A SINGLE END FAULT LOCATOR OF TRANSMISSION LINE BASED ON ARTIFICIAL NEURAL NETWORK

BỘ ĐỊNH VỊ SỰ CỐ SỬ DỤNG DỮ LIỆU ĐO TẠI MỘT ĐẦU ĐƯỜNG DÂY ĐƯỜNG DÂY TẢI ĐIỆN BẰNG MẠNG NƠRON NHÂN TẠO

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Received January 18, 2013; accepted April 18, 2013

ABSTRACT

Most numerical protection relays in Viet Nam use single ended fault location algorithms. While this method is simple and fast, the following commonly encountered factors can severely degrade accuracy such as high fault resistance, zero sequence, mutual coupling and non homogeneous power systems...

This paper presents fault location method for overhead transmission lines based on Artificial neural network (ANN), then prediction model and simulation analysis of 110kV overhead line have built by Matlab software. The trained ANN for fault classification and fault distance location was used Levenberg Marquardt training algorithm. This method selects magnitude of current and voltage form all phases of the overhead line as the inputs of the ANN that can output fast and precision result. The result shows that the ANN combines as analysis tool to provide fault information that is more reliability and accurate than provided by a traditional electromechanical relay and it also overcomes the limitations of the single ended fault location algorithms.

Keywords: numerical protection relays, location algorithms, zero sequence, non homogeneous power systems, fault location method

TÓM TẮT

Tại Việt Nam, hầu hết các rơle bảo vệ kỹ thuật số sử dụng thuật toán định vị sự cố sử dụng dữ liệu đo lường tại một đầu đường dây. Bên cạnh tính năng đơn giản và nhanh chóng, thì các yếu tố như điện trở sự cố, thành phần thứ tự không, hệ số hỗ cảm đường dây song song và hệ thống không đồng nhất... làm ảnh hưởng lớn đến cấp chính xác của phép tính.

Bài báo trình bày phương pháp định vị sự cố, sử dụng mạng nơron nhân tạo (ANN) cho mô hình hệ thống đường dây 110kV được xây dựng bằng phần mềm Matlab. ANN cho phép nhận dạng sự cố và xác định chính xác vị trí điểm sự cố bằng thuật toán huấn luyện Levenberg Marquardt. Để làm được điều này, phương pháp sử dụng giá trị độ lớn của dòng điện và điện áp các pha trên đường dây đưa vào đầu vào ANN và thu được kết quả đầu ra nhanh chóng và chính xác. Từ kết quả cho thấy ANN được kết hợp như là công cụ phân tích, cung cấp thông tin sự cố tin cậy và chính xác hơn rơle truyền thống và có thể khắc phục được các hạn chế của thuật toán đo lường tổng trở sử dụng dữ liệu tại một đầu đường dây.

1. INTRODUCTION

In Viet Nam, one terminal data algorithms are the most widely which also classified as the impedance based method, consists of calculating line impedances as seen from the line terminals and estimating distances of the faults on protective relays at each individual substation because of limited access of data between two substation terminals. However, the methods are impacted by too many factors in such techniques the influence of fault resistance and fault inception angle are not taken into account. Furthermore their accuracy is degraded when the line is fed from another terminal which make them do not have sufficient accuracy [1]. So that, we will demonstrate in this paper that new fault location method based on neural network gives significant advantage over single ended methods in accuracy and provides accuracy comparable with a fault locators at no extra cost.

This paper presents an application of ANN for fault estimation along with fault location in a double end fed single circuit 110kV transmission line by Matlab Simulink, which employs the fundamental components of three phase voltages and currents measured at one end only. The effects of varying fault location, fault time, fault resistance and remote source infeed have considered in this work. The obtained results clearly show that the proposed technique can accurately classify the fault type and locate faults on transmission lines under various fault conditions.

