A NEW FAULT LOCATION TECHNIQUE ON RADIAL DISTRIBUTION SYSTEMS USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In this paper, an effective fault location technique is proposed. Using the current samples of the distribution feeder measured at the substation, the proposed technique first determines the type of fault. Furthermore, an artificial neural network (ANN) is trained for each type of fault. The ANNs are trained to estimate the fault distance to the substation (FDANN).The Inputs of the ANNs are data of 3 phase voltages, currents and active powers of the feeder are measured at the substation in pre-fault and fault stages. The proposed method does not need data of loads of consumers. The proposed method is tested on IEEE 34-bus test feeder. Each ANN is trained by operating patterns. In order for ANNs cover the total operating space of the radial distribution network; fault location, fault resistance and loads are changed in each pattern. The outputs of ANNs for the operating test patterns, not presented in the training stage, are shown the accuracy of the ANNs. The trained FDANNs can estimate fault distance to the substation; even the structure of the distribution network is changed. Proposed method is effective while the input data are contained errors of measuring.

1. INTRODUCTION

A few fault location studies have been conducted on the distribution systems due to their high complexity and difficulty caused by non-homogeneity of line, fault resistance and load uncertainly. Previously proposed approaches for estimating the locations of distribution line faults consist of using voltages and currents measured at the line terminal. The methods used in this approach can be divided into two categories. The first category uses the high Frequency components of currents and voltages caused by the faults which start voltage and current travelling waves between the fault and the line terminals [1]. This method is similar to that proposed for transmission lines and is complex and expensive. The methods in the second category use the fundamental Frequency voltages and currents at the terminals of a line and parameters of the line and loads [2]. The method consists of calculating the line impedance as seen from the line terminal and uses the calculated impedance to estimate the distance of the fault from the line terminals. Reference [2] does not consider the dynamic nature of the loads and multiphase taps which are normally encountered in such cases. Another technique, that uses the fundamental frequency components of voltages and currents measured at the line terminal, has been proposed for estimating the locations of shunt faults on radial distribution lines [3, 4]. The technique is suitable for non-homogeneous lines with or without capacitor banks and dynamic loads. However, this technique does not consider the presence of the laterals in the distribution system. Utilities estimate fault locations in distribution lines by computing the impedance seen from the line terminal from the voltages and currents available from reclosers. The fact that a feeder has many branches compounds the complexity of finding fault location. This is mainly due to the fact that estimating the fault location based on the voltage and current signals yields more than one location. In recent years artificial neural networks have been proposed as an alternative method for solving certain complicated power system problems where the conventional techniques have not achieved the desired efficiency. In this paper, using data are measured at the substation, for each type of fault, an artificial neural network (ANN) is trained to estimate fault distance to the substation directly. The proposed method does not need data of loads of consumers. The proposed method is tested on IEEE 34-bus test feeder [5] simulated in DIgSILENT Power Factory 13.2 software. The outputs of the ANNs for operating test patterns, not presented in the training stage, are shown the accuracy of the ANNs. Sensitivity of the proposed method is assessed finally.

2. FAULT LOCATION TECHNIQUE USING ARTIFICIAL NEURAL NETWORK

Proposed technique contains two stages. First, the type of fault is determined using current phasors measured at the substation. Then an ANN is trained for each type of the fault. The ANNs are trained to estimate fault distance to the substation (FDANN), directly. The proposed method does not need data of loads of consumers. Inputs of the ANNs are data of 3 phase voltages, currents and active powers of the feeder are measured at the substation in pre-fault and fault stages. When a fault is detected, pre-fault active power, voltage and current phasors are saved. These are the phasors that were calculated one cycle before the inception of the fault. This margin is important to avoid an overlap of the pre-fault and fault data. Fault data are collected three cycles after the detection of the fault. This is done to minimize the effect of current of motors. It is worth considering that the distribution system is a radial network with many branches. That is why multiple fault locations might be selected as candidates. Using other protection instruments such as Fault Detector, actual fault location might be selected from among probable fault locations.

