Fault Detection and Localization in Transmission Lines Using Adaptive Neural Fuzzy Inference System

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The most important aspect of power system engineering is the identification and localization of faults in power transmission lines, which helps to guarantee the dependable and effective operation of electrical grids. To reduce downtime, avoid cascading failures, and preserve the stability of the power system. Fault localization facilitates the quick restoration of the power supply, lessens the impact on customers, and helps locate the fault precisely. This study describes an automatic fault location and detection (ANFIS) method for transmission lines using measurement data. ANFIS is designed and implemented to enable high-speed processing of real-time error detection and localization. For digital distance protection systems, it is proposed that ANFIS can not only detect problems but also locate them. When a three-phase fault occurs in a transmission line, the proposed technique can accurately identify the affected phases. ANFIS has been tested and trained on different types of field data. Using computer software based on Matlab, the field data are obtained by simulating faults in the Simulink Matlab model representing the transmission line at different points between Misan – Kut station 400 Kv along 200 Km. Phase current and voltage measurements are available at the buses and used as inputs of ANFISs. When it comes to fault detection and fault kind, Through simulated processes the output will illustrate the detection of fault and location with a very low error percentage, the results show that the approach's speed and selectivity are quite reliable and offer sufficient performance for applications involving transmission and distribution monitoring, and protection. The study highlights how crucial it is to quickly and accurately identify and localize faults in power transmission lines to maintain the stability and security of the power system.

Keywords: ANFIS techniques. Fault Detection. Localization. Protection. Transmission Line Faults.

1. Introduction

The possibility of unintentional contact between transmission network conductors and surrounding objects, including building walls, tree limbs, and ground surfaces, is always present. The fact that these items are near distribution network conductors increases the likelihood that these connections will occur frequently. Transmission line maintenance can help to ensure quality, safety, and a continuous supply of energy[1]. Applying maintenance requires early fault situation detection, determining the cause of occurrence and transmission equipment failure, and carrying out the necessary maintenance. One of the most essential components of power systems is transmission line protection systems. Power system faults typically result in large fluctuations in system parameters like current, voltage, power, power factor, and impedance. Rapid and precise identification of transmission line challenges is one of the most important issues about power system reliability. To prevent system collapse, accurate fault localization and detection are therefore essential. Using intelligent techniques like neural networks, fuzzy logic control, etc. is very important to developing the fast detection of faults and the effectiveness of the network[2]. The possibility of faults occurring in the transmission line is greater than alternative real power structure parts where it is exposed to the surrounding natural environment. Faults can occur at any point in the power system, and the most exposed parts are overhead transmission lines. Regarding the distribution system, transmission lines perform the most important part which is to transfer electric power from the generating station to load centers. Since the development of the distribution and transmission system, power system engineers have been an object for locating and detecting faults. The fault must be identified to prevent the transmission line from damage [3], Nonetheless, fault detection input could significantly help localize issues for quicker fault clearing and power restoration. [4] For quick reaction and reliable power supply, locating a transmission line failure in a power system is essential. [4]. For quick line isolation, the fault localization needs to be accurate. Various fault location techniques are available. A plethora of procedures are employed to recover transmission line faults. Traditionally, deep learning and traditional machine learning techniques have been used for transmission line identification and localization.[5]. Transmission line protection was initially accomplished using conventional techniques. Conventional techniques commonly employed for the identification, categorization, and localization of faults in transmission lines include the traveling wave method and the impedance measurement-based approach. [6]. When using impedance-based techniques, high fault impedance is not necessary for the distance relay to operate accurately and dependably. Instead, it depends on a low fault impedance. [7]. Impedance approaches, either single-end or two-end, are presented based on multiple current and voltage data obtained from a transmission line terminal. By determining the apparent impedance as observed from one line termination, the single-ended impedance-based approach aims to pinpoint the fault's location. Impedance-oriented approach High fault path impedance, line load, source characteristics, and shunt capacitance all contribute to the high fault position error.[8] [9]. one-ended and two-ended impedance-based fault location algorithms and demonstrate their application in locating real-world faults. To analyze both methods, various types of faults will be modeled and simulated [10]. To find the defect and solve the aforementioned issues, the two-ended impedance-based approach is used. Because current and voltage signals must be measured at both ends of the cable, this method has a significant computational cost. But increase the pinpoint accuracy to find the issue [11] [12].In [13] Using the absolute sum value of the coefficients in Multiresolution Signal Decomposition (MSD) based on the Discrete Wavelet Transform (DWT) is the method employed here. The HIF in the transmission line is then located using a fault indication and a fault criterion. The method devised can withstand any kind of fault. The correlation of forward and backward waves moving across a transmission line is employed by traveling wave-based methods to calculate the fault's distance. Locating faults in high resistance faults is less mistake-prone with this procedure. However, the biggest challenges are the high and costly sampling frequency, the computing load, and the practical implementation challenges. [14] [15]. founded on the idea that any disturbance to a transmission line causes traveling waves to be produced, which then move up the line. The transmission line's line capacitance, line inductance, and charging and discharging processes result in these waves. Waves travel at a speed that is nearly equal to the speed of light, with their frequencies ranging from a few kilohertz to several megahertz. [16]. Artificial neural networks, or ANNs, have been successfully used in various fault analysis fields for a long time. Being one of the most popular techniques in the artificial intelligence field, this method is crucial for creating effective power system fault analysis algorithms. The input layer, hidden layer, and output layer are the three main layers of a standard ANN model. [17]. The numerous uses of ANN in the development of fault analysis algorithms is made possible by a number of its advantages. When creating defect diagnostic models, ANN is incredibly useful. The ANN's innate capacity for self-learning is by far its most useful benefit. Only a few parameters need to be changed for it to work. Because the related path weights are updated by the ANN throughout the training process, the ANN is not sensitive to data loss caused by weight changes. Additionally, data parallel processing is a benefit in and of itself, making it easier to deploy for solving real-world issues like fault diagnosis. Additionally, ANN has certain flaws. [18]. In order to accurately update the weights and grow the ANN structure, it is necessary to train it utilizing vast and scattered data. In this regard, ANN approach is used in a number of research projects. [5] focuses on applying artificial neural networks to defect localization and detection in order to achieve high execution speed, accuracy, and precision. All in all, every approach has advantages and disadvantages, and the best approach will rely on the particular application and the properties of the data. For transmission line fault detection, a mix of these techniques can be applied to increase the precision and resilience of the system. This paper provides a novel use of ANFIS for localization and fault detection systems that permit high-speed relaying even in the presence of a high fault impedance in the fault path. Numerous three-phase faults have been the subject of in-depth simulation investigations using large-scale MATLAB-based computer programs. taking into account large differences in fault location, in order to validate the suggested strategy. The purpose of this computer software is to produce defective data. To train and test the suggested technique, utilize the generated fault data.

