ARCHIVES OF ELECTRICAL ENGINEERING VOL. 63(2), pp. 247-262 (2014)

DOI 10.2478/aee-2014-0019

Fault location technique using GA-ANFIS for UHV line

G. BANU[1], S. SUJA[2]

[1]*Suguna College of Engineering Coimbatore*
Coimbatore, India

[2]*Institute of Technology Coimbatore*
Coimbatore, India

e-mail: g.banusridhar@gmail.com, ssujacit@yahoo.com

(Received: 29.01.2014, revised: 24.03.2014)

Abstract: This paper presents an improved approach for locating and identifying faults for UHV overhead Transmission line by using GA-ANFIS. The proposed method uses one end data to identify the fault location. The ANFIS can be viewed either as a Fuzzy system, neural network or fuzzy neural network FNN. The integration with neural technology enhances fuzzy logic system on learning capabilities are proposed to analyze the UHV system under different fault conditions. The performance variation of two controllers in finding fault location is analyzed. This paper analyses various faults under different conditions in an UHV using Matlab/simulink. The proposed method is evaluated under different fault conditions such as fault inception angle, fault resistance and fault distance. Simulation results confirm that the proposed method can be used as an efficient for accurate fault location on the transmission line.

Key words: GA – ANFIS, Fault location, Fault resistance, one end data, UHV line

1. Introduction

In power systems, transmission and distribution lines are vital links that achieve the continuity of service from the generating plants to the end users. Protection systems for transmission lines are one of the most important parts in power systems. Fault location is a desirable feature in any protection scheme.

Accurate location of transmission line faults has been a subject of interest for several years. The major reason for this activity is that an accurate location of fault can reduce the time required for restoring service to customers. A very high degree of accuracy is thus required that cannot be achieved using conventional techniques; because of the wide variation in power system and fault conditions that occur in practice and these in turn can have a significant influence on the degree of accuracy achievable with conventional fault location techniques. Fault location is one of the most important functions to help power engineers find in the fault point and then restore soon.

The fundamentals of transmission lines protection were developed many years ago [1-2]. Some of them such as representing transmission lines by either first or second order differential equations and traveling-wave techniques have resulted in several commercial developments. However, both these approaches are based on deterministic computations on a well defined model of the system to be protected. This results in difficulty in taking system variation into account as the rules are fixed. They do not have the ability to adapt dynamically to the system operating conditions, and to make correct decisions if the signals are uncertain.

Two-terminal fault-location techniques employing measurements at both ends of the line have been proposed in [3-5]. The unsynchronized measurements were presented for estimating the fault location and synchronization angle between measurements from different terminals of the line. ANN based approach [6] was proposed and tested to classify and locate the fault of a single end fed medium voltage cables.

Recently, intelligent soft computational techniques such as Artificial Neural Network (ANN), Fuzzy Inference System (FIS) and (ANFIS) can model superiority of human knowledge features. They also re-establish the process without plenty of analysis. Thus these techniques are attracting great attention in an environment that is obvious with the absence of a simple and well-defined mathematical model.

Fuzzy Inference Systems (FIS) based techniques have the potential advantage over conventional techniques in significantly improving the accuracy in fault locations. This is so by virtue of the fact that FISs have 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.

Therefore this makes FIS ideally suited for providing a high degree of accuracy in fault location under wide variety of different system and fault condition. However the fuzzy inference system can be useful only if the parameters of fuzzy systems such as parameters of membership function and rules are tuned well.

An adaptive network based approach presented in [7] to choose the parameters of fuzzy system using a training process. In this technique an adaptive is used to find the best parameter of fuzzy system. Many researchers have studied the application of neural networks to overcome most of the problems.

The fuzzy set theory is also used to solve uncertainty problem [8-12]. The use of neural nets in applications is very sparse due to its major limitation. The power system operation in transient period cannot be easily described by artificial explicit knowledge because it is affected by many unknown parameters. The integration of neural network into the fuzzy logic system makes it possible to learn from the prior obtained data sets.

A new and accurate fault location algorithm using Adaptive Network-Based Fuzzy Inference System (ANFIS) for a network with both transmission lines and under-ground cables was proposed [13]. It uses fundamental frequency of three-phase current and neutral current as inputs while fault location are calculated in term of kilometer distance.

The neural networks are used [14] to improve the operation of fuzzy inference system, and a method based on neural network (NN) algorithm combined with Fuzzy K-nearest neighbor (K-NN) decision rule was presented for fault detection and classification on transmission lines.

An algorithm for fault detection and classification of low impedance faults and high impedance faults using ANFIS was presented [15]. This algorithm can detect and classify fault type in a transmission line based on RMS value of phase currents and zero sequence current.

In this paper an accurate fault location algorithm for UHV line which is based on GA-ANFIS are proposed. The GA-ANFIS Techniques is to find a fault location in Transmission line. The system has been simulated using MATLAB2011 b. Six inputs are used to train the ANFIS in order to classify the fault type, detect the faulty section and accurately locate the faults on each part of the combined line. The proposed method is tested under different fault conditions such as different fault locations, different fault inception angles and different fault resistances. The simulation results confirm the validity and high accuracy of the new algorithm.

