ACCURATE FAULT LOCATION TECHNIQUE FOR UHV LINE

G Banu
Arjun College of Technology, Tamil Nadu, India
gbanusridhareee@gmail.com

Dr. S. Suja
Coimbatore Institute of Technology, Coimbatore, Tamil Nadu, India

Abstract: *The quality and high reliability has to be maintained to deliver the electrical power without interrupt. Hence the Location of fault point accurately is very essential. In this paper, different algorithms are proposed for fault classification and identifying the fault location. The Artificial Neural network, GA-ANFIS, DWT + GA-ANFIS algorithms are proposed to identify the fault point at different inception angles, different fault resistance and different location. The system uses the voltage and current one end of transmission line.*

Key words: *ANN, GA-ANFIS, DWT+GA-ANFIS, Fault location, UHV line.*

1. Introduction.

One of the most important components of the power system is a transmission line. According to rapid growth in the power grid all over the world, a huge number of new transmission and distribution lines have been installed. The most important factor is that the continuous supply of electricity and power is affected by a fault in the power system. Due to the natural reasons, the portion of these faults occurs which cannot be avoided completely and beyond the control of mankind. Hence, it is important to have a protection system that detects any abnormal current flow, identifies the fault type and locates the fault position accurately.

Traditional line fault detection used to heavily rely on visual inspections of the faulted line parts which resulting in long and tedious aerial patrols. These fault detection methods were prone to errors and expensive. Thus, the automatic fault locators are required to detect the fault location. If two terminal data are used for fault identification, the system requires communication channel between two ends of transmission line.

The protection of transmission line is very important in power system. The time taken to restore the service is reduced by an accurate fault location. The high accuracy could not achieved by conventional methods due the variation in fault conditions.

Recently the different algorithms and techniques are approached for fault location identification such as continuous wavelet and discrete wavelet combined with ANN, ANFIS, FUZZY system.

The combined artificial neural network and ANN based directional protection scheme have been proposed [1] for double circuit transmission lines. This method uses the data from one side of the transmission line for fault section identification. The ANN and Wavelet based fault location scheme is also compared with ANFIS based fault location method. The Adaptive Network-Based Fuzzy Inference System (ANFIS) and discrete wavelet transform (DWT) have been proposed [2] to identify the fault location in high voltage transmission line. The fault location is identified using different fault inception angles and fault resistances.

The Finite Impulse Response (FIR) filter and Support Vector Machine (SVM) have been implemented [3] for finding the short circuit faults on 230 kV transmission line. A simple fault location algorithm has been proposed [4] for multi-terminal 735 kV transmission line. The method is independent of fault resistance and source impedance. By using this algorithm, the fault location is identified for symmetrical and unsymmetrical faults.

A fuzzy logic based algorithm with discrete wavelet transform has been proposed [5] for IEEE 13 for identifying the various faults in the electrical distribution system for an unbalanced distribution electrical power system. This technique is capable of identifying the different types of faults. In this method, the effect of fault inception angles, other parameters of the system are negligible. The SVM technique has been proposed [6] to find the fault type and fault distance has been estimated in 400 kV transmission line. The proposed technique uses the post fault current data and the samples are preprocessed using wavelet packet transform. The fault is tested very near to two source end. The fault location error in this proposed method is less than 0.21%. Then the thyristor controlled series capacitor is connected at the middle of the transmission line with the same method for fault location estimation. The result gives the accuracy as 98.36% and fault location error percentage is greater than 0.29%.

The wavelet and neural network are used [7] for fault location using one end data. In this method, the internal faults are differentiated from external faults. At different frequency bands, the signals are extracted using wavelet transform. The influences from the system condition and prefault load are removed by signal preprocessor.

An impedance-based fault location method with eight different configurations has been proposed by [8] for double-circuit transmission lines. The types of fault

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and fault resistance are not needed for this approach.

The voltage and current from one end are used to find the fault distance. The Fast Discrete S-Transform has been used by [9] for fault location using variation in fault types, fault locations and fault resistances. The computational cost is reduced by using the different types of frequency scaling, band pass filtering, and interpolation techniques.