2.1. Determination the type of fault

If one or more of the line currents (I_a, I_b, I_c) are greater than a threshold (I_t) it is assumed that a fault has occurred. The magnitude of the zero sequence current increases beyond its normal value when a ground fault is experienced. If the magnitude of the estimated zero sequence current (I_0) is more than a threshold (I_{t0}) it is assumed that one or two phases are short circuited to ground. The type of fault determines from the fault current phasors using table 1.

Table 1. Determination the type of fault

type of fault	$\lvert I_a \rvert > \lvert I_t \rvert$	$\lvert I_b \rvert > \lvert I_t \rvert$	$\lvert I_c \rvert > \lvert I_t \rvert$	$\lvert I_0 \rvert > \lvert I_{t0} \rvert$
A-G	true	false	false	true
B-G	false	true	false	true
C-G	false	false	true	true
A-B	true	true	false	false
A-C	true	false	true	false
B-C	false	true	true	false
A-B-G	true	true	false	true
A-C-G	true	false	true	true
B-C-G	false	true	true	true
A-B-C	true	true	true	-

2.2. Fault location estimator FDANN

In this paper, a multilayer feed forward neural network is adopted and trained for fault location analysis. Figure 1 illustrates flowchart of proposed method.

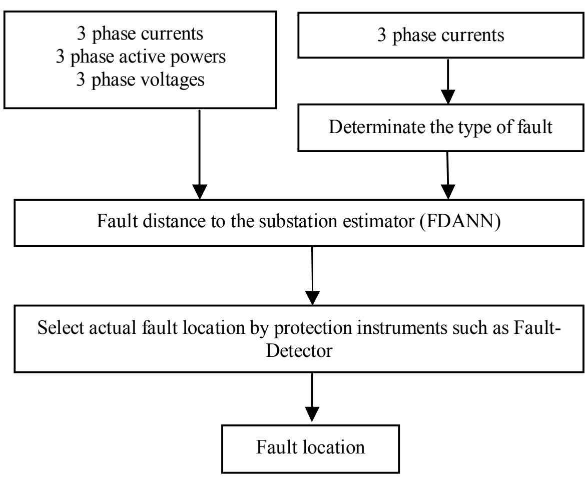

Figure 1. Flowchart of the proposed fault location method by using the FDANN

3. SIMULATION STUDIES

In order to demonstrate the effectiveness of the proposed fault location approach, the FDANN is applied for IEEE 34-bus test feeder consisting of 34 nodes, 32 lines, 6 spot loads, 19 distributed loads and 2 shunt capacitors [5]. The capacitors are connected to nodes 844 and 848. **This feeder is a radial network with unbalanced loads and non-homogeneity lines.** The base voltage of feeder is 24.9 kV. There is a 24.9/4.16 kV transformer between nodes 832 and 888. That is why; the line between nodes 888 and 890 is 4.16 kV. Nine lines are single phase. This feeder is simulated in DIgSILENT Power Factory 13.2 software. Appendix 1 shows single line diagram of the studied feeder.

3.1. Training data

In order to ANNs cover the total operating space of the radial distribution network; fault location, fault resistance and loads were changed in each pattern. Each pattern is contained data which achieved from load flow of the feeder in pre-fault and fault stages. In order to the voltage of every node does not exceed 0.90pu and 1.05pu; spot loads and distributed loads selected properly. For each pattern, steady state pre-fault operating condition and fault condition associated with all line faults are calculated. Then these values are passed to FDANNs for training and testing. Training data should be able to represent whole operating space of feeder. For this purpose, 2366 patterns are produced for each type of fault as follow. For each kilometer of every line 25 short circuits are faulted. The location of every fault is selected randomly on each line. In each fault case unbalanced loads are produced randomly and fault resistance are produced randomly between [0, 50] ohm. Having different voltage level, line between nodes 888 and 890 is not presented in training patterns. Each case is simulated in DIgSILENT Power Factory 13.2 software and 3 phase current phasors, voltage phasors and active power phasors of feeder are calculated at the substation. Pre-fault phasors are calculated one cycle before the inception of the fault and fault phasors are calculated there cycles after the inception of the fault. The zero sequence current is used as an input of FDANNs for presenting effect of ground fault.

