Open Conductor Fault Detection and Classification in Power Transmission Lines using ANFIS

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Abstract **-** This paper proposes a new use of the adaptive neuro-fuzzy inference system (ANFIS)-based algorithm for the detection and classification of open-circuit faults on transmission lines. Using just the single-end measurements, the three-phase voltage data on bus 1 is measured, and then a simple feature extraction is performed on these signals to obtain the maximum value of the signal of each phase, which is also compared with a threshold to detect and classify faults. To verify the suggested idea, various open conductor fault simulations are performed on 230 kV, 50 Hz, and 100 km transmission lines in MATLAB/Simulink. The performance of the suggested technique is analyzed through different fault locations and fault types; the simulation results demonstrate the effectiveness of the suggested approach.

Keywords **-** Adaptive neuro-fuzzy inference system (ANFIS); open conductor faults; transmission lines protection; fault detection and classification.

I. INTRODUCTION

One of the most crucial parts of any power system are the transmission lines, which act as connectors for transferring electricity from power plants to consumers. The transmission lines can easily be affected by different types of unavoidable faults, these faults can be classified as shunt (short-circuit) faults and series (open conductor) faults that can occur in one conductor, two conductors or in all three conductors and any type of them can cause damage thus they must be cleared as soon as possible to ensure an uninterrupted supply of power. The main objective of the transmission lines protection system in this regard is fault detection and classification.

In the literature, a variety of protection schemes for protecting transmission lines during open conductor faults have been proposed such as impedance-based method, The symmetrical components was used by the authors of [1] to derive the compensated values of impedance. The impedance measurements made by protective distance relays are the foundation of this paper [2]. Another technique is used in [3], where the authors proposed a technique based on the sequence current component to detect open conductor faults, this method has many drawbacks like detects only the faults occurring near the breakers or near where the suggested detection device is implemented and there is no fault classification. The Discrete Fourier Transform was also used with the help of Naive Bayes classifier in detection and classification of open conductor faults like suggested in [4].

Various protection schemes based on artificial intelligence have been suggested for transmission lines protection such the artificial neural network ANN, in [5] the authors present a protection method based on artificial neural networks for detecting single conductor open faults in parallel transmission lines. In [6] demonstrates a method based on ANNs for enhancing distance relays performance during open conductor faults in transmission lines, the drawback of both these methods is detecting only one conductor open faults which is not enough. Using the discrete Fourier transform (DFT) to extract relevant features from the current signals of the six-phase, the K-nearest neighbor (KNN) based protection method has been described in [7] for six-phase transmission line's open conductor fault detection and classification system. A fuzzy logic also used like in [8] where the fuzzy inference system (FIS) was created for detection and classification of open conductor faults. A comparative study was proposed in [9] between fuzzy logic and ANN for short-circuit and open conductor fault in transmission lines.

All the methods mentioned before have a drawback as some of them detects only one open conductor fault and doesn't detect the other fault types, or doesn't consider fault classification, in addition the there is no consideration to the response time of the detection and classification systems which is a key factor.

This paper presents a novel use of the Adaptive neuro-fuzzy inference system (ANFIS) for open conductor fault detection and classification, two ANFIS models were created, ANFIS detection model detects whether there is a fault or the system is clear and operates in normal condition and ANFIS classification model classify the fault type and identify which phase is faulted. Both ANFIS model use the three phase voltages extracted at only one end. Several tests, including different fault locations and fault types, have been used to examine the performance of the suggested models. The simulation results demonstrate that the suggested ANFIS models are capable of detecting all types of open conductor faults and identifying the faulty phase correctly in only a few milliseconds.

The structure of the paper is as follows: In Section 2, the proposed test power system simulation model used in this work is given. The proposed method based on ANFIS is introduced in Section 3. Whereas Section 4 introduced the proposed scheme, the exploitation of ANFIS, and how to implement it, Section 5 discussed the obtained simulation results and the conclusion of this paper in Section 6.