The single ANN and Modular ANN have been proposed [10] to identify the fault location for double circuit line. The fault location has been identified at different fault conditions, fault resistance. The different fault inception angles are also considered. Compared to single ANN, the modular ANN gives accurate result in fault location.

A two terminal impedance based fault location algorithm has been used by [11] with distributed model. The algorithm utilizes unsynchronized measurements of voltages and currents from two ends of a line. The wavelet with artificial neural network technique has been presented in [12] to detect the High Impedance Fault (HIF) and Low Impedance Fault (LIF) for distribution feeder. For low resistance fault, the resistances are considered as 0 and 30 ohms. For high resistance fault, the resistance has been considered as above 200 ohms. The current signals are extracted by using DWT which is used as input to ANN to identify the fault. But the fault distance is not identified.

The Adaptive Network-Based Fuzzy Inference System is proposed [13] to determine the fault location for underground and overhead transmission line. The zero sequence current and 3 phase currents are used as input to ANFIS and fault types are determined. The faulty section is identified whether the fault is in underground or overhead cable.

The ANN-wavelet (MRA) has been proposed [14] to classify the L-G fault and find the fault location. The spectrum energy D1and D5 are obtained by wavelet transform. The faults are classified by neural network as pattern classification. The different fault conditions are studied at various inception angle and fault resistance. The discrete wavelet transform and feed forward neural network has been proposed[15] to locate faults on the transmission line using one end post fault current signals. The accurate fault location is produced by the analysis which is around 3.2 % error. The proposed work uses the different algorithms such as Single ANN, Modular ANN, GA-ANFIS, Wavelet + GA-ANFIS to find the fault location and classify the different faults accurately. The 1000 KV, 360 km extended between the transmission lines has been considered for this study. The transmission line with distributed parameters is taken for analysis and uses the data from one end of the transmission line. The proposed algorithms use three phase voltage and current for fault classification and identify the fault location at different location, resistances and inception angles.

2. Modular ANN

The protection to transmission line is provided during fault by using artificial neural network which identify the fault location .The training of single ANN based fault detector takes a long time and also the memory requirement is high for singular ANN while training process. If the fault patterns or data set are increased, the complexity of ANNs increases. Due to this, the redundancy of ANN may be caused. It leads to numerical problems and probability of mapping the input- output behavior is quite low. In modular concept, the overall task is divided into some sub-tasks. Each sub-task is accomplished by an individual neural network. The computational time is reduced in the modular ANN due to high learning capability and of parallel processing. The different networks are designed for each type of fault. The networks are trained with suitable training data.

The 3 phase voltage, current (real and imaginary) and inception angle (7 inputs) are given as input to the proposed artificial neural network with one output (fault distance). The fault samples are generated and various fault conditions i.e different fault locations, fault resistance and inception angle are considered.
The three layer feed forward network has been used for all types of fault and tanh is as transfer function of hidden layer. Based on the network structure transfer function and learning algorithm is chosen. The ANN for LG, LL, LLG, LLL and LLLG faults is developed with different operating condition. The target and input are obtained from the simulation and training data is preprocessed. The network architecture has been created and trained till network setting parameters are reached. The single ANN based fault detector and classifier is trained using Levenberg–Marquardt training algorithm due to its fast convergence. Based on fault location, the training data are generated using MATLAB.

The 240 different types of faults are used to test the network with different fault locations (250km, 200km, 150km, 100km), fault resistance (100 Ω ,60 Ω ,30Ω,50 Ω). Fault inception angles (200°, 120°, 0°,90°). The 8800 fault patterns are taken for training. The 10 post fault samples is extracted from 240 various faults while testing the phase. After training and testing, the fault location is obtained as output.

3. GA-ANFIS

The ANFIS consists of either 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.

3.1 Training Data

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The training data used to train the ANFIS of the fault location unit are taken : i) Fault distance (D_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 fault time (T_f) iv) Fault resistances (R_f) 30, 50,60 and 100 ohms.

There are 444 training data. The input data to the ANFIS of the locating unit are the impedances of the three phases (magnitude and phase i.e. six inputs) after dividing them by their no-fault values. They are taken from the fundamental values of the voltage and current measurements after evaluating Fourier transform every 20 msec. The output data from the ANFIS are the normalized fault distance value.