3.2. Training FDANNs

All 2366 training patterns are divided into two categories as training patterns and test patterns. 75 percent of patterns are used as training patterns and the others as testing patterns. Using Neural Network Toolbox of MATLAB 7.8.0 software, individual FDANNs are trained by the algorithm of Levenberg-Marquardt. For each type of fault is shown in table 1, one FDANN is trained. Error of each FDANN for the testing patterns, not presented in the training stage, is shown in table 2. Error of each FDANN for testing patterns is evaluated using equation 1:

$$mse = (1/n)\sum_{i=1}^{n}(FD_i - Y_i)^2 \quad (1)$$

Where:
mse: mean squared error
n: number of testing patterns
FD_i: fault distance to substation of ith pattern
Y_i: FDANN output of ith pattern
Table 2 shows the test errors of single phase short circuits are bigger than the other errors.

Table 2. Error of each FDANN for the testing patterns

type of fault	Error of FDANNs for testing patterns (mse)
A-G	0.024
B-G	0.028
C-G	0.026
A-B	0.0057
A-C	0.0053
B-C	0.0058
A-B-G	0.0030
A-C-G	0.0035
B-C-G	0.0032
A-B-C	0.0016

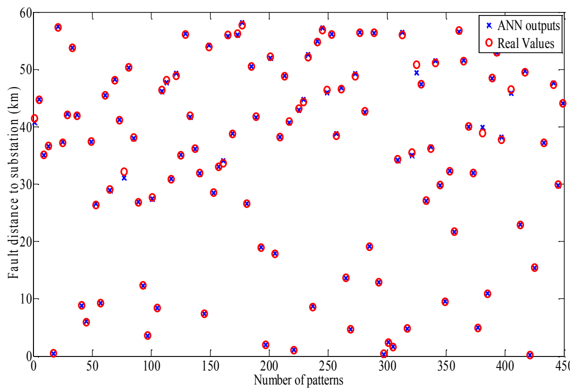

Figure 2. FDANN outputs and target values for the test patterns of A-G fault

3.3. Effect of changing of the structure of the feeder on performances of FDANNs

In this paper, performances of FDANNs are assessed when the structure of the distribution network is changed. Two new structures are assumed for the distribution feeder. In first structure (S1), configurations of eight lines are changed; but the lengths of them are fixed. The configurations of the lines of the network are explained in reference [5]. Table 3 shows difference between the basic structure of the feeder and the changed structure (S1). Error of each FDANN for testing patterns of this new structure (S1) is shown in table 4. Figure 3 illustrates the outputs of FDANN compared target values of the test patterns of A-G fault for S1. Results of table 4 shows that the trained FDANNs can estimate fault distance to substation; even the structure of the distribution network is changed. In second structure (S2), two new lines are added to the base network. First line (L1) is connected to node 822. The length of L1 is 5km and number of its configuration is 303 [5]. Second line (L2) is connected to node 840. The length of L2 is 5km and number of its configuration is 301 [5]. Node 822 and node 840 are farthest terminals. Distances of nodes 822 and 840 to the substation are 51.11km and 57.68km respectively. The outputs of the trained FDANNs are acceptable when fault occurs on two new lines. Error of each FDANN for faults occurred on two new lines are shown in table 4.