II. PROPOSED TEST SYSTEM

The proposed algorithm has been applied on the test system shown in Figure 1. This system consists of a 230 kV /50hz source with a ∠0° phase angle connected to a 230kv/50hz source with ∠27° phase angle through an AC overhead transmission line. The distance between the sources is 100 km. at the sending end (bus 1), the voltage signals is measured, and the data collected at bus 1 is given to the algorithm to be treated and exploited. The simulation parameters of the power system model used are given below.

S_b=500MVA, U_b= 230 kV, l=100 km,
For 1km: R=0.103Ω, L_l=0.0013H, C_l=8.2e-9F

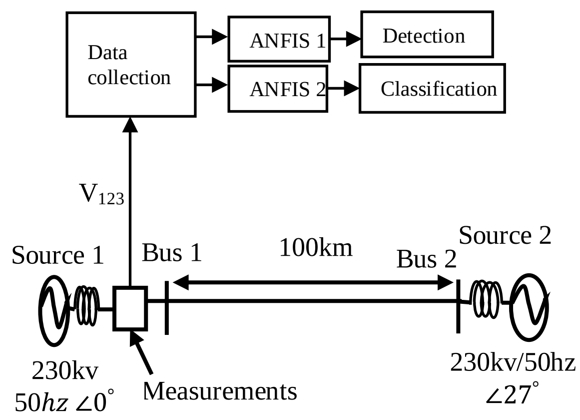

Fig. 1. Implementation of the ANFIS in test power system.

III. PROPOSED ALGORITHM

Adaptive network-based fuzzy inference system "ANFIS is a data learning technique that adopts a fuzzy inference system model to transform input into a targeted output."[10]. ANFIS is a FIS that is built on the basis of adaptive networks which are the superset of all feed-forward neural networks. This allows to combine neural network pattern recognition with fuzzy logic system robustness in ANFIS. Without relying on complicated mathematical quantitative analyses,

First it was introduced by Jang in 1993 [11], The ANFIS consists of a five feed forward neural network layers in which the fuzzy rules considered are the Takagi-Sugeno technique [12]. Fig. 2 shows the ANFIS architecture with two inputs. [13]provide a detailed description of it. The "hybrid learning method," which combines the least-squares estimation (LSE) method and the gradient descent method, is the technique used for ANFIS training. This hybrid learning method uses a forward pass and a backward pass for each level. The input data are used in the forward pass, and the final output is calculated. The total output can be described as a linear combination of the subsequent parameters when the parameter values in the premise part are fixed, and the linear parameters can be determined using the LSE approach. Then the Error signals are propagated from the fifth layer to the first layer during the backward pass. using the gradient descent method, the premise parameters are updated. To choose the ideal number of necessary rules and initial conditions for the parameters, subtractive clustering is used.

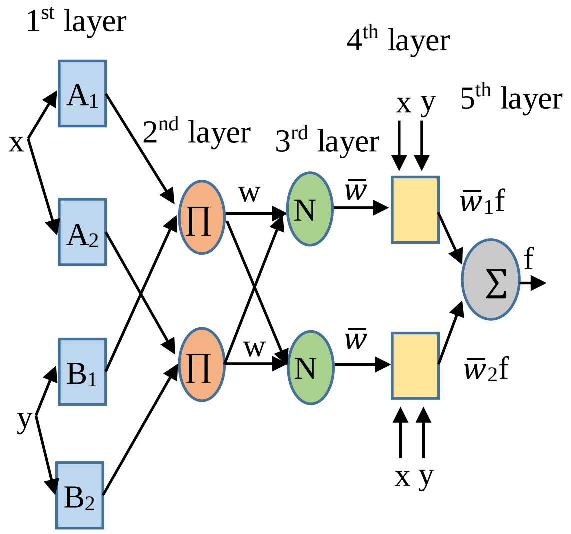

Fig. 2. ANFIS architecture.

Each layer of ANFIS has a unique function. For computing input and output as indicated below.

Layer 1: The input data is fuzzified in this layer. The crisp inputs are mapped into fuzzy inputs. The mathematical formulas utilized in this layer is as follows:

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad (1)$$

ai,bi,ci are parameter known as premise parameters.

Layer 2: This layer employs a variety of fuzzy operators, mostly the AND to fuzzify the inputs. The following equation gives the product of fuzzy operators.