2. GA-implementation

The MATLAB software is used to implement the GA for training the ANFIS. Each chromosome in the GA consists of 53 genes which represent all the ANFIS parameters. These genes include 3 genes for the input scaling factor, 1 gene for output scaling factor, 42 genes for the premise parameters of the ANFIS-structure. The universe of discourse (UOD) foe each input variable was selected to be from -6 to 6, keeping in mind that other range can be used since there are input and output scaling factors. Four real coded GA operators were used in this work. These operators include the hybrid selection, the elitism, the crossover and the mutation operator, which is a combination of the roulette wheel and the deterministic selection. The procedure of the real coded GA adopted to train the ANFIS to find the fault location are:

Step 1. Initialize the crossover probability (P), the mutation probability (P), the population size, and the maximum number of generations.

Step 2. Generate randomly the initial population of chromosomes within certain limits. Each of these chromosomes represents the entire premise and consequent parameters along with the input and output scaling factors for ***ANFIS controller.*** **(this is the red graph in a GA ANFIS graph)**

Step 3. Evaluate the objective function for each chromosome in the population using the integral square of errors (ISE) criterion, which has the following form:

$$\text{fitness} = \frac{1}{\varepsilon + \text{objective function}}\,.$$

Step 4. Put in descending order all the chromosomes in the current population (that is, the first one is the fittest). Then apply the elitism strategy described before.

Step 5. Select two individuals from the current population utilizing the hybrid selection method, and then apply the real-coded crossover and mutation operators described previously to generate two new chromosomes.

Step 6. Put the resulting two chromosomes in the new population.

Step 7. Repeat Step 5 until all the chromosomes in the new population are generated, that is, until the new population size is equivalent to the initial (old) population size.

Step 8. Replace the initial (old) population with the new population.

Step 9. Stop if the maximum number of generations is reached, and the first chromosome in the last generation is the optimal controller found by the GA, otherwise increase the generation counter by one and go to step 3.

3. Adaptive network – based fuzzy inference system

3.1. ANFIS architecture

The ANFIS is a fuzzy Sugeno model of integration where the final fuzzy inference system is optimized via the ANN training. The ANFIS makes use of a hybrid learning rule to optimize the fuzzy system parameters of first-order Sugeno system, which can be graphically represented by Figure 1. It maps inputs through input membership functions and associated parameters, and then through 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 modeled.

In order 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 $x1$ is $A1$ and $x2$ is $B1$, then $y1 = p1x1 + q1x2 + r1$,

Rule 2. If $x1$ is $A2$ and $x2$ is $B2$, then $y2 = p2x1 + q2x2 + r2$,

Where [$A1$, $A2$, $B1$, $B2$] are called the premise parameters. [pi, qi, ri] are called the consequent parameters, $i = 1, 2$.

The consequent parameters (p, q, and r) of the nth rule contribute through a first order polynomial of the form:

$$yn = pnx1 + qnx2 + rn. \tag{1}$$

Where xn are the inputs, yn are the outputs within the fuzzy region specified by the fuzzy rule, pn, qn, and rn are the design parameters that are determined during the learning process.

3.2. ANFIS hybrid training rule

ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with a least squares type of method. ANFIS is much more complex than the fuzzy inference systems, and is not available for all of the fuzzy inference system options. Specifically, ANFIS only supports Sugeno-type systems, and these must have the following properties:

1) Be first or zeroth order Sugeno-type systems.
2) Have a single output, obtained using weighted average defuzzification. All output membership functions must be the same type and either be linear or constant.
3) Have no rule sharing. Different rules cannot share the same output membership function, namely the number of output membership functions must be equal to the number of rules.
4) Have unity weight for each rule. The ANFIS architecture consists of five layers with the output of the nodes in each respective layer represented by *Oli.*

Where i is the i[th] node of layer l. The following is a layer by layer description of a two input two rule first-order Sugeno system. The equivalent ANFIS architecture is shown in Figure 1.The node functions in the same layer are of the same function family, as described below

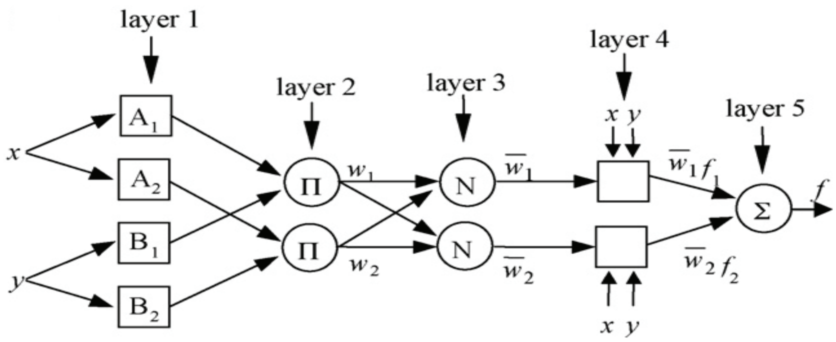

Fig. 1. ANFIS structure

Layer 1. Generate the membership grades

Each node in this layer is an adaptive node. The outputs of this layer are the fuzzy membership grade of the inputs, which are given by

$$O1i = \mu Ai\,(x), \tag{2}$$

where $O1i$ is membership function of $\mu Ai\,(x)$ and A is the linguistic label associated with this node. In this layer parameter of each MF are adjusted.