Table 3. Difference between the line configurations of the basic structure of the feeder and the changed structure (S1)

Terminal nodes of line	Length of line (km)	Configuration of the basic structure	Configuration of new structure (S1)
806-808	9.8237	300	301
850-816	0.1	301	300
852-832	0.003	301	300
834-842	0.085	301	300
820-822	4.188	302	303
824-826	0.9236	303	304
846-848	0.1615	301	300
862-838	1.481	304	303

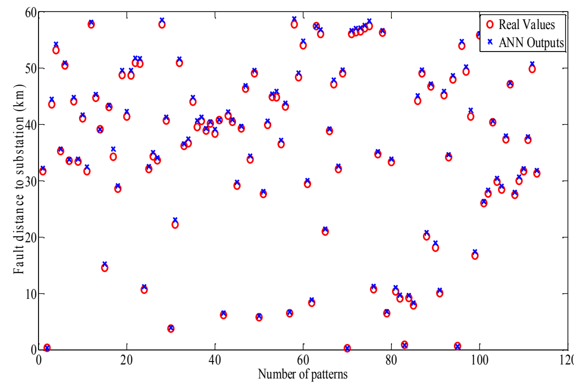

Figure 3. FDANN outputs and target values for the test patterns of A-G fault on structure S1

Table 4. Error of each FDANN for the testing patterns of the changed structures

type of fault	Error of FDANNs for testing patterns (mse)	
	S1	S2
A-G	0.204	0.181
B-G	0.208	0.164
C-G	0.207	0.160
A-B	0.175	0.162
A-C	0.171	0.165
B-C	0.178	0.163
A-B-G	0.163	0.152
A-C-G	0.165	0.150
B-C-G	0.162	0.154
A-B-C	0.148	0.133

3.4. Sensitivity studies

The accuracy of the fault location estimates depends on the accuracy of the input data. The accuracy of the voltage and current phasors depends on the quality of transducers that sample voltages and currents. Sensitivity studies are performed to determine the effect of the errors in the input data on the accuracy of the proposed technique. The ranges of errors in voltage and current phasors are selected considering the IEC standards for voltage and current transformers. In this paper, for sensitivity study, 2366 patterns are regenerated with Errors in voltage phasor magnitudes from -5% to +5% while errors for current phasors magnitude are varied from -3% to +3%. Errors for active power phasors magnitude are varied from -7.5% to 7.5%. These new patterns which are contained errors of measuring are divided into training and testing patterns. Then for each type of fault, an FDANN is trained using the new training data. Table 5 shows the error of each FDANN for the testing patterns while all input data are contained errors of measuring.

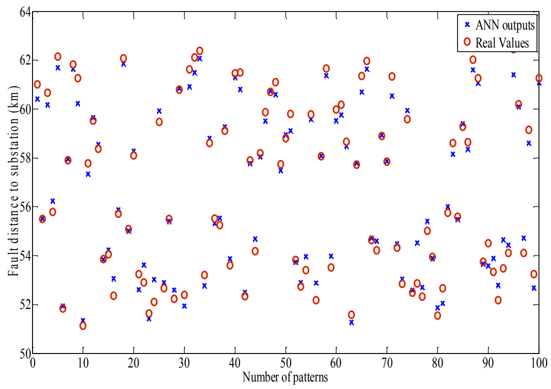

Figure 4. FDANN outputs and target values for the test patterns of A-G fault on structure S2 (faults on 2 new lines)

4. CONCLUSIONS

In this paper, a novel approach has been proposed for fault location by means of artificial neural network (ANN) as an interpolating tool. The ANNs are trained to estimate fault distance to the substation (FDANN) for each type of fault. Inputs of the ANNs are data of 3 phase voltages, currents and active powers of the feeder are measured at the substation in pre-fault and fault stages. The proposed method is tested on IEEE 34-bus test feeder successfully. The outputs of the ANNs for operating test patterns, not presented in the training stage, are shown the accuracy of the ANNs. The performances of the trained FDANNs are tested successfully when the structure of the feeder is changed. The accuracies of the FDANNs are acceptable while data are contained errors of measuring.

Table 5. Error of each FDANN for the testing patterns that are contained errors of measuring

type of fault	Error of FDANNs for testing patterns (mse)
A-G	0.041
B-G	0.042
C-G	0.040
A-B	0.0096
A-C	0.0092
B-C	0.0098
A-B-G	0.0081
A-C-G	0.0084
B-C-G	0.0082
A-B-C	0.0065

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Appendix 1

Single line diagram of IEEE 34-bus test feeder: