFIS and GA-ANFIS are proposed to analyze the UHV system under different fault conditions. The performance of two systems are compared and analyzed using Matlab software. The result shows that GA-ANFIS approach is fast and effective Technique to determine the fault location.

KEYWORDS: ANFIS, GA-ANFIS, Fault location, UHV Line, One end data.

INTRODUCTION

When fault occurs in transmission line it is important to detect the fault location. An accurate fault location can reduce the time required for restoring service. Transmission line fault location techniques use the fundamental power frequency component and high frequency component. The latter is also referred to as travelling wave methods due to their use of travelling wave theory.

All techniques use one end information or information from both ends of faulted line. The system requires communication channel between local and remote terminals for fault location algorithm using two end data, thus making it necessary to use data from local terminal only. Fault location algorithms based on only local terminal voltage and data need some simplified assumptions. The parameters of fuzzy systems, parameters of membership function and rules are tuned well. An adaptive network based approach presented [1] to choose the parameters of fuzzy system using a training process. Artificial Intelligent based technique has been used to improve the accuracy in fault location. In transmission lines fault diagnosis is presented [2]. The use of separate ANNs, for faults involving earth and not involving earth has proved to be convenient way of classification of transmission faults based on RBF neural networks[3].

A hybrid fuzzy logic system developed by the authors to improve the accuracy of fault location [4-5].

Intelligent soft computational techniques are obviously employed with absence of a simple and well defined mathematical model and characterized by non-random uncertainties. It is associated with imprecision in real time systems [6]. The Fuzzy system is used to solve uncertainty problems [7].

The use of an artificial neural network was proposed for locating fault [8-11]. This approach considers small configurations of distribution network in terms of line length. However the ANN requires large amount of voltage and current data. The support vector machine and Fuzzy classifier are used to locate the faults within zones and areas [12].

To Cite This Article: G.Banu and S.Suja, Accurate fault location technique for UHV line using one end data, 2015. Advances in Natural and Applied Sciences, 9(17): Pages: 233-239
A real-time fault diagnosis system was implemented to detect the fault location in a distribution system [13]. This real-time system uses detection modules of voltage and current sensors and a data processing unit.

An algorithm was presented for fault detection and classification using the different impedance value using ANFIS from one end data [14-17]. The fuzzy logic based approach for identifying the type of fault (whether line to ground or double line to ground) [18].

Fuzzy logic technique is effective and has been proposed for fault classification[19]. The fuzzy logic uses simple IF-THEN relations. However it at the same time has some limitations.

GA-ANFIS Technique was presented for Fault location using one end data [20]. The artificial neural network cannot describe the power system operation in transient period, because it is affected by many unknown parameters. But the ANFIS Technique describe the system easily from the obtained data.

Wavelet singular entropy (WSE) technique which indicates the uncertainty of the energy distribution in the time-frequency domain is used [21] to extract features from fault transients for the fault diagnosis in EHV transmission lines.

A GA-ANFIS Technique is presented in this paper to find the accurate fault location for UHV transmission line. To illustrate the accuracy of the fault location. 1000 KV line with a distance of 360 km is considered. This system utilizes the voltage and current waveforms of the fault data from the one end only. This approach overcomes the difficulties associated with conventional algorithms. To tune the parameters of the FIS, adaptive network is trained based on with off-line data. The ANFIS and GA-ANFIS techniques are compared to find a fault location for UHV line. The system has been simulated using MATLAB.

2. GA- Implementation:

The MATLAB software is used to implement the GA for training the ANFIS. Each chromosome in the GA consists of 46 genes which represent all the ANFIS parameters. These 46 genes include 3 genes for the input scaling factor, 1 gene for output scaling factor, 42 genes for the premise parameters of the ANFIS structure.

3. Adaptive Neuro Fuzzy Inference System:

3.1 ANFIS architecture:

The ANFIS is a fuzzy Sugeno model of integration where the final fuzzy inference system is optimized via the ANNs training. The ANFIS makes use of a hybrid learning rule to optimize the fuzzy system parameters of first-order Sugeno system. It maps inputs through input membership functions and associated parameters, and then through output membership functions to outputs. The initial membership functions and rules for the fuzzy inference system can be designed by employing human expertise about the target system to be modeled.

In order to improve the training efficiency, a hybrid learning algorithm is used to tune the parameters of the membership functions. The consequent parameters are identified by least squares estimate.

3.2 ANFIS Hybrid Training Rule:

ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned using either a back propagation or in combination with a least squares type. Specifically, ANFIS only supports sugeno-type systems,

Layer 1. Generate the membership grades:
Layer 2. Generate the firing strengths.
Layer 3. Normalize the firing strengths.
Layer 4. Calculate rule outputs based on the consequent parameters.
Layer 5. Sum all the inputs from layer 4.

Fault Detection Technique:

To evaluate the performance of the proposed scheme, the power system configuration for this study is taken as 1000 kV line with 360 km. Distributed parameter model is used for modeling of the overhead line. The proposed fault location algorithm requires the three phase currents and the three phase voltage at the sending end of the overhead line. This system has been simulated using MATLAB to prepare the inputs for the GA and ANFIS.

The parameters of power system model:

Line length = 360 km
Line voltage = 1000 kV
Frequency = 50 Hz

Transmission line impedance per km:

• Negative sequence impedance = 0.0225 + j0.01738
• Zero sequence impedance = 0.2188 + j 0.0032829
Training data:
The training data used to train the ANFIS of the fault location unit are taken at
1. Fault distance
2. All types of faults
3. Inception angle
4. Fault resistance

Testing data:
The testing data are chosen at different fault distances, different fault resistances, different fault inception angle and different fault types.

The percentage error of distance is defined as the formula given below

\[
\% \text{ Error (D)} = \frac{\text{Actual fault distance} - \text{calculated fault distance}}{\text{Total distance}} \times 100
\]

\[
\% \text{ Error (R)} = \frac{\text{Actual fault resistance} - \text{calculated fault resistance}}{\text{Actual fault resistance}} \times 100
\]

3.3 ANFIS learning algorithm:
A backward pass is made to alter premise parameters using gradient based learning. This process of learning is named Hybrid Learning. The backward pass learning employs learning in a similar way as to the back-propagation in neural networks. The design process of the ANFIS fault detector goes through the following

1. Generation of suitable training data:
The limit of input parameters should be determined precisely to use the ANFIS technique for fault detection. The output indicates where the fault occurred. Due to limited available amount of fault data, it is necessary to generate training/testing data using simulation. To generate data for the typical transmission system, a computer program has been designed to generate training data for different faults.
The fault for different fault conditions are simulated in MATLAB simulink. (i.e. a-g, b-g, c-g, a-b, b-c, c-a, ab-g, bc-g, ca-g, a-b-c-g and a-b-c fault). The parameters that have been taken into account for each fault type are:
1. Variation of fault resistance $[30, 50, 60, 100]$ Ω
2. Variation of fault angles $[0, 90, 120, 200]$ degree
3. Variation of fault locator $[100, 150, 200, 250, 300]$ km.

Due to space limitation, all numerical training and testing data cannot be included. Some of the training/testing data are shown in Figures. 2-4.

2. Selection of a suitable ANFIS structure for a given application:
Various ANFIS are designed to detect all types of faults accurately on transmission lines.

3. Training the ANFIS:
The suitable data are presented as input data to ANFIS. Various network configurations were trained in order to establish an appropriate network with satisfactory performance. The ANFIS is trained to detect presence of fault and classify the fault position.

4. Evaluation of the trained ANFIS:
When network is trained, ANFIS should be given an acceptable output for unseen data. When output of test pattern and network’s error reach an acceptable range, the membership functions and fuzzy rules are well adjusted. All of these steps above are done off-line.

There are 25 rules, which are sufficient to assign a detector using ANFIS.
A total combination is 60 (3 values of Zf, 4 values of fault angles, 5 values for fault distance) which has been chosen for fault simulation studies. The total training cases are 660 (for 11 fault cases). The total combination of test cases are $39600(60 \times 660)$.

From the results given, it is observed that the proposed fault classification technique is capable of determining the fault type accurately in all cases of fault.
**Testing Data:**

Impedance of the transmission line is based on its distance. When fault occurs in any point of the line, impedance varies with respect to line distance and variation in impedance impacts on the current. In this system, the rules have been trained to detect normal current and abnormal current. Based on the Impedance of the transmission line, various rules in ANFIS controller are framed to find the distance/resistance as per present current and voltage values. It again tunes the result with the GA testing, training data to produce accurate result. Fault current samples are taken from GA i.e. Optimum current and voltage are produced based on the current samples. The optimum current and voltages are taken as testing data for ANFIS on its distance.

4. **GA-ANFIS:**

Impedance of the transmission line is based on its distance. When fault occur in any point of the line impedance get vary with respect to line distance, variation in impedance impact on the current. The different current and voltage values are given to GA to obtain the optimum value(error). For every iteration the optimum value is obtained. The voltage and current ratings are taken as input to the GA. Based on the fitness function the GA produces testing data to ANFIS. The reference current and voltage are taken on UHV line.

\[ I_{ref}=23000 \text{ A}; V_{ref}=1000000 \text{ V}; \]

In GA from 0 to 23000 A, 4500 samples are taken and error value is determined which is testing data to Anfis. Error \((i) =1/(I_{ref}-I(i))\);

The training data for ANFIS is produced by Fuzzy Logic Controller based on the parameters of transmission line as shown in Figure 1. The training data is tuned using neural network.

![Fig. 1: Training data](image)

The neural network to tune the fuzzy logic controller is taken as sugeno type of fuzzy. The parameters of ANFIS have adjusted via training (similar as for neural network schemes). The structure of an ANFIS with six inputs and one output. The architecture comprising by input, fuzzification, inference and defuzzification and output layers.

In this paper Back propagation method of optimization is taken with 100 epochs. The training data for fault resistance and fault distance in ANFIS are shown in Figure 2.

![Fig. 2: Training data: (a) for fault Resistance (b) Training data for fault distance](image)

This is minimized by fine tuning, such as GA output is taken as testing data for finding the resistance and fault location as shown in Figure 3. Again the ANFIS output is tested against the testing data from GA. It produces less error in output.

![Fig. 3: GA Testing data: (a) f or fault resistance (b) for fault distance](image)

The Figure 4 shows the testing and training data of GA-ANFIS for fault resistance and fault distance respectively. The output scaling factor (minimum error) is obtained from GA which is testing data i.e input for ANFIS. The ANFIS is tuned by using the GA output to get accurate fault distance.
Fig. 4: Testing and Training data: (a) for resistance (b) for fault location

The process flowchart of GA-ANFIS system is shown in Figure 5.

Fig. 5: Process flow chart of GA-ANFIS system

5. Simulation Result and Analysis:
   In a power system 75% of fault is line to ground fault. For this study with considering 100 km, 150 km, 200 km, 300 km as fault distance steps in overhead line and 0, 90, 120, 200 degree as fault inception angle steps. For this condition 300 patterns are produced. These patterns are applied to train the ANFIS for all type of faults. The fault parameters are same for both ANFIS and GA-ANFIS.

5.1. Unsymmetrical fault:
   Single line to ground faults:
   The fault resistances are 50 Ω, 100 Ω patterns are produced for training the ANFIS. Once the training procedure is done completely, the networks are tested using simulated fault patterns with the training data and fault parameters, the system is simulated. Once the training procedure is done completely, the networks are tested using simulated fault patterns.

GA-ANFIS:

Fig. 6: Fault parameter: (a) Phase voltage (b) Phase current

From the simulink the fault parameters are obtained at the instant of 0.2 s, when fault occurs at phase b at a distance of 150 km, 100 ohm resistance (GA-ANFIS) as shown in Figure 5. The current is 7000 A at a fault line. Similarly the fault parameters have been obtained for rest of faults.

The result is obtained using the equation 1 &2 (for 0 inception angle at 150 km) such as

\[
\% \text{ Error} (D) = \frac{150 - 150.7}{360} \times 100 = -0.194
\]
% Error (R) = \frac{50 - 50.65}{50} \times 100 = -1.3

Table 1 shows the percentage error of Fault distance and the percentage error of Fault resistance at 50 ohms for line to Ground fault and at 60 ohms for two phase short circuit fault, 30 ohms for three phase short circuit fault at a distance of 150 km at different inception angle for both ANFIS and GA-ANFIS.

### Table 1: ANFIS & GA-ANFIS result at 150 km

<table>
<thead>
<tr>
<th>Fault inception angle (degree)</th>
<th>ANFIS Distance (km)</th>
<th>GA-ANFIS Distance (km)</th>
<th>ANFIS Resistance (Ω)</th>
<th>GA-ANFIS Resistance (Ω)</th>
<th>ANFIS Error %</th>
<th>GA-ANFIS Error %</th>
<th>ANFIS Error %</th>
<th>GA-ANFIS Error %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>150.7</td>
<td>150.3</td>
<td>-0.194</td>
<td>-0.0833</td>
<td>50.65</td>
<td>50.25</td>
<td>-1.08</td>
<td>-0.5</td>
</tr>
<tr>
<td>90</td>
<td>150.75</td>
<td>150.25</td>
<td>-0.208</td>
<td>-0.069</td>
<td>50.75</td>
<td>50.3</td>
<td>-1.5</td>
<td>-0.6</td>
</tr>
<tr>
<td>120</td>
<td>150.7</td>
<td>150.3</td>
<td>-0.194</td>
<td>-0.0833</td>
<td>50.7</td>
<td>50.35</td>
<td>-1.4</td>
<td>-0.7</td>
</tr>
<tr>
<td>200</td>
<td>150.8</td>
<td>150.4</td>
<td>-0.222</td>
<td>-0.111</td>
<td>50.7</td>
<td>50.35</td>
<td>-1.4</td>
<td>-0.7</td>
</tr>
</tbody>
</table>

Figure 7 shows the % error of Fault distance for ANFIS and GA-ANFIS at 150 km and 90 degree Inception angle. The resistance are considered in this case 50 ohms for line to ground faults and 60 ohms for 2 phase short circuit fault, 30 ohms for 3 phase short circuit fault. From this Graph, it is proved that GA-ANFIS gives accurate fault distance comparatively.

### Fig. 7: Fault Distance error in %

The Figure 8 shows % error of fault resistance for ANFIS and GA-ANFIS at 200 km distance and 90 degree inception angle.

### Fig. 8: Fault Resistance error in %

**Conclusion:**
This paper proposes a new algorithm for fault location in a UHV line based on GA Adaptive Network based Fuzzy Inference system and ANFIS System. To estimate the accuracy of the proposed algorithm, a wide variety of conditions such as different fault types, different fault inception angles and different fault resistance are simulated and results presented. The simulation result of GA-ANFIS is compared with the ANFIS. Based on the obtained results, it can be concluded that the GA-ANFIS method is very effective to classify the fault type and find the exact location and resistance of fault.

REFERENCES