3.2 The ANFIS 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.

3.3 Training of ANFIS

In this step the suitable data are collected as input data to ANFIS's. An appropriate network has been established by training the various network configurations with satisfactory performances. The fault is detected by training the ANFIS where the fault position is. The trained ANFIS is evaluated using test patterns until getting satisfactory performance.

When Network is trained, an acceptable output should be given by ANFIS for unseen data. An acceptable range of network error and output of test pattern are reached, and then the fuzzy rules and the functions of membership are adjusted well. These steps are done in off-line.

The training is a tool to adjust the ANFIS parameters (same neural network schemes). An ANFIS structure is designed with six inputs and one output. The ANFIS has the following design parameters:

- Type-Sugeno
- Two linguistic terms for each input membership function
- 16 rules (resulting from number of inputs and membership function terms
- 16 linear terms for output membership
- function
- Triangular function
- Fuzzy operators: product (and), maximum

3.4 ANFIS training model for single phase fault

The 39600 test cases are generated for all types of faults. From the results given, it is observed that the proposed fault location technique is capable of determining the fault type accurately in all cases with accuracy. Fig. 1 and 2 show training data of GA-ANFIS for fault distance and resistance.

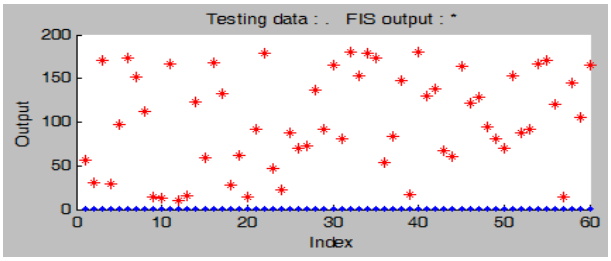


Fig. 1. Fault distance training data.

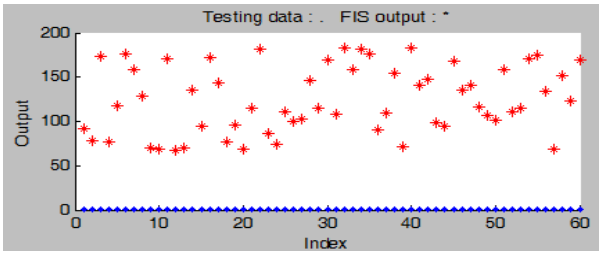


Fig. 2. Fault resistance training data.

3.5 Testing Data

The current value are given to controller of ANFIS continuously from the source file**.** The rules are trained which detects the abnormal and normal current. The different rules are framed for fault resistance and location based on the present current value. An accurate result is produced by tuning the result using the training and testing data of GA. The optimum current and voltages are produced which are taken as testing data for ANFIS.

4. GA-ANFIS

If the adaptive system has more number of input data, there will be noisy measurement in designed model. After a certain point, overfitting of training data set is caused in the model. As the training takes place up to over fitting point, the model error for testing data decreases. Then the error suddenly increases. Hence, the testing and training data are collected and stored in separate files and used for training and testing the model. For this purpose Genetic Algorithm has been used in the proposed work

The different current and voltage values are given to GA to obtain the optimum value (error). From each and every iteration, the optimum value is obtained. The minimum error obtained from GA is a (testing data) input to ANFIS.

5. DWT with GA-ANFIS

Wavelet is a more powerful technique in processing the stochastic signal compared to the conventional method, as the waveform is analyzed in time scale region. The Wavelet Transform performs time localization of the different frequency components of a given signal.

The features extracted from DWT having useful features to determine the fault detection. To analyze the fault location, the current signals are taken from one end in the transmission line. The faults currents are

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simulated by using MATLAB for LLL, LL, LG, LLLG, LLG fault condition. The signals are sampled at a frequency of 20 KHz (20000 samples per cycle). The sampling time is 50 μs which corresponds to sampling frequency. Different filters such as biorthogonal symle anddaubechies, are considered for fault location and the results are analyzed. The Daubechis has been selected for signal extraction, as it has good performance and gives quick response. Based on the % energy of different dB levels, db12 is chosen due its high energy level.