Layer 2. Generate the firing strengths

The nodes are fixed nodes denoted as π, indicating that they perform as a simple multiplier. Each node in this layer calculates the firing strengths of each rule via multiplying the incoming signals and sends the product out. The outputs of this layer can be represented as

$$O_i^2 = wi = \Pi_{j=1}^{m} = \mu Ai(x)\,. \tag{3}$$

Layer 3. Normalize the firing strengths

The nodes are also fixed nodes. They are labeled with *N*, indicating that they play a normalization role to the firing strengths from the previous layer. The ith node of this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}. \tag{4}$$

Layer 4. Calculate rule outputs based on the consequent parameters

Each node in this layer is adaptive node and in this layer parameters of output are adjusted. This output usually is a linear function of input. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial. Thus, the outputs of this layer are given by

$$O_i^4 = y_i = \overline{w}_i f_i = w_i\left(p_i x_1 + q_1 x_2 + r_i\right) \quad i = 1, 2, 3\ldots \tag{5}$$

Layer 5. Sum all the inputs from layer 4

There is only single fixed node labeled with ∑. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O_i^5 = \sum_i yi = \sum_i \overline{w}_i f_i = \left(\overline{w}_1\ x_1\right)p_1 + \left(\overline{w}_1\ x_2\right)q_1 + \overline{w}_1\ r_1 + \left(\overline{w}_2\ \ x_2\right)p_2 + \left(\overline{w}_2\ x_2\right)q_2 + \overline{w}_2\ \ r_2\,. \tag{6}$$

It is in this last layer that the consequent parameters can be solved for using a least square algorithm. Let us rearrange this last equation into a more usable form:

$$\left[w_1x_1\ \ w_1x_2\ \ w_1\ \ w_2x_1\ w_2x_2\ \ w_2\right]\begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} = XW\,. \tag{7}$$

When input-output training patterns exist, the weight vector (**W**), which consists of the consequent parameters, can be solved for using a regression technique.

4. Perfomance evaluation

4.1. Power system model

The power system configuration for this study is taken as 1000 kV line with 360 km as shown in Figure 2. Distributed parameter model is used for modeling of the overhead line.

The proposed fault location algorithm requires only the three phase currents and voltage at the sending end of the overhead line. This system has been simulated using MATLAB to prepare the inputs for the GA-ANFIS.

4.2. Faulty section detection

Different fault types at various locations of each section of the system under study with different inception angles and fault resistances are used for training and testing the ANFIS for faulty section determination.

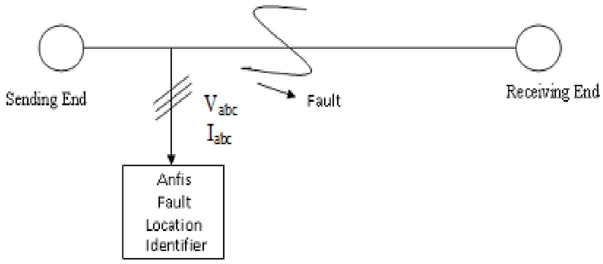

Fig. 2. Single line diagram of system model

4.3. Accurate fault location using ANFIS

All types of faults with different inception angles, different locations and different fault resistances in both sections of the combined overhead line le are simulated to evaluate the performance of the proposed fault location algorithm. The system under study is shown in Figure 2. In the following sections some of the results are presented. The percentage error is defined as the formula given below

$$\%\text{Error} = \frac{\text{Actual fault location} - \text{Calculated fault location}}{\text{Total length of line}}.$$

4.4. Training data

The training data used to train the ANFIS of the fault location unit are taken at: i) Fault distance (Df), ii) All type of faults (i.e. single phase to ground, phase to phase, double phase to ground or three-phase fault), iii) Inception fault time (Tf) 2 msec, iv) Fault resistances (Rf) 0, 30, 50, 60 and 100 ohms.

There are 660 training data. The input data to the ANFIS of the locating unit are the impedances of the three phases (magnitude and phase i.e. 6 inputs) after dividing them by their non 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.

4.5. 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.

4.6. Training data

The training data used to train the ANFIS of the fault location unit are taken at

1. Fault distance
2. All types of faults

3. Inception angle
4. Fault resistance.

4.7. The ANFIS locator

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

4.8. Testing data

Impedance of the transmission line is based on its distance. When fault occurs in any point of the line impedance get vary with respect to line distance Variation in impedance impact on the current. ANFIS controller receives current value continuously from source file**.** It has trained rules to detect normal current and abnormal current. Various number of rules in ANFIS controller is framed to find the distance/resistance as per present current value.