2. POWER SYSTEM UNDER STUDY

The power system model is simulated in MATLAB® 2010 software as show in Fig.1. It is a 110 kV, 50 Hz, 50km transmission line system. This model consists of:

1. The transmission line: three phase section line is used to represent the transmission line. Line sequence impedance:

   RL1=0.0321 (Ω), RL0=0.347(Ω).

   LL1=0.473 (mH), LL0=1.370(mH).

   CL1=0.038 (μF), CL0=0.038 (μF).

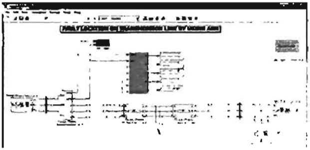

Fig.1. Power system model simulated in Matlab Simulink software.

2. A numeric display block to indicate the calculated random per unit length of the fault location and fault types.
3. Three phase fault block to deduce fault types and specify the parameters.
4. Three-phase measuring blocks to measure the three phase line and load current and voltage values.
5. An ANN based relay FL is located at bus S has been developed for fault detection and fault distance location that will be presented detail in section III.
6. Preprocessing of Voltage and Currents signal: Preprocessing is a useful method that significantly reduces the size of the neural network and improves the performance and speed of training process. Three phase voltages and three phase current input signals were sampled at a sampling frequency of 1 kHz and further processed by simple 2nd-order low-pass Butterworth filter with cut-off frequency of 400 Hz. Subsequently, one full cycle Discrete Fourier transform is used to calculate the fundamental component of voltages and currents. The input signals were normalized in order to reach the ANN input level (0, 1) [2], [3].

3. PROPOSED ANN BASED FAULT LOCATOR

The various steps used to implement a neural network in the fault classification and distance location algorithm in transmission line is described in fig 2.

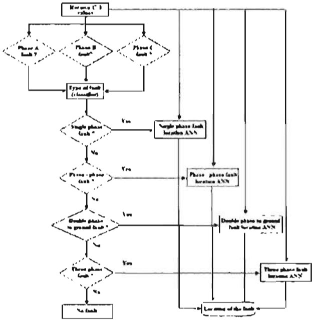

Fig.2 Flowchart depicting the outline of the proposed scheme.

The entire data that is collected is subdivided into two sets namely the training and the testing data sets. The first step in the process is fault detection. Once we know that a fault has occurred on the transmission line, the next step is to classify the fault into the different categories based on the phases that are faulted. Then, the third step is to pin point the position of the fault on the transmission line. The goal of this paper is to propose an integrated method to perform each of these tasks by using artificial neural networks. For each of the different kinds of faults, separate neural networks have been employed for the purpose of fault location [5].

A. Selecting the ANN architecture

The network inputs chosen here are the magnitudes of the fundamental components (50 Hz) of three phase voltages and three phase currents of at one end.

The basic task of fault classification is to determine the type of fault along with the phase. The four inputs [Ia, Ib, Ic, In] and four outputs [A, B, C, N] are designed for the fault classification network as shown in fig.3. Four outputs corresponding to three phases A, B, C and neutral are present in the fault loop [4].

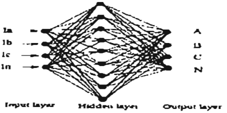

Fig.3. ANN consisting of four inputs, one hidden layer with five neurons and four outputs.

Similarly, for fault location task, where we have to determine the distance to the fault, it is decided that the distance to the fault in km with regard to the total length of the line would provided the only output by the fault location network. Va, Vb, Vc, Ia, Ib, and Ic for phases have been selected as input to neural network, thus total 6 inputs are given to neural network for fault location task.

The determination of number of neurons in hidden layers is very important as it affects the training time and generalization property of neuron network. The most popular approach to finding the optimal number of neurons in hidden layer is by trial and error. The finally selected of suitable network shows satisfactory results.

For fault classification task, the selected network structure as shown in Fig. 3. The final determination of the neural network requires the relevant transfer functions in the input, hidden and output layers to be established. The function "logsig" in input layer, hidden layer and "satlin" in the output layer is used. Depending on the fault type, which occurs on the system, various outputs of the network should be 0 or 1 as shown in table 1.

