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FAULT LOCATION DETECTION FOR UHV LINE

[1]BANU.G
Electrical & Electronics Engineering Department, EASA College of Engg & Technology, Coimbatore, Tamil Nadu,India

Abstract- This paper presents two different approaches to determine the fault distance under different types of fault on transmission line. The proposed technique uses two methods such as Modular ANN and ANFIS to find fault detection on UHV transmission line using one end data. Fault conditions are simulated using Matlab/simulink to obtain voltage and current signals. The proposed algorithm is tested for different locations, different inception angles and different types of faults. The performance of two systems are compared and analyzed. The result shows that
ANFIS approach gives correct fault location with better accuracy.
Keywords**: Modular ANN, ANFIS , Fault location, UHV Line , One end data.**

I. INTRODUCTION

An overhead transmission line is a part of the main components of an electric power system. As transmission lines are exposed to nature, the probability of fault occurrence on a transmission line is quite large.Due to rapid growth of power grid all over the world, a huge number of new transmission and distribution lines are installed. Due to the increased deregulation, reliable and uninterrupted supply is required by consumers who are very sensitive to power outages. However, the transmission lines are exposed to a fault because of lighting, short circuits, faulty equipment, mis-operation, human errors, overload, and ageing. For the reliability of fault protection of modern power system, a precise fault location system is required, which plays an important role in the power system due to cost reduction and less time for energy supply restoration.

The main protections in UHV line often adopts the pilot scheme to achieve fast-tripping for the whole lines, such as current differential protection, negative directional pilot protection and pilot distance protection. The requirements for backup protection are also to be with least time delay and maximum protection zone. Distance protection is certainly the first choice, but the influence of shunt capacitance should be included, especially used for backup protection with the possibility of line length nearly 1000 km distance.

Since 1990s, a large number of works have been published in employing ANNs to the protection purpose in (Osman *et al.* [1]. Such works are based on pattern recognition and function fitting and try to deal with those aspects above that can severely influence the protective scheme. This enormous interest in ANNs is related to the enormous potentialities of this tool.
Majority of the work mentioned here made use of feed-forward multilayer perceptron technique. Purusothama *et al.*[2] proposed the ANN approach to estimate the fault location and fault resistance on 400 kV transmission line. In this technique, local end data and two end data were used.

A novel fault classification technique of double circuit lines based on a combined unsupervised/supervised neural network was presented [3] (Aggarwal *et al.* 1999). It considered only A-G, B-G, A-B-G, and A-C faults and other types of faults have not been considered.

The SVM approach was also used by Salat *et al.* [4] to single circuit transmission lines for fault location. Das *et al* used a fault classification algorithm based on the fuzzy logic system was presented. Nevertheless, this algorithm is valid only for a less range variety of fault resistance. Lahiri *et al.* [6] proposed the modular neural network for fault direction discrimination at 230 kV transmission line. The direction of fault for different input vectors were discriminated by using modular ANN. The fault distance was not identified and classified.
Now a days, the intelligent computational techniques such as ANN, Fuzzy Inference System (FIS), and ANFIS are used to find the fault location. Without much analysis, the process is re-established by using intelligent computational techniques. Thus, these techniques are used without a simple and well-defined mathematical model. Mahanty *et al.* [7] proposed fuzzy logic technique to identify the fault location. This approach used only the current samples from one end. The different types of fault have been identified.

A combination of a fuzzy logic and ANN was proposed by Souza *et.al.* [8], in which the information from alarms and protection relays were processed for identifying the faulty section and faulted components. A combination of wavelet and ANN approach using two end data has been proposed in Silva *et al*[9]. for fault identification and detect the fault location. The approach uses the oscillographic data from the fault recorders by using the communication networks between the digital fault recorder and remote end. The different techniques like wavelets, impedance method, and ANN were used to analyse voltage and current signals. This method provides the fault location in kilometres instead of exact fault point which eventually provide information about fault location in terms of kilometre distance rather than the exact fault point [10].