Impedance of the transmission line is based on its distance. When fault occurs in any point of the line impedance get vary with respect to line distance Variation in impedance impact on the current. ANFIS controller receives current value continuously from source file**.** It has trained rules to detect normal current and abnormal current. Various number of rules in ANFIS controller is framed to find the distance/resistance as per present current value.

5.Training the ANFIS

In this step the suitable data which are collected in step (1) are presented as input data to ANFIS. Various network configurations were trained in order to establish an appropriate network with satisfactory performances. The ANFIS is trained to detect presence of fault, where the fault position is.

Evaluation of the trained ANFIS using test patterns until its performance is satisfactory.

When Network is trained, ANFIS should be given an acceptable output for unseen data. When output of test pattern and network's error reached an acceptable range then, fuzzy system is adjusted in the best situation which means the membership functions and fuzzy rules are well adjusted. All of these steps above are done off-line.

The parameters of ANFIS have adjusted via training (similar as for neural network schemes). The structure of an ANFIS with six inputs and one output is shown in Figure 3. 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 number of inputs and membership function terms),
- Fuzzy operators: product (and), maximum (or), product (implication), maximum (aggregation), average weight (**defuzzification).**

There are 16 rules, which are sufficient to assign a detector using ANFIS. Some of these rules are as follows:

1. If (Ia is mf1) and (Ib is mf1) and (Ic is mf1) and (Va is mf1) and (Vb is mf2) and (Vc is mf2) then (Output is out1mf1) (1)
2. If (Ia is mf1) and (Ib is mf2) and (Ic is mf2) and (Va is mf1) and (Vb is mf2) and (Vc is mf1) then (Output is out1mf2) (1)

3 If (Ia is mf1) and (Ib is mf3) and (Ic is mf3) and (Va is mf1) and (Vb is mf2) and (Vc is mf3) then (Output is out1mf3) (1)

4. If (Ia is mf1) and (Ib is mf4) and (Ic is mf4) and (Va is mf3) and (Vb is mf1) and (Vc is mf3) then (Output is out1mf4) (1)
5. If (Ia is mf1) and (Ib is mf5) and (Ic is mf5) and (Va is mf1) and (Vb is mf2) and (Vc is mf3) then (Output is out1mf5) (1)

.
.
.

15. If (Ia is mf5) and (Ib is mf4) and (Ic is mf4) and (Va is mf4) and (Vb is mf4) and (Vc is mf4) then (Output is out1mf24) (1)
16. If (Ia is mf5) and (Ib is mf5) and (Ic is mf5) and (Va is mf5) and (Vb is mf5) and (Vc is mf5) then (Output is out1mf25) (1)

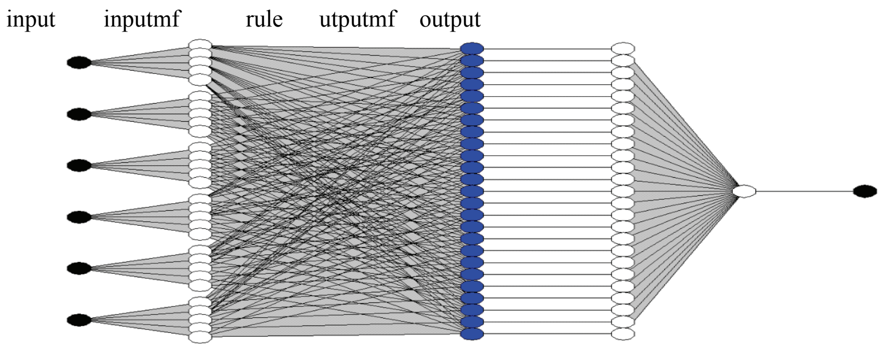

Fig. 3. Structure of ANFIS

The Figure 3 shows the structure of ANFIS which is used to find the fault detection.

Therefore, there are 3 values for fault impedance, 4 values for fault angle and 5 values for fault distance. Thus, a total combination of $5 \times 4 \times 3 = 60$ has been chosen for fault simulation studies. For each of these combinations, all five types of short-circuit faults can be applied at any point on the transmission line. Hence in aggregate, Different fault simulation studies are possible. The performance of the proposed scheme has been trained for all of these $11 \times 60 = 660$ training cases.

The Figure 4 shows the training data of ANFIS for fault resistance and Figure 4b shows the training data for Fault distance.