2. Adaptive Neural Fuzzy Inference System (ANFIS algorithm):

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid computational model that combines concepts from fuzzy logic and neural networks. The five levels that make up ANFIS are the fuzzification layer, rule layer, normalization layer, defuzzification layer, and output layer. The first layer converts input values into fuzzy values using membership functions[19]. The second layer generates the firing strengths for the rules, the third layer normalizes them, the fourth layer computes the defuzzified values, and the last layer returns the output. To identify and learn patterns, ANFIS employs a training algorithm that combines a least squares approach with back propagation gradient descent. It approximates nonlinear functions using fuzzy IF-THEN rules that can be learned, which makes it a universal estimator with greater predictive power than conventional techniques like multiple linear regression (MLR) [2].

Because of its ability to adjust to uncertainties and nonlinear relationships in data, the ANFIS architecture makes it possible to represent complex systems. Compared to other approaches, ANFIS may produce accurate predictions with comparatively reduced error rates by fusing neural network training with fuzzy logic principles [2].

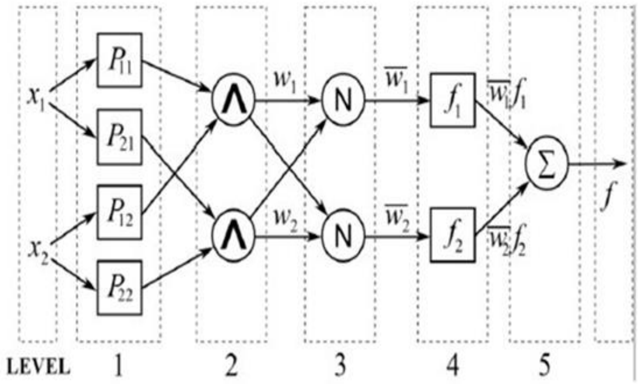


Figure.1 The structure of the ANFIS [20].

ANFIS follows a five-layer architecture consisting of:

Fuzzification Layer: This section is referred to as the "fuzzification layer."

Membership functions are used by the fuzziness layer to generate fuzzy clusters based on input values.

Various membership functions, including the triangle function (trimf) and the generalized bell function (gbell), may be employed in this section.

In membership functions, parameters like {a, b, c} define the shape of the membership function; these parameters are referred to as antecedent parameters.