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y),\ i=1,2,3,4 \quad (2)$$

Layer 3 (Normalization): The input is normalized in this layer. The sum of all obtained signals divided by each signal. The mathematical equation is as follows:

$$\overline{w}_1 = \frac{w_i}{w_i+w_2} \quad (3)$$

Layer 4 (Defuzzification): In this phase, a normalized signal is gained once more via a linear equation created from the output signal's membership function, as shown in the equation;

$$\overline{w}_1 f_i = \overline{w}_1 \times (p_i x + q_i y + r_i) \quad (4)$$

Here $\overline{w}_1$ is normalized strength that is obtained in layer 3 and $(p_i x + q_i y + r_i)$ is a parameter set known as consequent parameters

Layer 5: The final stage of ANFIS is referred to as neuron addition. This adds up all of the defuzzification signals, Gj.

$$G_i = \sum \overline{w}_1 f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (5)$$

IV. PROPOSED SCHEME

The basic method consists of the following:

• Exploiting the voltage signal (3 phases) at one end of bus 1.

• process the obtained three-phase voltage signals and extracting the max values of each phase.

• Normalization of all the extracted values in the range ±0.01

• If the computed the extracted value is greater than the threshold, a fault is detected in the corresponding phase, or there is no fault.

The flowchart of the suggested method is presented in Figure 3.

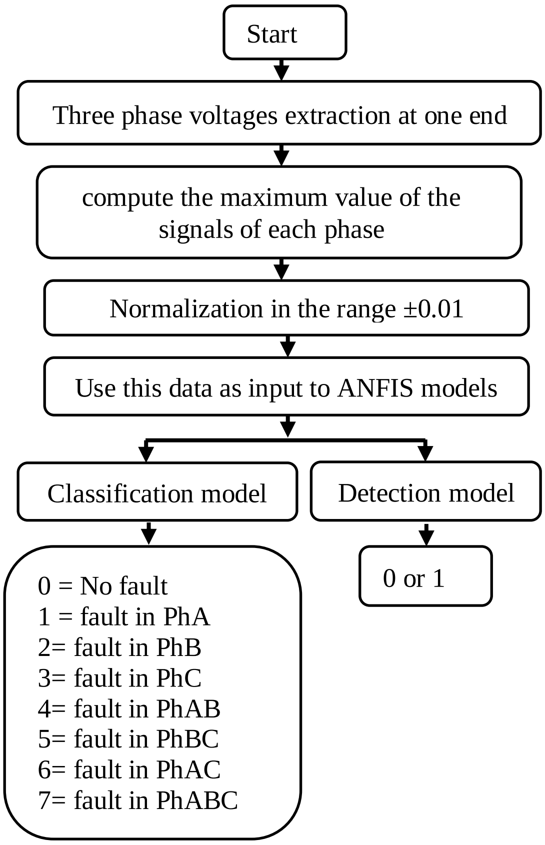

Fig. 3. Flowchart of proposed algorithm.

A) *ANFIS detection model*

To detect the fault, a Sugeno-type ANFIS is developed (fig. 3 and 4). It has one output and three inputs. The inputs of the detection model are chosen as the maximum of the voltage of the three phase that are measured at bus 1. Output is the fault detection 0 means there no fault or the system is clear and 1 means the occurrence of the fault. Each input has two membership functions. The type gauss2mf is selected as the membership function. The ANFIS fault detection model is trained using data corresponding to different fault locations from 10 km to 99 km with 10 steps (10:10:90) in addition to 1km and 99km at the boundaries of the line near the buses to ensure the detection for the entire line and for all types of faults. for the training The hybrid learning method is used.

B) *ANFIS classification model*

Similar to detection model the same parameters with the same structure , three input and one output are used to create the classification model figure 4 , the diffrence is in the output that have eight different values from 0 to 7 corresponding to the fault type , 0 indicates no fault, 1 indicates fault in phase A, 2 indicates fault in phases B,3 indicates fault in phase C, 4 indicates fault in phase AB, 5 indicates fault in phase BC, 6 indicates fault in phase AC, 7 indicates fault in phase ABC.