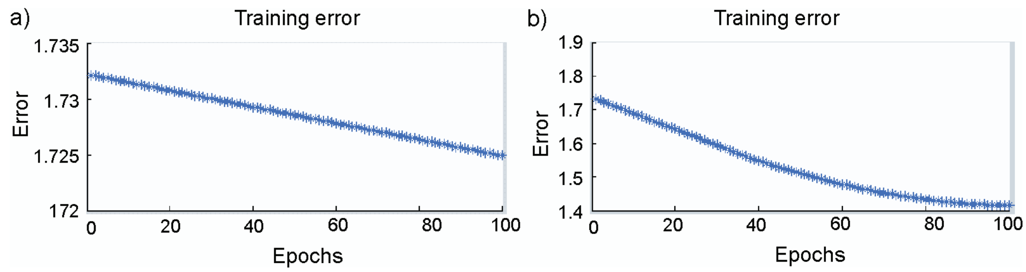

Fig. 4. a) Training data for fault resistance (GA); b) Training data for fault location (GA)

On the other hand, the performance of the proposed scheme has been checked for different cases. The total combination of test cases is $660 \times 60 = 39\,600$. However, as it is not feasible to include in the paper all of the numerical results corresponding to these 39 600 test cases due to space limitations, the output values (which indicate the fault type) obtained from the ANFIS results for a few representative test cases are shown in Figure 4. It is evident from the results obtained in the analysis that there are a small floatation in the ANFIS output.

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 The Fig. 5 shows the testing and training data of GA-ANFIS for fault resistance and Fault distance

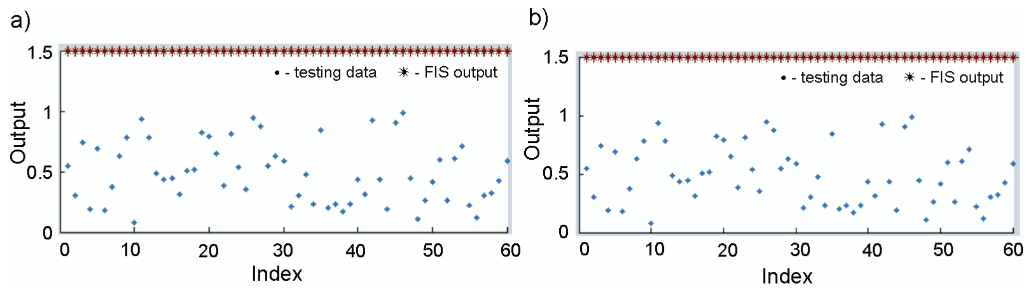

Fig. 5. a) Testing data for ANFIS (Rf); b) Testing data for ANFIS(d)

ANFIS controller receives current value continuously from source file**.** It has trained rules to detect normal current and abnormal current. Various number of rules in ANFIS controller is framed to find the distance/resistance as per present current value. It again tunes the result with the GA testing, training data to produce accurate result. Fault current samples are taken from GA i.e. Optimum current and voltage are produced based on the voltage and current samples. The optimum current and voltages are taken as testing data for ANFIS.

Testing Data

Impedance of the transmission line is based on its distance. When fault occurs in any point of the line impedance get vary with respect to line distance Variation in impedance impact on the current. ANFIS controller receives current value continuously from source file**.** It has trained rules to detect normal current and abnormal current. Various number of rules in ANFIS controller is framed to find the distance/resistance as per present current value.

6. GA-ANFIS

Impedance of the transmission line is based on its distance. When fault occur in any point of the line impedance get vary with respect to line distance, variation in impedance impact on the current. The different current and voltage values are given to GA to obtain the optimum value (error). For every iteration the optimum value is obtained. The output scaling factor (minimum error) is obtained from GA which is testing data i.e input for ANFIS. The ANFIS is tuned by using the GA output to get accurate fault distance.

7. Analysis of test result

Single line to ground faults

In a power system 75% of fault is line to ground fault. In this study with considering 100 km, 150 km, 200 km, 300 km as fault distance steps in overhead line and 0, 90,120 200° as fault inception angle steps. The fault resistances 50 Ω, 100 Ω are considered. Once the training procedure is done completely, the networks are tested using simulated fault patterns.

The Figure 6 a, b show the fault current and voltage waveform when fault occurs at phase b at a distance of 150 km, 50 Ω resistance (GA-ANFIS) at 0.1 sec. The fault current is 9000 A. The maximum percentage error is – 0.11.

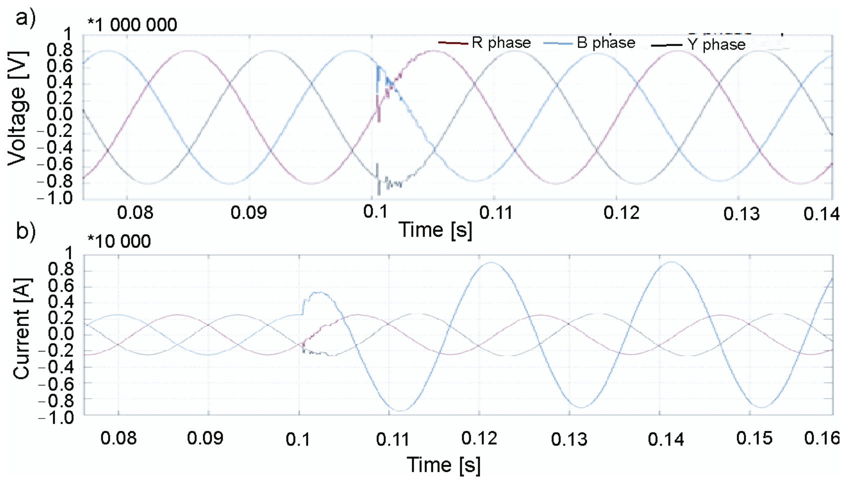

Fig 6. a) Voltage waveform, b) Current waveform

Phase to phase fault

In this case the fault distance are taken as 100 km,150 km, 200 km, 300 km and fault inception angles degrees steps are 0, 90, 120, 200°. Three fault resistance 30 Ω is considered.