Under a different fault condition, the ANFIS was proposed by Sadeh *et al.* [11] to find a fault and classify the fault type for both overhead and underground transmission line It used the fundamental frequency of three-phase current and neutral current as inputs while fault location was calculated in term of kilometre distance. The neural networks were used to improve the operation of the fuzzy inference system. The work presented in this paper deals with fault distance location using Modular artificial neural network and ANFIS for all the types of faults in a transmission lines. Throughout the study a 1000 kV transmission line of 360 km length has been chosen as a representative system. The work reports the results of extensive "offline" studies using the Matlab and its associated toolboxes: Simulink, Sim Power Systems and Neural Network Toolbox. The neural networks based scheme has been developed for transmission line using fundamental components of three-phase voltages and currents. A large number of fault samples data have been generated using MATLAB considering wide variations on fault conditions such as fault locations, fault resistances, fault inception angle, and fault types.
The following two ANN architectures were explored for this task:
(i) Modular ANN for all type of faults(consisting five ANN modules).
(ii) ANFIS for all type of faults

II. Modular ANN

ANN characterized by a series of independent neural networks is known as modular ANN. Each independent neural network is used as a module and it is operated on separate inputs to accomplish some subtask of the task. The outputs of each module are taken by the intermediary and the output is produced by processing it. The intermediary only accepts the modules' outputs; it does not respond to signal. The modules do not interact with each other. A large, unwieldy neural network is reduced to smaller in the modular network and more manageable components which are the major benefits of the modular neural network. There are some tasks which appear for practical purposes.

The connections are increased at daunting rate as nodes are added to the network. The computation time depends on the number of nodes and their connections. Hence, any increase in nodes causes drastic consequences in the processing time. The task is further compartmentalized. So the possible connections are limited, and the subtasks are executed more efficiently.

In this approach, any task is divided into some of the possible subtasks where each one is accomplished by an individual neural network. Finally, all network outputs were integrated to achieve the overall task. Obviously, the approach has the advantages of simplicity, higher accuracy, less training sets and training time, easier interpretation, model complexity reduction, and better learning capability.

Thus, the memory requirement of the modular network is not large. In a modular network, the training data is reduced according to the type of fault. Hence, it does not require large memory during the training process. Four different ANN modules were developed to process different fault type, i.e. phase to ground fault, double phase to ground faults, phase to phase faults and three phase faults. Based on the fault type, an appropriate network detects and classifies the fault.

In recent times, the conventional standalone ANN was used in (Coury *et al.* 2002) to protect the three - phase single and double circuit lines, because of its adaptability and nonlinear mapping behaviour. The architectures and learning rules (supervised and unsupervised) were varied in the conventional ANN. In three- phase transmission line, the three- phase voltage and current were taken as input patterns for conventional ANN. If the fault patterns or data set were increased, the complexity of ANN was increased. Due to this, the redundancy of ANN was caused. It led to numerical problems and probability of mapping the input- output behaviour is quite low.

Hence, the modular ANN is proposed in the present work. The large data set from a large number of faults with the different fault condition. The computational time is reduced in the modular ANN due to high learning capability and of parallel processing. The proposed MANN approach locates all types of fault in the transmission line, by using the different neural network structure for different types of fault.

2.1 Selection of Input and Output of Network

The number of inputs and outputs are one of the main factors to determine the right size and architecture for the neural network. For the less number of inputs, the network will be small. However, sufficient input data should be ensured to characterize the problem. The data from one end were used for the fault location.
Hence, the network input chosen here are the magnitudes of the fundamental components (50 Hz) of three-phase voltage and three-phase current of the circuit. As the basic task of fault location is to determine the distance to the fault, fault distance location (L_f), in km about the total length of the line, is the only output provided by the fault location network. Thus, the input X and the output Y of the fault location network are given by:

$$X= V_a, V_b, V_c, I_a, I_{b,} I_c \quad (1)$$

$$Y=L_f \quad (2)$$

The purpose of the fault location task is to estimate the exact fault location. Consequently, only obtained outputs by the fault location algorithm corresponding to the fault distance will be provided by the proposed modular neural network based on fault locator.