Table 1: Neural network desired outputs

Fault type	A	B	C	N
AN	1	0	0	1
BN	0	1	0	1
CN	0	0	1	1
AB	1	1	0	0
BC	0	1	1	0
AC	1	0	1	0
ABN	1	1	0	1
BCN	0	1	1	1
ACN	1	0	1	1
ABC	1	1	1	0

For fault distance location task, the architectures of ANN as shown in table 3. The function "logsig" in input layer, hidden layer and "purelin" in the output layer for FL is used.

B. Training process

Simulation results using data from the power system model presents in table 2 that contains the parameter values used to generate data training sets for the ANNs of the fault detector and the fault locator. Each type of faults at different fault locations, fault resistance and fault times have simulated. The total number of fault simulated are 11 (fault locations) x 9 (fault resistance) x 10 (type of faults) x 2 (fault times) 1980 for fault classification and fault distance location task.

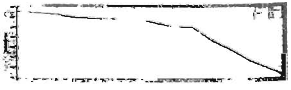

Fig.4. Mean-square error performance of the network

Table 2. Parameter settings for generating training patterns.

Case No	Parameters	Set value
1	Fault type	AG, BG, CG, AB, BC, AC, ABG, BCG, ACG, ABC
2	Fault location L_f [km]	1, 5, 10, 15, 20,25, 30, 35, 40, 45, 49
3	Fault time [s]	0.06s, 0.065s
4	Fault resistance R_f [Ω]	1, 3, 5, 7, 10, 20, 30, 40, 50

For fault classification task, the next step is to divide the total data into training, validation and test subsets. One fourth of the data (495) for the validation set, one fourth for the test set (495) and one half for the training set (990) have been used. The data sets were picked as equally spaced points throughout the original data. The networks for fault classification was trained using Levenberg–Marquardt training algorithm of neural network toolbox of Matlab with the mean squared error set goal at 1e-06. This learning strategy converges quickly to the desired set goal. The mean squared error (mse) of fault classification for training data set decreases in 14 epochs to 1.54e-7 as shown in figure 4 by blue line. Further, the validation and test curves are very similar. The best validation data set performance curve is shown in green having "mse" of 1.8257e-7 in 14 epochs a for fault classification estimation.

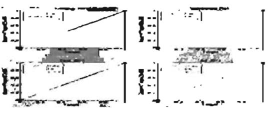

Fig.5. Regression fit of the outputs vs. targets for the network

Fig 5 shows a plot for the best linear regression result that relates the targets to the outputs. The correlation coefficient (r) is a measure of how well the neural network's targets can track the variations in the outputs (0 being no correlation at all and 1 being complete correlation). The correlation coefficient in this case has been found to be 1 in this case which indicates excellent correlation.

Table 3. Architectures of ANN Based Fault Locators

S. No	Type of network locator	Number of neurons: Input layer	Hidden layer		Output layer	MSE	No. of epoch
1	AG	6	2		1	9.8e-7	446
2	BG	6	5		1	9.8e-7	226
3	CG	6	9		1	9.9e-7	231
4	AB	6	25	4	1	9.9e-7	342
5	BC	6	22	4	1	9.7e-7	429
6	AC	6	20	4	1	9.8e-7	398
7	ABG	6	7		1	9.9e-7	350
8	BCG	6	6		1	9.5e-7	148
9	ACG	6	3		1	9.9e-7	387
10	ABC	6	35	16	1	9.9e-5	342

For fault distance location task, the total number of fault simulated of training data is 1980 for the fault location estimation task, and it does not require a separate validation or testing set. The desired and actual output of FL obtained after training with the Levenberg–Marquardt training algorithm, fault location estimation network as shown in table 3. The number is epochs required for training varies from 148 to 446 to reduce the mean square error below 9.91e-5. As the training is done off line, the iterations and time required for training are not of great concern.