The Figure 7 a, b shows the fault current and voltage waveform when fault occurs between the line b and c at a distance of 150 km, 50 Ω resistance. The current is 14 KA at a fault line.

Once the training procedure is done completely, the networks are tested using simulated fault patterns not presented during the training process. The maximum percentage error is – 0.138. These values indicate that the training process is done successfully.

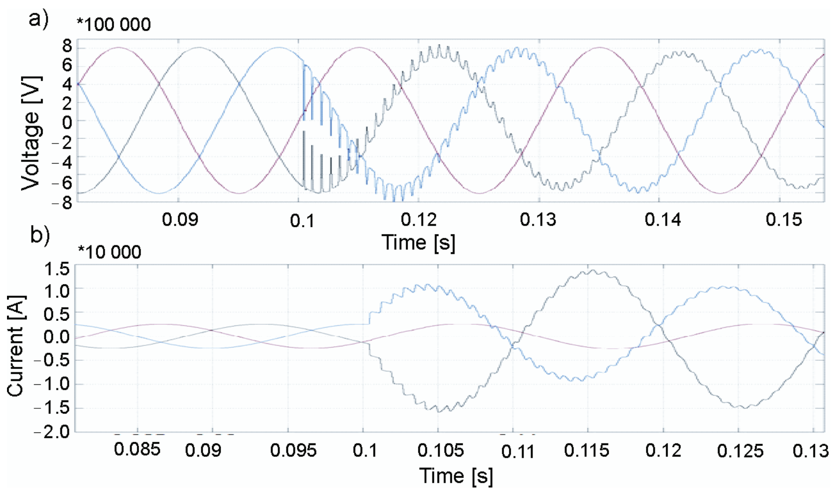

Fig .7. a) Voltage waveform, b) Current waveform

Double phase to ground fault

In this case the fault distance are taken as 100 km, 150 km, 200 km, 300 km and fault inception angles steps are 0, 90, 120, 200°. Three fault resistances 50 Ω, 100 Ω are considered. These patterns are applied to train the ANFIS.

The current is 14 KA at a fault line. Once the training procedure is done completely, the networks are tested using simulated fault patterns not presented during the training process.

The Figure 8 a, b shows the fault current and voltage waveform when fault occurs between line b and c and ground at a distance of 150 km, 50 Ω resistance (GA-ANFIS).

These values indicate that the training process is done successfully. The maximum percentage error is – 0.138.

Three phase fault

In this case the fault distance are taken as 100 km, 150 km, 200 km, 300 km and fault inception angles steps are 0, 90, 120, 200°. The fault resistance 30 Ω is considered. The Figure 9 a, b shows the fault current and voltage waveform when fault occurs between line a, b and c. at a distance of 150 km, 50 Ω resistance. The current is 24 KA at a fault line.

Once the training procedure is done completely, the networks are tested using simulated fault patterns not presented during the training process. The maximum percentage error is – 0.388. These values indicate that the training process is done successfully.

Three phase to ground fault

In this case the fault distance are taken as 100 km, 150 km, 200 km, 300 km and fault inception angles steps are 0, 90, 120, 200°. The fault resistance100 Ω 50 Ω are considered.

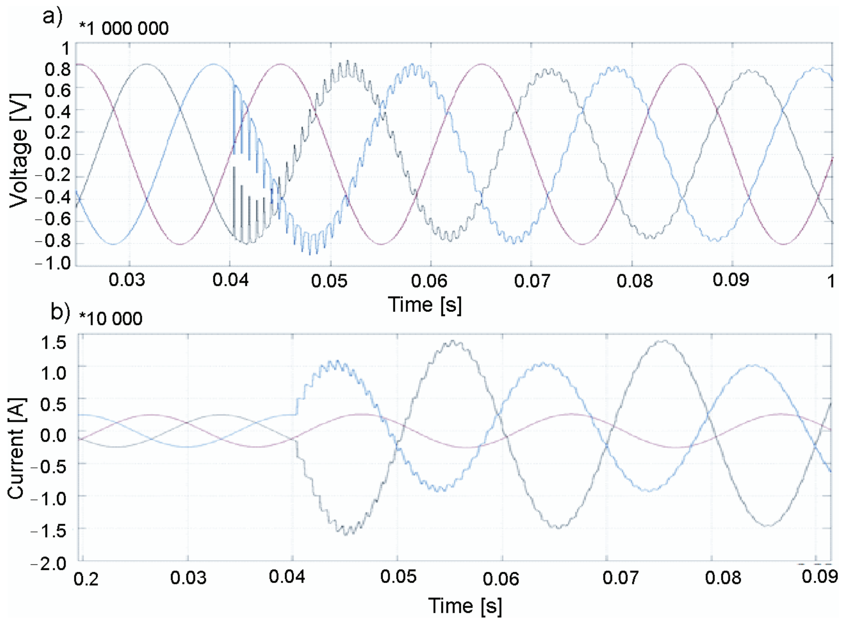

Fig. 8. a) Voltage waveform, b) Current waveform

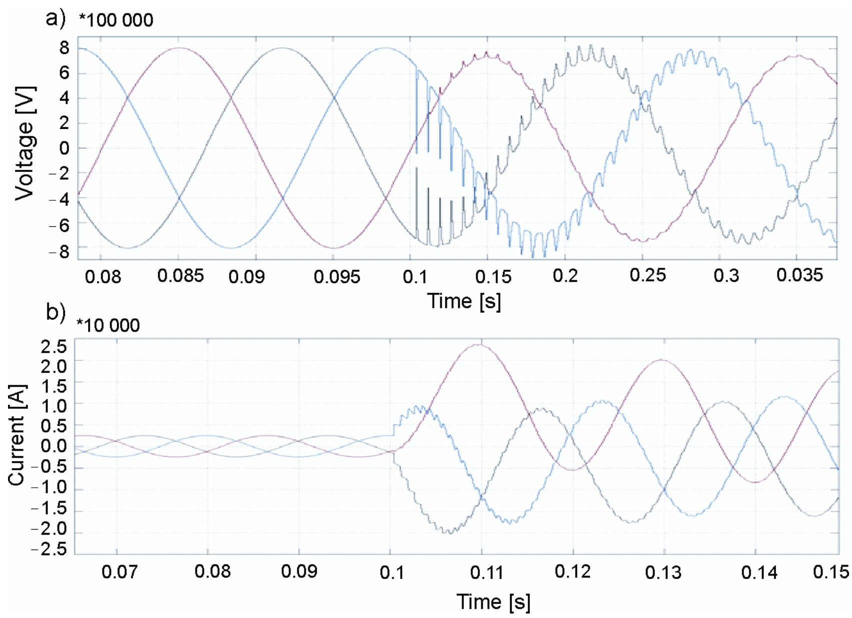

Fig. 9. a) Voltage waveform, b) Current waveform

The Figure 10 a, b shows the fault current and voltage waveform when fault occurs between 3 phases and ground at a distance of 150 km ,50 Ω resistance.

The current is 24 KA at a fault line. Once the training procedure is done completely, the networks are tested using simulated fault patterns not presented during the training process.

The maximum percentage error is – 0.388. These values indicate that the training process is done successfully.

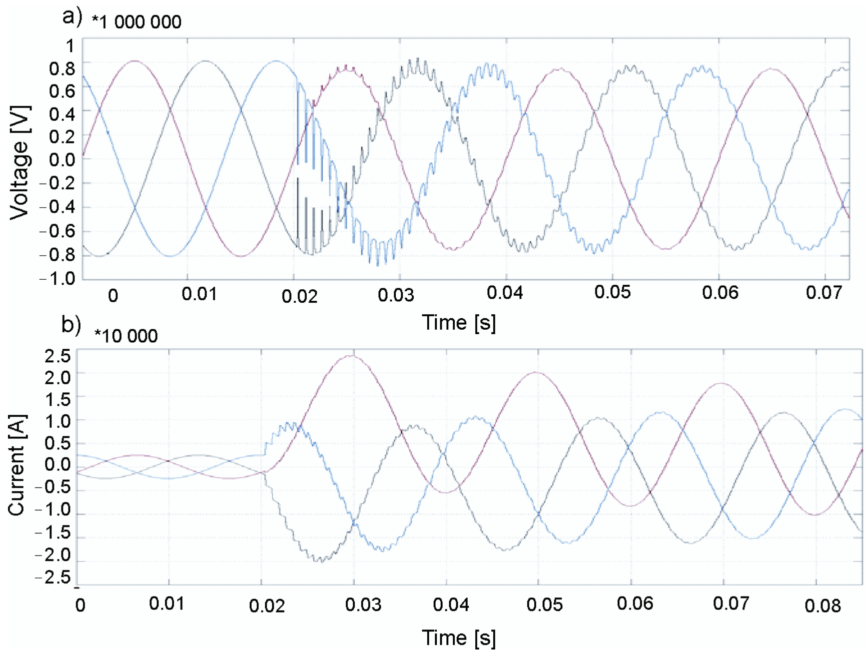

Fig. 10. a) Voltage waveform, b) Current waveform

From the result given in Table 1 it is observed that the proposed Technique is capable of determining the fault resistance and fault distance accurately in all cases.

The Table 1 shows the Fault resistance error at different fault condition and Table 2 shows the distance error at different fault condition.