Fig.3 depicts detail d1 to d6 of the fault signal at db10 when 3 phase fault occurs at 0.2s (4000th sample).

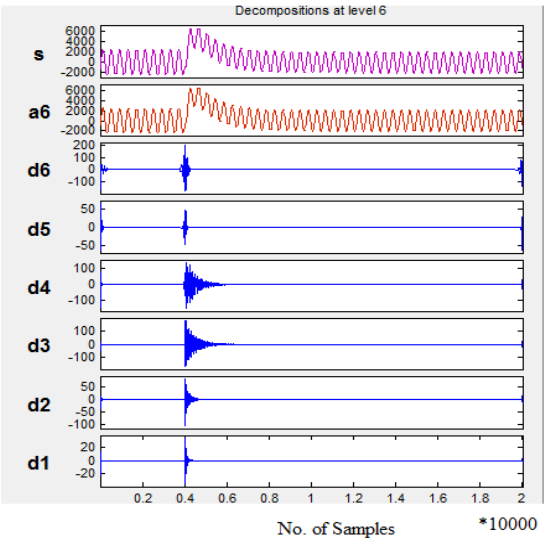


Fig. 3. Current signal from d1 to d6 & a5

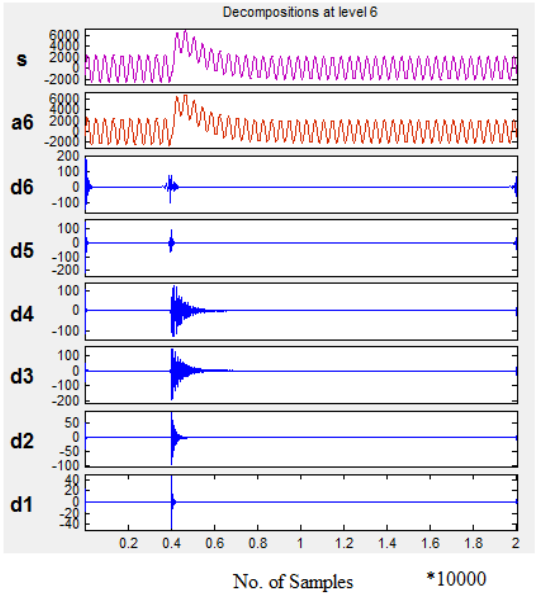


Fig. 4. Current signal from d1 to d6 & a5

From the Figs 3 & 4, it is considered that the harmonics are reduced at 5th level. Hence signal of a5 is used as input for fault detection. The approximation 5 is used as the summations of wavelet coefficients for all types of faults. The signal of desired signal is obtained from repetitive decompositions which uses the low pass and high pass filter. The signals are decomposed into 5 levels such as A1, D1 to A5, D5. The frequency 20000 HZ are decomposed into 5 levels. The details of frequency range upto 5 levels are given below

I level: 5 kHz to 10 kHz (fs/4– fs/2).
II level: 2.5 kHz to 5 kHz (fs/8– fs/4).
V level: is 312.5Hz to 625Hz

The optimum value is obtained by giving the approximate coefficients to GA. The testing data is produced by GA based on the fitness function. The current is taken as input to the GA. I_{ref}=23000 A. The 4500 samples are taken from 0 to 23000A current range and the system determines the error value which is testing data to ANFIS. The Fuzzy Logic Controller produces the training data to ANFIS based on the transmission line parameters.

The ANFIS structure is designed with six inputs and one output. The architecture consists of inference, defuzzification, input Fuzzification and output layers.

In the proposed method, back propagation method of optimization is taken with 100 epochs. The training data for fault location and fault resistance in ANFIS is minimized by giving GA output which is testing data.. Again the ANFIS output is tested against the testing data from GA. It produces less error in the output. The output is (fault distance and fault resistance) obtained from ANFIS.