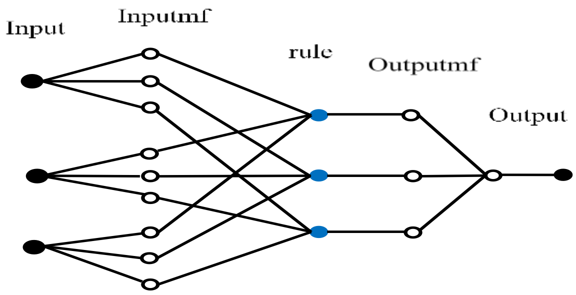

Fig. 4. ANFIS Model Structure.

V. RESULTS

To evaluate the Adaptive neuro-fuzzy inference system (ANFIS), different types of open conductor faults in the transmission line have been created and analyzed in MATLAB/Simulink, like single-line open conductor fault, double-line open conductor , and three-phase open conductor fault. After the start of the simulation, the faults were generated at 0.1 s. The simulation results have been plotted for 0.2 s. The applied ANFIS fault detection and classification models are based on voltage signals obtained at bus 1. The different case studies are detailed in the following. All the voltage signals are measured in per unit.

A) Single phase open -circuit fault (PhA)

Figures 5 shows the voltage signals of an open conductor fault (1L) fault in phase A, It can be seen from the figures that the voltage of the faulty line highly increases during the open conductor fault, while the voltage of the healthy line doesn't change. figure 6 shows the performance of the detection ANFIS based model, noticing that it was 0 before the fault, after the occurrence of the fault at 0.1 it becomes 1 indicating detecting of fault only in 5.5 ms which considered very fast detection time.

Figure 7 shows the performance of the classification ANFIS based model, it can be notice after the occurrence of the fault at 0.1 it becomes 1 indicating that the fault is in phase A, hence performing type classification in just 19.5 ms.

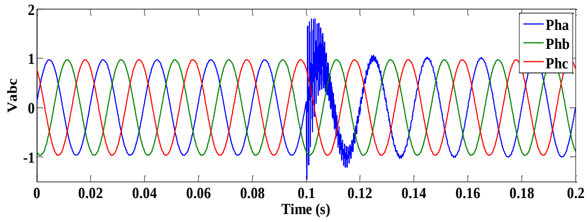

Fig. 5. Three phase voltages during open conductor fault at phase A

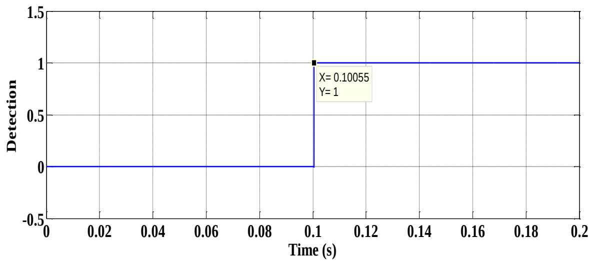

Fig. 6. Detection of the open conductor fault

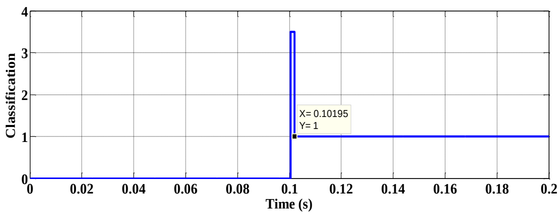

Fig. 7. Classification of an open conductor fault in phase A

B) Double phase open -circuit fault (PhAB)

In this case a double phase open conductor fault (PhAB) was tested, the voltage signals are shown in figures 5, It can be seen from that the voltage of the faulty lines highly increases during the open-circuit fault, while the voltage of the healthy line doesn't change. figure 6 shows the performance of the detection ANFIS based model, noticing that it was 0 before the fault, after the occurrence of the fault at 0.1 it becomes 1 indicating detecting of fault only in 1.5 ms which considered very fast detection time.

figure 7 shows the performance of the classification ANFIS based model, it can be notice after the occurrence of the fault at 0.1 it becomes 4 indicating that the fault is in phase A and phase B, hence performing type classification just in 19.5 ms.

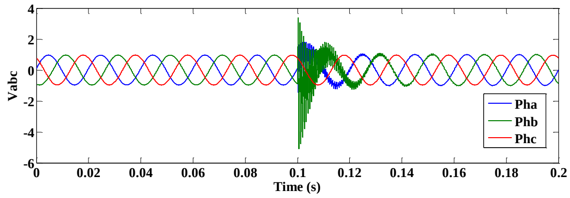

Fig. 8. Three phase voltages during OC fault at phaAB

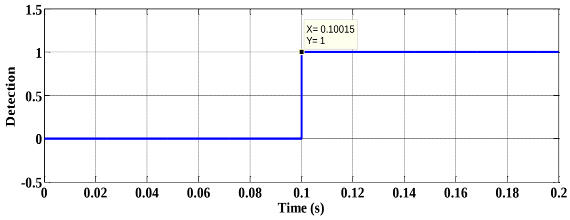

Fig. 9. Detection of the open conductor fault.

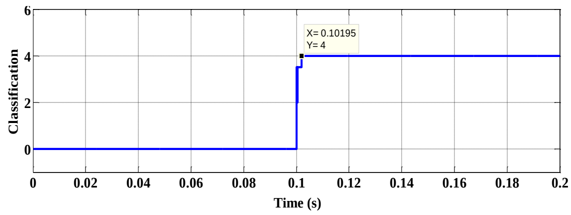

Fig. 10. Classification of an open conductor fault in phase A and phase B

C) Three phase open -circuit fault (PhABC)

Similarly, a Three phase open conductor fault (PhABC) was tested, the voltage signals of all three phases A, B and C, are shown in figure, It can be seen that the voltage of all three phases highly increases during the open-circuit fault, figure 6 shows the performance of the detection ANFIS based model, the detection time is 1.5 ms after the occurrence of the fault at 0.1.

figure 7 shows the performance of the classification ANFIS based model, it can be notice after the occurrence of the fault at 0.1 it becomes 7 indicating that the fault is in all three phases A, B, and C, hence performing type classification in just 19.5 ms.

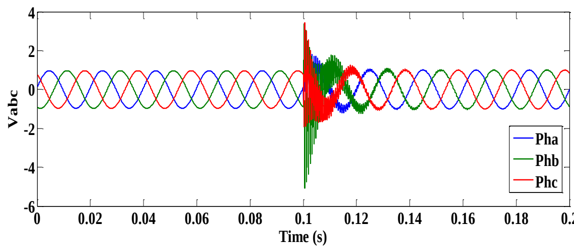

Fig. 11. Three phase voltages during open conductor fault at phase A , phase B and phase C.

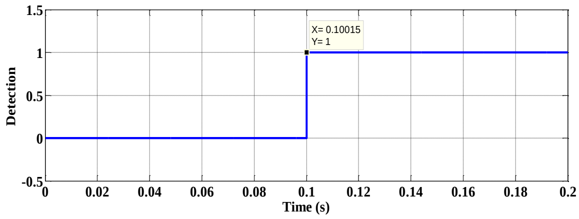

Fig. 12. Detection of the open conductor fault.

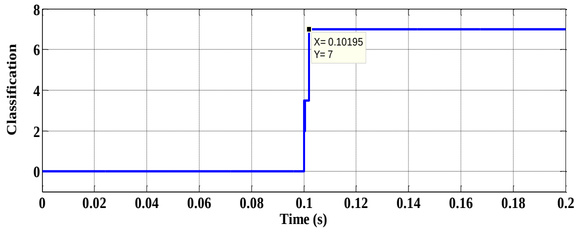

Fig. 13. Classification of an OC fault in phaABC.

VI. CONCLUSION

This paper presents a new application of Adaptive neuro-fuzzy inference system (ANFIS) method in the detection and the classification of transmission lines series faults. In the suggested method, the desired features are obtained from voltage data in only one-end. various faults are generated through simulation in a test power transmission system for different fault type classification and different fault locations in the entire line , two separate ANFIS models were used one model for detection and one model for the classification, both models have 100 % accuracy and were able to detect the fault and classify the type correctly every time in addition both were very fast in producing the output in just few milliseconds, in general the proposed method obtained very promising results, showing that it is reliable, accurate and fast.

VII. REFERENCES

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