Table 1. Fault condition and percentage error of resistance at 90° degree inception angle (150 km,100 Ω)

Fault	**Actual resistance [Ω]**	**Calculated resistance [Ω]**	**Resistance error [%]**
Single phase fault	50	50.205	−0.41
	100	100.2	−0.2
Two phase to Ground fault	50	50.35	−0.7
	100	100.4	−0.4
T hree phase to Ground fault	50	50.4	−0.8
	100	100.7	−0.7
Two phase short circuit fault	30	30.55	−1.83
Three phase short circuit fault	60	60.45	−0.75

Table 2. Fault distance error at different distances in overhead line at 50 Ω fault resistance inception angle (90 degree)

Fault type	**Distance error [%]**		
	Actual distance (km)	GA-ANFIS result (km)	Error (%)
Single phase fault	100	100.3	−0.0833
	150	150.25	−0.06942
	200	200.3	−0.083
	250	250.4	−0.11
	300	300.3	−0.083
Two phase to Ground fault	100	100.5	−0.138
	150	150.4	−0.111
	200	200.3	−0.0833
	250	250.4	−0.111
	300	300.3	−0.083
Three phase to Ground fault	100	100.3	−0.0833
	150	150.4	−0.111
	200	200.2	−0.055
	250	250.3	−0.083
	300	298.6	−0.388
Two phase short circuit fault	100	100.5	−0.138
	150	150.4	−0.111
	200	200.3	−0.083
	250	250.4	−0.11
	300	298.5	−0.138
Three phase short circuit fault	100	100.3	−0.083
	150	150.5	−0.138
	200	200.1	−0.333
	250	250.3	−0.083
	300	298.5	0.416

8. Conclusion

This paper proposed a new algorithm for fault location in overhead transmission line based on the GA-Adaptive Network-Based Fuzzy Inference System. The algorithm consist of faulty section determination and fault location. To estimate the accuracy of the proposed algorithm, a wide variety of conditions such as different fault types, different fault inception angles and different fault resistances on the overhead line and on the underground cable are simulated and some of the results are presented. Based on the obtained results, it can be concluded that the proposed method is very effective to find the exact location of fault such that the maximum percentage error is kept below −0.083% (250 km).

Refernces

[1] Rao S.S., *Switchgear and Protection*. 10th Edition, KHANNA Publishers, Delhi (1994).
[2] Carpenter W.M., *IEEE Guide for Protective Relay Applications to Transmission Lines.* IEEE Std, C37. 113 (1999).
[3] Sachdev M., Agarwal R., *A technique for estimating transmission line fault locations from digital impedance relay measurements.* IEEE Trans. Power Del. 3(1): 121-129 (1998).
[4] Izykowski J., Molag R., Rosolowski E., Saha M., *Accurate location of faults on power transmission lines with use of two-end unsynchronized measurements.* IEEE Trans. Power Del. 21(2): 627-633 (2006).
[5] Girgis A.A., Hart D.G., Peterson W.L., *A new fault location technique for two-and three-terminal lines*. IEEE Trans. Power Del. 7(1): 98-107 (1992).
[6] Khorashadi-Zadeh H., Aghaebrahimi M.R., *A novel approach to fault classification and fault location for medium voltage cables based on artificial neural network.* International journal of computational intelligence 2(1): 1304-2386 (2005).
[7] Jyh-Shing Roger Jang, *ANFIS: Adaptive Network Based Fuzzy Inference System.* IEEE Transaction on systems 23(3) (1993).
[8] Mohamed D.F., *A New Design of an Intelligent Digital Distance Protective Relay.* PhD Dissertation Submitted to the Office of GraduateStudies of Cairo University (2007).
[9] Vasilic S., *Fuzzy Neural Network Pattern Recognition Algorithms For Classification Of The events In Power System Network.* Ph. D. Dissertation Submitted to the Office of Graduate Studies of Texas A&M University (2004).
[10] Abeer Galal Saad, *Digital Relaying of High Voltage Transmission Lines by Artificial Neural Networks.* Master Dissertation Submitted to the Office of Graduate Studies of Cairo University (2004).
[11] Dash P.K., Pradhan A.K., Panda G., *A Novel Fuzzy Neural Network Based Distance Relaying Scheme*, IEEE Transactions on Power Delivery 15(3): 902-907 (2000).
[12] Coury D.V., Jorge D.C., *Artificial Neural Network Approach to Distance Protection* IEEE. Transactions on Power Delivery 13(1): 102-108 (1998).
[13] Sadeh J., Afradi H., *A new and accurate fault location algorithm for combined transmission ines using adaptive network-based fuzzy inference system.* Journal of Electric Power System Research 79(11): 1538-1545 (2009).
[14] Nan Zhang, M. Kezunovic, *Coordinating fuzzy ART neural networks to improve transmission line fault detection and classification.* IEEE PES, General Meeting, San Francisco (2005).
[15] Yeo S.M. et. al., *A novel algorithm for fault classification in transmission lines using a combined adaptive network and fuzzy inference system.* Electrical Power and Energy Systems 25: 747-758 (2003).