The percentage error of fault distance is defined by using the formula

% Error =

$$\frac{\text{Actual fault distance} - \text{calculated fault distance}}{\text{Total length}} \times 100\% \qquad (1)$$

The percentage error of fault resistance has been calculated by the formula

% Error (R) =

$$\frac{\text{Actual resistance} - \text{Calculated resistance}}{\text{Actual resistance}} \times 100 \qquad (2)$$

The fault distance error is also calculated at $90°$ and $120°$ inception angle and at a 200 km location and the result is given in Table 1.

The fault resistance error is also calculated at $0°$ and $120°$ inception angle and at a 150 km location and the result is given in Table 2.

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Table 1
The Percentage Error of Fault Distance for 200 km

Fault type	Inception angle	Fault Distance (200 km)			Error percentage		
		Modular ANN	GA-ANFIS	DWT+GA-ANFIS	Modular ANN	GA-ANFIS	DWT+GA-ANFIS
L-G	90	201.5	200.3	200.1	-0.416	-0.083	-0.027
	120	201.2	200.2	200.2	-0.33	-0.083	-0.05
LL-G	90	201.5	200.3	200.1	-0.44	-0.083	-0.027
	120	201.6	200.3	200.2	-0.44	-0.083	-0.05
LLL-G	90	201.2	200.2	200.1	-0.33	-0.05	-0.027
	120	201.1	200.1	200.1	-0.3	-0.027	-0.027
LL	90	201.6	200.3	200.1	-0.44	-0.083	-0.027
	120	201.6	200.3	200.2	-0.44	-0.083	-0.05
LLL	90	201.1	200.1	200.1	-0.3	-0.027	-0.027
	120	201.1	200.1	200.1	-0.3	-0.027	-0.027

Table 2
The Percentage Error of fault resistance at 150 km

Fault type	Inception angle	Fault Resistance at 150 km			Error percentage		
		Modular ANN	GA-ANFIS	DWT+GA-ANFIS	Modular ANN	GA-ANFIS	DWT+GA-ANFIS
L-G	0	101.4	100.3	100.3	-1.4	-0.3	-0.3
	120	101.3	100.3	100.3	-1.3	-0.3	-0.3
LL-G	0	101.4	100.4	100.2	-1.4	-0.4	-0.2
	120	101.4	100.3	100.2	-1.4	-0.3	-0.2
LLL-G	0	101.3	100.7	100.3	-1.3	-0.7	-0.3
	120	101.3	100.7	100.3	-1.3	-0.7	-0.3
LL	0	60.8	60.45	60.25	-1.3	-0.75	-0.41
	120	61	60.5	60.2	-1.6	-0.83	-0.33
LLL	0	31	30.55	30.25	--3.3	-1.83	-0.83
	120	31	30.55	30.3	-3.3	-1.83	-1

The percentage error of fault distance for modular ANN, GA-ANFIS and DWT+GA-ANFIS are compared at 200 km distance and 90 degree inception angle for different faults. The comparison graph is shown in Figure 5.

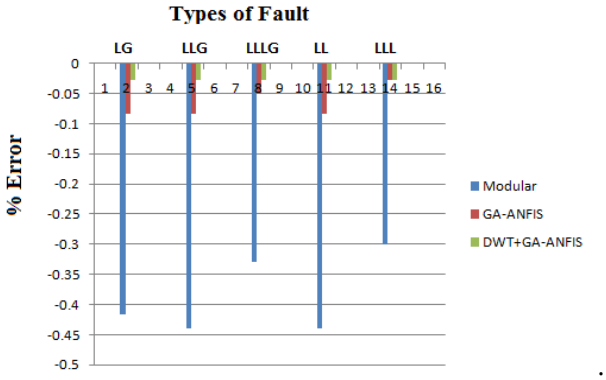


Fig.5. Comparison graph of algorithms.

From the comparison result it is proved that DWT with GA-ANFIS algorithm gives better accuracy in fault location.

6. Conclusion

In this paper, the modular ANN, GA_ANFIS and DWT+GA-ANFIS algorithms proposed to find the fault location and fault resistance. The fault distance and resistance are determined for both symmetrical and unsymmetrical faults at different conditions such as different fault location, resistance and fault inception angle. The results of all algorithms are compared. The comparison result shows that the DWT with GA-ANFIS approach gives better accuracy.

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