2.2 Fault Patterns Generation and Processing

As the network is trained with suitable examples of the relevant phenomenon, the fundamental characteristics of the problem can be learnt by a network. The fault location was estimated by the fault locator the transmission line. While the number of hidden layers and neurons in the layer were chosen, its attribute should be maintained well for generalization. This is the major issue while designing the architecture of ANN based on a heuristic approach.

The ANN architecture includes the number of inputs and the number of neurons in hidden layers which are determined by testing with various network configurations. After several trials with modification of the ANN architecture, a three-layer neural network has been used to obtain the best performance with seven inputs, one output, and the optimal number of neurons in the hidden layer. The architecture of a single ANN-based fault locator is 7-10-1.

2.3 Training Data

A large number of training data were generated for different ANNs based on fault location using MATLAB software. The various fault conditions were considered as prescribed in such as different fault locations L_f, different fault inception angles and various fault (R_f =30Ω, 50Ω ,60Ω, 100Ω). The total number of ground faults simulated were = 7(3 LG+3LLG +1LLLG)*4 no. of fault locations (L_f =100 km,150 km, 200 km, 250km)*4 fault inception angle (Φ_i = 0°, 90°,120°, 200°)*2(fault resistance) = 224.

The total number of line faults simulated were = 4(3 LL+1LLL)*4 no. of fault locations(100 km,150 km ,200 km, 250 km)*4 (fault inception angle 0°, 90°,120°, 200°)*2(fault resistance) = 128.The total fault cases were 352. The neural network was trained with 120 voltage data and 120 current data. The 352 fault cases were analysed with these 240 training data Training matrices were built in such a way that the network trained produces an output corresponding to the fault distance location.

III. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

ANFIS is a simple data learning technique in which a given input is transformed into a target output by using a fuzzy-inference system model. The membership functions, if-then rules and then fuzzy logic operators are involved in it. The Mamdani and Sugeno models are the two types of fuzzy system. The Sugeno model was developed by Takagi-Sugeno-Kang in 1985. There are five main processing stages in ANFIS operation, including input fuzzification, application of fuzzy operators, application method, output aggregation, and defuzzification.

3.1 Fuzzy Inference System

Based on if-then rules and fuzzy reasoning, the output is derived by a fuzzy inference system which is a nonlinear mapping. The domain and range of the mapping could be fuzzy sets or points in multidimensional spaces

FIS based technique has the potential advantage over conventional techniques in significantly improving the accuracy in finding the fault locations due to fact that FIS has the capability of non-linear mapping. Fuzzy inference system can find a very close relationship between samples of voltages and currents of the line and location of faults on transmission lines.

FIS is ideally suited for providing a high degree of accuracy in fault location under a wide variety of different system and fault condition. However, as the parameters of membership function and rules are tuned well, the fuzzy inference system could be useful. The fuzzy set theory is also used to solve the uncertainty problem. The use of neural nets in applications is very sparse due to its major limitation. The artificial explicit knowledge cannot easily describe the power system operation in the transient period, as many unknown parameters affect the system. By integrating the neural network into the fuzzy logic system, learning from the prior obtained data sets is made possible.

The neural networks are used to improve the operation of a fuzzy inference system, and a method based on neural network algorithm combined with a fuzzy decision rule was presented for fault detection and classification on transmission lines. Seven inputs were used to train the ANFIS to classify the fault type, detect the faulty section and accurately locate the faults on each part of the combined line.

3.2 ANFIS Architecture

The ANFIS consists of either a fuzzy system with the neural network or Fuzzy Neural Network (FNN). The learning capabilities of the fuzzy logic system are enhanced by integrating with neural technology. The ANFIS makes use of a hybrid learning rule to optimize the fuzzy system parameters of the first-order Sugeno system. It maps inputs through input membership functions and associated parameters, and then 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 modelled.

To improve the training efficiency and eliminate the possible trapping due to local minima, a hybrid learning algorithm is employed to tune the parameters of the membership functions. It is a combination of the gradient descent approach and least-squares estimate. During the forward pass, the node outputs advance until the output membership function layer, where the consequent parameters are identified by the least squares estimate. The backward pass uses the back propagation gradient descent method to update the premise parameters, based on the error signals that propagate backward.

For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as:

Rule 1 If x_1 is A_1 and x_2 is B_1, then $y_1 = p_1x_1 + q_1x_2 + r_1$,

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Rule i If x_1 is A_i and x_i is B_i, then $y_2 = p_ix_1 + q_i x_i + r_i$,

The premise parameters are denoted by A_1, A_2, B_1, and B_2. The consequent parameters are considered as p_i, qi, and r_i, where i = 1, 2...n. The consequent parameters are represented by p, q, and r. The consequent parameters of the nth rule contribute through a first - order polynomial of the form given in Equation 3.

$$y_n= p_nx_1 + q_nx_2 + r_n \qquad (3)$$

Where, x_n are the inputs, y_n are the outputs within the fuzzy region specified by the fuzzy rule p_n, q_n, and r_n are the design parameters that are determined during the learning process.

3.3 Training Data of ANFIS

The training data used to train the ANFIS of the fault location unit were taken : i) Fault distance (L_f) ii) All type of faults (i.e. single phase to ground, phase to phase, double phase to ground and three-phase fault iii) Inception angle (Φ_i) iv) Fault resistances (R_f) . There are 444 training data. The input data to the ANFIS of the locating unit were the impedances of the three phases (magnitude and phase i.e. six inputs) after dividing them by their no-fault values. They were taken from the fundamental values of the voltage and current measurements. The output data from the ANFIS was the normalized fault distance value.

3.4 ANFIS Fault Locator

The ANFIS locator consists of six neurons in the input layer (i.e. N=6), four triangular membership functions for each input (i.e. F=4), and constant membership function for the output.

3.5 Testing Data

The impedance of the transmission line is based on its distance. When a fault occurs at any point, the line impedance gets vary on line distance variation which impacts on the current. ANFIS controller receives current value continuously from the source file**.** It has trained rules to detect normal current and abnormal current. Various numbers of rules in ANFIS controller is framed to find the distance/resistance as per the current value.

The ANFIS has the following design parameters:

- Type-Sugeno,
- Triangular functions,
- Two linguistic terms for each input membership function,
- 16 linear terms for output membership functions,
- 16 rules (resulting from a number of inputs and membership function terms),

IV. SIMULATION RESULTS AND ANALYSIS

In this study, different fault distance in overhead line and fault inception angles (0°, 90°, 120°, 200°) are considered for all types of faults. The different resistance values (30 Ω, 50 Ω, 60 Ω, 100 Ω) are considered for different faults. At various locations, different types of fault were tested to find out the maximum deviation of the calculated distance L_c measured and the actual

Fault location L_a . The percentage error was defined for fault location by using the formula given below.

$$\% \text{ Error (D)} = \frac{L_a - L_c}{L_T} \times 100 \quad (4)$$

$$\frac{\text{Actual fault distance} - \text{ANN output}}{\text{Total length of the line}} \times 100 \quad (5)$$

Single Phase to Ground Fault (L-G)

The network is tested by presenting different fault cases with varying fault locations and fault inception angles. The network is tested for single phase to ground fault (BN) at different fault distance, inception angles, and fault resistance R_f = 50 Ω & 100 Ω.

Phase to Ground Fault (L-L-G)

The network is tested for the two phase to ground fault (ABN) at different fault distances, inception angles, and fault resistance R_f = 50 Ω & 100 Ω..

Three Phase to Ground Fault (LLLG)

The network is tested for the three phase to ground fault (ABCN) at different fault distances, inception angles, and fault resistance R_f = 50 Ω & 100 Ω.

Two Phase Short Circuit Fault (L-L)

The network is tested for the two phase fault (BC) at different fault distances, inception angles, and fault resistance R_f = 60 Ω

Three Phase Short Circuit Fault (L-L-L)

The network is tested for the three phase fault (ABC) at different fault distances, inception angles, and fault resistance $R_{f=}$.30 Ω. The fault distance error is also calculated for Modular ANN and ANFIS at different fault conditions, different inception angle and at a different location and the result is given in Tables 1 and 2.

Table 1: Results of Fault Distance (Modular ANN and ANFIS) at 100 km

Type	Actual Distance (km)	Inception Angle(°)	Modular ANN	ANFIS	Modular ANN	ANFIS
Single phase to ground	100	0	101.5	100.8	-0.4167	-0.2222
		90	101.55	100.8	-0.4306	-0.2222
		200	101.5	100.86	-0.4167	-0.2389
Two phase to ground fault	100	0	101.55	100.8	-0.4306	-0.2222
		90	101.55	100.5	-0.4306	-0.1389
		200	101.5	100.8	-0.4167	-0.2222
Three phase to ground	100	0	101.55	100.8	-0.4306	-0.2222
		90	101.5	100.7	-0.4167	-0.1944
		200	101.4	100.7	-0.3889	-0.1944
Two phase short circuit	100	0	101.45	100.8	-0.4028	-0.2222
		90	101.45	100.5	-0.4028	-0.1389
		200	101.4	100.8	-0.3889	-0.2222
Three phase Short circuit	100	0	101.5	100.8	-0.4167	-0.2222
		90	101.5	100.7	-0.4167	-0.1944
		200	101.4	100.7	-0.3889	-0.1944

Table 2: Results of Fault Distance (Modular ANN and ANFIS) at 200 km

Type	Actual Distance (km)	Inception Angle(°)	Modular ANN	ANFIS	Modular ANN	ANFIS
Single phase to ground	200	0	201.5	200.7	-0.4167	- 0.1944
		90	201.5	200.7	-0.4167	0.1944
		200	201.2	200.7	-0.3333	- 0.1944
Two phase to ground fault	200	0	201.6	200.8	-0.4444	- 0.2222
		90	201.6	200.7	-0.4444	- 0.1944
		200	201.6	200.7	-0.4444	- 0.1944
Three phase to ground	200	0	201.1	200.8	-0.3056	- 0.2222
		90	201.2	200.8	-0.3333	- 0.2222
		200	201.1	200.6	-0.3056	- 0.1667
Two phase short circuit	200	0	201.8	200.8	-0,5000	- 0.2222
		90	201.6	200.7	-0.4444	- 0.1944
		200	201.6	200.7	-0.4444	- 0.1944
Three phase Short circuit	200	0	201.1	200.1	-0.3056	- 0.0278
		90	201.1	200.1	-0.3056	- 0.0278
		200	201.5	200.5	-0.4167	- 0.1389

For the analysis, fault location of 100 km was considered at various inception angles, the maximum error in fault location identification by Modular ANN is -0.4306 % and in ANFIS -0. 2389 %. At 200 km , the maximum error is identified in Modular ANN is -0.4444 and -0.2222 in ANFIS.

The result of proposed algorithms for different faults (LG, LLG, LLLG, LL, LLL) at 90°inception angle for 150 km has been compared in the Figure 1.

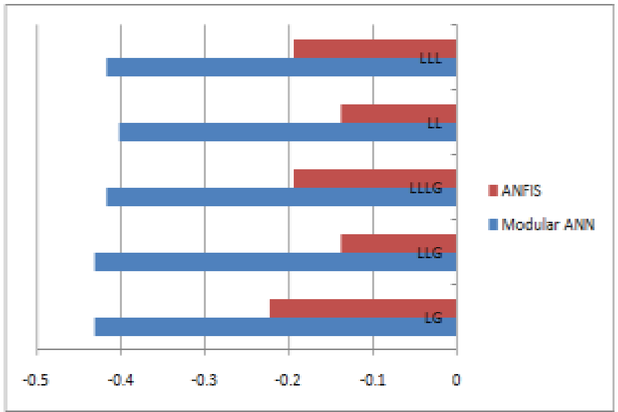

Figure. 1. Performance analysis of proposed system

From the analysis, it is proved that proposed ANFIS technique delivers accurate output compared to Modular ANN.

IV. CONCLUSION

Modular neural network and ANFIS modules were developed for determining the correct fault distance location in UHV transmission line. In modular and ANFIS approach, four different ANN modules for fault detection and classification according to the type of faults (LG, LL, LLG, and LLL and LLLG) have been developed, tested under different resistance, inception angle at different distance for different fault types. The comparison of the test results shows that the ANFIS approach is more accurate.

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