These parameters, which are listed in Equations (1) and (2), are used to calculate the membership degrees of each member function.

The membership degrees that come from this layer are displayed using

Transform input variables into fuzzy values. Produce the membership grading system this label has a node that is adaptable. The fuzzy membership grade of the inputs is the layer's executed output, and it looks like this:

$$\mu_{Ai}(x) = \text{gbellmf}\,(x;a,b.c) = \frac{1}{1+ |\frac{x-c}{a}|\hat{}(2b)} \qquad (1)$$

$$O^1 i = \mu_{Ai}(X) \qquad (2)$$

where $O^1 i$ is the membership function. $\mu_{Ai}(X)$ Every MF made a change to this layer parameter[21]. The linguistic label attached to this node is A.

Rule layer: Based on the inputs, determine the firing strengths for each rule or generate the firing strengths. This layer is called as rule layer[20]. Firing strengths (wi) for the rules are generated by using membership values computed in the fuzzification layer.[22] wi values are found by multiplying the membership values as the following (3).

$$O_i^2 = w_i = \mu_{Ai}(x) \,.\, \mu_{Bi}(x) = 1\ \mu_{Ai}(X) \quad (3)$$

$i = 1, 2, \ldots$

Normalization layer: Ensures that the sum of the firing strengths is one by normalizing them. Moreover, the nodes are fixed nodes. The nodes that bear the N label indicate that the firing strengths have been normalized from the previous layer. This layer's $iitth$ node determines the ratio of the firing strength of the ith rule to the total firing strength of all the rules:

$$O^3{}_i = \hat{w} = \frac{wi}{w1+w2} \quad (4)$$

A layer of defuzzification: Determines the weighted average of the effects linked to the firing strength of each rule.

This layer is called as defuzzification layer. Weighted values of rules are calculated in each node of this layer as given in (5). This value is calculated by using first-order polynomial.

$$O^4{}_i = y_i = \hat{w}_i f_i = \hat{w}\,(p_i x_1 + q_i x_2 + r_i)\ , \quad (5)$$

$i = 1,2,3,\ldots..$

$\hat{w}$ is the output of the normalization layer and pi, qi, ri is the parameter set. These are called the conclusion parameters. The number of conclusion parameters of each rule is one more than the number of inputs. For example; in the structure of the ANFIS with four inputs, the number of conclusion parameters of each rule is five.[22]

Output layer: It is referred to as the final layer.

The outputs acquired for each rule in the defuzzification layer are added up to determine the real output of ANFIS.[22]

$$O^5{}_i = \text{overall output} = \sum_i \hat{w}i\ fi = \frac{\sum_i wifi}{\sum_i wi} \ (6)$$

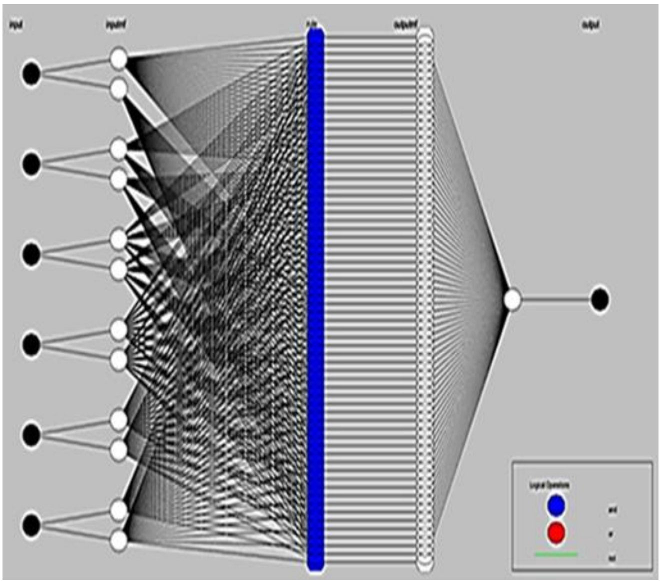


Figure 2. ANFIS design for a first-order Sugeno model with six inputs and six rules.

3. Proposed Fault Detection Based on ANFIS in Transmission Lines

The two-terminal transmission line model's modeling details are presented in this part. The Simulink software version 2022a and MATLAB were used to create the transmission line model. The transmission line model development goal was to produce a model that could measure voltage and current at both buses on each side of the line. The development of the Simulink model utilized in this work was based on transmission lines between two stations, The transmission line model consists of two stations as shown in Fig.5, each with a 400 KV and 5000 KVA modeling block one in Misan (the South West Networks) and the other in Kut station, which is connected by a 400 KV 3. phase, 200 km transmission line. Fig.4 displays the Simulink model in Matlab. Two equivalence mutual impedance blocks, two voltage, and current V-I measurement blocks (the buses on each side), and the transmission line topology indicate the whole load in each city with load (1000 MW, 150 Var)..