4. TEST RESULTS OF ANN BASED FAULT CLASSIFICATION AND LOCATOR

The trained ANNs based Fault detector and locator modules were then extensively tested using independent data sets consisting of fault scenarios never used previously in training. Fault type, fault location and fault time were changed to investigate the effects of these factors on the performance of the proposed algorithm.

The estimation accuracy in fig 6 to 14 is evaluated by the percentage error calculated as:

$$\%Error = \frac{|\text{Actual Location} - \text{Estimated Location}|}{\text{line the of Length Total}} \times 100$$

A. Test results of single phase to ground fault

The network is tested for single phase to ground fault. The test results of ANN based fault classifier and locator modules are shown in fig 6, 7 and 8.

Fig.6. Test results of "A" phase to ground fault

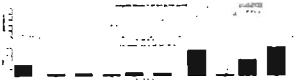

Fig.7. Test results of "B" phase to ground fault

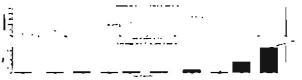

Fig 8. Test results of "C" phase to ground fault

Reviews: Output of ANN for CG fault is the highest error. The estimated fault location is 45.621km at 82.5ms, R_f = 85Ω as against the actual fault location 47km as shown in Fig. 8 thus it is located accurately with Max error is 2.759% of the line length.

B. Test results of phase to phase fault

The test results of the ANN based fault classifier and fault locator module for phase to phase faults are shown in Fig.9, 10 and 11.

Reviews: Output of ANN for AB fault is the highest error. The estimated fault location is 48.335km at 82.5ms, R_f = 85Ω as against the actual fault location 47km as shown in Fig. 9, thus the fault located is estimated accurately with 2.669% error.

Fig.9 Test results of "AB" fault

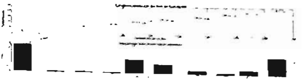

Fig.10. Test results of "BC" fault

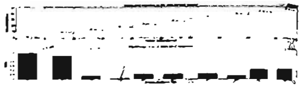

Fig.11. Test results of "AC" fault

C. Test results of double phase to ground fault

The network is tested for double phase to ground faults. The test results of ANN based fault classifier and locator modules are shown in fig 11, 12 and 13.

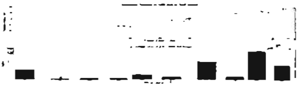

Fig.11. Test results of "ABG" fault

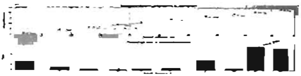

Fig.12.Test results of "BCG" fault

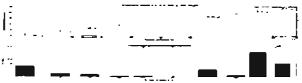

Fig.13 Test results of "ACG" fault

Reviews: Output of ANN for BCG fault is the highest error. The estimated fault location is 43.131km at 80ms, R_f = 75Ω as against the actual fault location 42km as shown in Fig. 12 thus it is located accurately with max error is 2.262% of the line length.

D. Test results of three phase fault

Fig. 14 shows the test results of the ANN based fault classifier and fault locator module for "ABC".

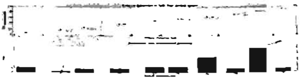

Fig.14. Test results of "ABC" fault

Reviews: The estimated fault location is 43.52km at 80ms, R_f = 75Ω as against the actual fault location 42km, thus the fault located is estimated accurately with max error is 3.044% of the line length.

5. CONCLUSTION

This paper introduces an accurate fault location technique based on ANN is developed, as an ANN is trained to classify the fault type and separate ANNs are designed to accurately locate the actual fault position on a transmission line. In all the fault cases, the proposed ANN is able to respond to the fault correctly in a timely fashion. The faults identified just in 20ms after the fault inception, which shows that the ANN is able to detect and classify the fault quit fast. The ANN outputs remain stable after identifying the fault. Also the fault location results show that the errors in locating the fault are in the range of 0.04% to 3.044%. Thus, all test results are correct with reasonable accuracy.

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