ANN AND IMPEDANCE COMBINED METHOD FOR FAULT LOCATION IN ELECTRICAL POWER DISTRIBUTION SYSTEMS

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ABSTRACT

Power distribution systems play important roles in modern society. When distribution system outages occur, fast and proper restoration are crucial to improve the quality of services and customer satisfaction. In this paper, an accurate algorithm is suggested for single line to ground fault location. In this algorithm we use the parameters (fault resistance and apparent impedance) as inputs of an artificial neural network; (ANN) has been chosen to give in output the faulty section. Test results are obtained from numerical simulation using a real under-ground distribution feeder data from “Independent agency for the distribution of water and Electricity, and liquid cleansing of Kenitra”, Morocco.

Keywords: Artificial Neural Network, Apparent Impedance, Fault Location, Fault Resistance, Single Line-To-Ground Fault.

1. INTRODUCTION

Distribution networks are dispersed in each urban and rural region, and are crossed from each alley and street. Each distribution feeder has many laterals, sub-laterals, load taps, balanced and unbalanced load and different types of conductors [1]. Power distribution systems (PDSs) are subjected to fault conditions caused by various sources such as adverse weather conditions, equipments failure and external object contacts. Owing to the expansion of distribution network, it is very difficult and complicated to locate the fault in these networks.

Currently the only technique used for locating faults in distribution systems of electric power is the visual inspection of FPI (Fault Passage Indicators) which imposes an important time of restoration.

In recent years, many techniques have been proposed for automated FL (Fault Location) in the distribution systems [2-6], but these methods aim the location of the exact position of the fault which
affects their accuracy, and hinders their practical implementation. This led us to work on the location of the faulty section knowing that the companies already have the tools to search for the exact position of the fault in the section located off (vehicle of fault research). In order to efficiently increase the level of automation, and reduce the time of restoration of distribution systems, a new algorithm is presented in this article Fig. 1.

The main objective of the proposed methodology is to determinate apparent reactance which varies with the fault resistance; these parameters ($R_F$, $X_m$) are used as inputs of an artificial neural network (ANN) to have in the output the faulty section.

The proposed method was validated using real under-ground distribution feeder data and Matlab as an analysis tool.

The remainder of this paper is organized as follow: The estimation of the apparent reactance and the fault resistance is explained in sections 2 and 3 respectively; Section 4 presents the use of ANN to locate the faulty section of line; the tests’ results are shown in Section 5, whereas the conclusions of this work are presented in Section 6.
2. ESTIMATING THE APPARENT REACTANCE

The equations needed to calculate the apparent impedance and reactance from node t to the fault depend on the type of the fault. For us, we use the phase to ground fault parameters using the voltage and current at the time of fault and neglecting the effects of varying loads [7].

\[ Z_m = \frac{V_{am}}{I_{am}} \]
\[ X_m = \text{Im}(Z_m) \]

Where
- \( Z_m \) is the apparent impedance from node t to the fault;
- \( X_m \) is the apparent reactance from node t to the fault;
- \( V_{am} \) is phase m sending-end voltage (in Volts);
- \( I_{am} \) is phase m sending-end current (in amperes).

3. FAULT RESISTANCE ESTIMATION

After detection and classification of the faults, the FL process is initialized. First, the system is divided into \( n \) branches, where \( n \) is the number of possible paths (end nodes). For each branch, the fault resistance is estimated, using an impedance-based method [8-12]. After the estimation of the fault resistance and the apparent reactance, the procedure for determining the faulty section is started.

3.1 Mathematical development

The system illustrated in Fig. 2, contains a local bus, a generic faulted distribution line with constant fault resistance (\( R_F \)), and an equivalent load.

It is possible to show that for a single phase-to-ground fault in phase \( m \):

\[
\begin{bmatrix}
  x \\
  R_F
\end{bmatrix} = \frac{1}{M_{1m} I_{Fmi} - M_{2m} I_{Fmr}} \begin{bmatrix}
  I_{Fmi} & -I_{Fmr} \\
  -M_{2m} & M_{1m}
\end{bmatrix} \begin{bmatrix}
  V_{sm} \\
  V_{Fmi}
\end{bmatrix}
\]

Where the subscript indices \( r \) and \( i \) represent, respectively, the variables real and imaginary parts; the variables are as follow:

- \( V_{sm} \) phase m sending –end voltages (in volts);
- \( V_{Fmi} \) phase m fault-point phase voltages (in volts);
- \( x \) fault point to local bus distance (in kilometers);
- \( I_{Fmi} \) fault current (in amperes).
Also, $M_{1m}$ and $M_{2m}$ are defined in (3) and (4):

\[ M_{1m} = \sum_k (Z_{mkr} I_{Skr} - Z_{mk} I_{Ski}) \]  
\[ M_{2m} = \sum_k (Z_{mkr} I_{Ski} - Z_{mk} I_{Skr}) \]  

Where

- $k$ phases $a, b$ and $c$;
- $Z_{mk}$ impedance between phase $m$ and $k$ [Ω/km];
- $I_{Ski}$ phase $k$ sending-end current (in amperes).

The fault resistance is estimated by (5):

\[ R_F = \frac{-M_{2m} V_{Smr} + M_{1m} V_{Smi}}{M_{1m} I_{Fmi} - M_{2m} I_{Fmr}} \]  

From (5) it is possible to obtain the fault resistance from the parameters of the system: the fault current and the sending-end voltages. Since voltages are already known, an iterative procedure that updates the fault current is used to estimate the fault resistance.

### 3.2 Fault Current Estimation Procedure

In equation (5) the only unknown parameter is the fault current $I_{Fmr,i}$. All other variables are system parameters or measured variables.

Referring to Fig. 2, the fault current can be obtained by (6)

\[ I_{Fa} = I_{Sa} + I_{Ra} = I_{Sa} - I_{La} \]  

Where $I_{La}$ is the phase $a$ load current.

Nevertheless, the load current during the fault period is different from the prefault load current, due to voltage drops and systems dynamics during the fault. For this reason, an iterative technique used to estimate the load current during the fault, is described as follow: [12]

1) Load current during the fault $I_{La}$ is assumed to be the same as the prefault load current.
2) The fault current is calculated using (6)
3) Fault resistance is estimated using (2), (3), and (4).
4) Fault-point voltages are estimated using (7)

\[
\begin{bmatrix}
V_{Fa} \\
V_{Fb} \\
V_{Fc}
\end{bmatrix}
= 
\begin{bmatrix}
V_{Sa} \\
V_{Sb} \\
V_{Sc}
\end{bmatrix}
- 
\begin{bmatrix}
Z_{aa} & Z_{ab} & Z_{ac} \\
Z_{ba} & Z_{bb} & Z_{bc} \\
Z_{ca} & Z_{cb} & Z_{cc}
\end{bmatrix}
\begin{bmatrix}
I_{Fa} \\
I_{Fb} \\
I_{Fc}
\end{bmatrix}
\]  

(7)

5) Load current $I_{La}$ is updated using the fault-point voltages in (7) and (8):

\[ I_{La} = \begin{bmatrix} Y_{aa} & Y_{ab} & Y_{ac} \end{bmatrix} \begin{bmatrix} V_{Fa} \\
V_{Fb} \\
V_{Fc}
\end{bmatrix}^T \]  

(8)
\[ Y_{pq} = [ (l - x)Z_{pq} + Z_{Lpq} ]^{-1} \]  

Where

\[ Z_{pq} \] is the line impedance (mutual or self) between phase \( p \) and \( q \);
\[ Z_{Lpq} \] is the load impedance (mutual or self) between phase \( p \) and \( q \);
And \( l \) is the total line length.

6) Check if \( R_F \) has converged, using (10)

\[ |R_F(\alpha) - R_F(\alpha - 1)| < \delta \]  

Where \( \delta \) is a previously defined threshold value and \( \alpha \) is the iteration number.

7) If \( R_F \) has converged, stop the procedure; otherwise, go back to step 2).

The output of this procedure is the fault resistance, used with apparent reactance as inputs of our neural network.

4. NEURAL NETWORK STEP

4.1 Neural Network Application to FL

Artificial Neural Networks (ANNs) can be applied to fault analysis because they are a programming technique applicable to problems in which the information appears in a vague, redundant, distorted, or massive form. Also, they are able to learn using examples [13].

In the problems of FL, they are potentially applicable because:

- Many parameters must be considered;
- There are methods to simulate examples in a quick and reliable way;
- The ANN output is very fast, because its working consists in a series of very simple operations.

Although the programming using ANNs has great advantages, it also presents some disadvantages. Among them, the complexity of the type and network architecture selection (number of layer, number of neurons per layer, activation functions, learning algorithms parameters, etc.) can be emphasized.

The FL problem in distribution lines using ANNs consists in defining a neural network that allows obtaining the faulty section, using a small number of electrical parameters measured in a line terminal.

4.2 Selecting the Right Architecture

One factor in determining the right size and structure for the network is the number of inputs and outputs that it must have. The lower the number of inputs, the smaller the network can be. However, sufficient input data to characterize the problem must be ensured. As the apparent reactance includes the fault information in spite of varying with the fault resistance, we have chosen to use it as inputs of our ANN to have the faulty section in the output. Thus the network inputs \( X \) and output \( Y \) is:

\[ X = [X_m, R_F] \]  

(11)
Once how many inputs and outputs the network should have was decided, the number of layer and the number of neurons per layer was considered. After several trials, it was decided to use a neural network with thirty neurons in the hidden layer.

The final determination of the neural network requires the relevant transfer functions to be established. After analyzing various possible combinations of transfer functions used, such as logsig, tansig and linear functions, the tansig function was chosen as transfer function for the hidden layer, and the purelin function in the output layer [14].

4.3 Learning Rule Selection

The back-propagation learning rule is used in perhaps 80-90% of practical applications [15]. Improvement techniques can be used to make back-propagation more reliable and faster. The back-propagation learning rule can be used to adjust the weights and biases of networks to minimize the sum-squared error of the network. As the simple back-propagation method is slow because it requires small learning rates for stable learning, improvement techniques such as momentum and adaptive learning rate or alternative method to gradient descent, Levernberg-Marquard optimization can be used. Various techniques were applied to the different network cases, and it was concluded that the most suitable training method for architecture selected was based on the Levernberg-Marquard optimization technique.

4.4 Training Process

Order to train the network, a suitable number of representative examples of relevant phenomenon must be selected so that the network can learn the fundamental characteristics of the problem, and once the training is completed, the network provides correct results in new situations not envisaged during training.

The system that we have studied is a part of the underground distribution network of Independent Agency for the distribution of water and Electricity and liquid cleansing of Kenitra, Morocco.

It is a line from 20 KV distribution network of total length 7.5 Km, composed of 18 sections of different lengths, simulated using distributed parameter line model as shown in Table 1.

Matlab [16] simulates several cases of fault at different FL between 0-100% and for several fault resistances 0-100 Ω. Preprocessing is used to reduce the size of the neural network and improve the performance and the speed of learning. [17]

The apparent reactance and the fault resistance are calculated for each case using the sending-end current and voltages; the inputs were normalized in order to limit them between -1 and +1; the number of simulated faults is 10 at different locations and for 10 different resistances. Therefore, the total number is 18 * 10 * 10 = 1800.

The next step is to divide the data up into 70% for training, 20% for validation and 10% for test. The mean square error of our network is shown in Fig. 3.

5. TEST RESULTS

After training, the proposed algorithm is extensively tested using data never envisaged to verify the effect of the fault location (close or far from the input of the section), and of the fault resistance (0-100 Ω) on the performance of this method.

The performances of a neural network are usually measured by the errors on the training, validation and test sets, but often useful to investigate the network response in more detail.

Fig. 4 shows four curves, the first shows the outputs of training data according to their desired outputs, the second track outputs of validation data according to their desired outputs, the third
shows the outputs of test data according to their desired outputs and the fourth groups all the curves presented before. We can easily see that the outputs obtained have values around the desired value so this is a good result in condition not to have two confused outputs or an output far than their desired one. To verify this condition, the mean square error must have values between -0.5 and +0.5 to approach it to the desired value Fig. 5. Or values between -1 and +1 if we use MATLAB function round to close all numbers to the nearest integer Fig. 6.

In analyzing the results we can see that 98.5% of the values of the curve are located within the range of tolerance that has already defined [-0.5 0.5], which lets say 98.5 % of faults are recognized.

Figure. 3: Training figure using Levenberg-marquardt algorithm

Figure. 4: Regression analysis of training, validation and test data
Figure 5: Error on the outputs

Figure 6: Error on the outputs using MATLAB function ROUND

<table>
<thead>
<tr>
<th>TABLE 1: STUDIED SECTIONS OF LINES PARAMETERS</th>
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<tbody>
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<td>Section of line</td>
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6. CONCLUSION

The proposed algorithm allows us to locate the faulty section using the neural network that receives the apparent reactance and resistance of fault, calculated using the sending-end current and voltage, as inputs.

The performances of this algorithm are verified by several tests simulating 1800 case of phase to ground faults.

Simulation results show that 98.5% of simulated faults are exactly located, and for the rest (1.44%), this method indicates that the fault is located in the section before or after the one that is really faulty.

7. REFERENCES