The 400 KV, 200 Km transmission line (overhead lines) constant is displayed in Table (2).

The value of genuine transmission lines between two stations is taken into consideration when selecting a pi-section transmission line with impedance values.

Table (1) displays the fault parameters of the suggested model.

The 200 km long, 50 Hz, 400 kV transmission line will be simulated by the transmission line models utilized at every stage of this study. The line is fractured into nine segments in this particular work. The line between two stations (the π model transmission line) as shown in Fig. 4 with variable reactor and resistor values is located in the middle of the block. Each value of reactors and resistors in the transmission line at the beginning of the line is multiplied by (L), and the reactors and resistors at the end of the line are multiplied by (1-L).

L: It is considered a variable because the location of the fault is unknown.

So the transmission line is divided into ten sections from 0 to 90 percent of the line length. The block of fault detection and location is located on the line applying three phases to the ground (symmetrical fault). All information on the constants for (132 and 400) KV overhead lines that are used in the Simulink was taken from southwest networks in Misan as shown in Table (2). This section will make it easier for the researcher to find the fault zone. Compile information on transmission line faults, such as fault distances (the location of the problem). You can do this by multiplying the transmission line length value by (10 - 90) percent and gathering data from nine parts. The measurements of the three-phase voltage and three-phase currents taken from the buses, as shown in Fig. 6, show the data extraction in the Matlab Simulink model as a data features block that collects the three-phase voltages and currents and class data block that determines the zone of the three-phase fault after applying the three-phase fault by the fault type and location block, as shown in fig. 5. every feature data is gathered in a matrix of dimensions 6 by 600 with six inputs; this data will be fed into ANFIS modeling techniques, which are suitable for defect localization and detection. ANFIS stands for Adaptive Neuro-Fuzzy Inference.

Table (1) the suggested model's fault parameters

System components	**Parameters /units**	**Value**
Short circuit level (S)	*$5000*10^6$*	MVA
Fault capacitance Cs	*F*	Infinite
Switching time (t)	*Seconds*	0.1
Ground resistance Rg	*Ohms*	0.01
Fault resistance Rf	*Ohms*	0.1
Frequency	*Herts*	50
Phase to phase voltages (RMS)	*Voltage*	400
Active Power (load)	*Watts*	$1000*10^6$
Inductive reactive power QL(Load)	*Var*	$150*10^6$

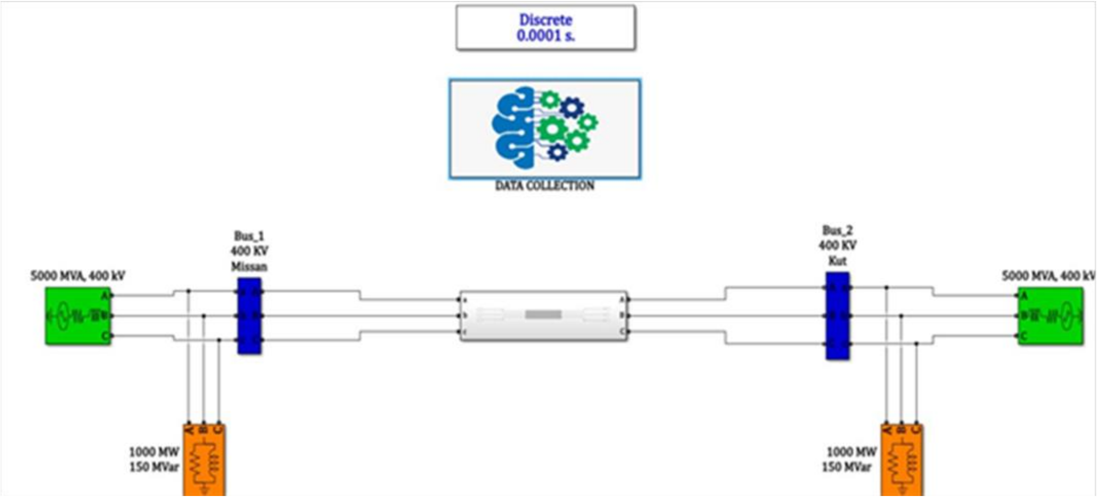


Figure 3. A 400 KV 3.phase, 200 km transmission line Simulink model.

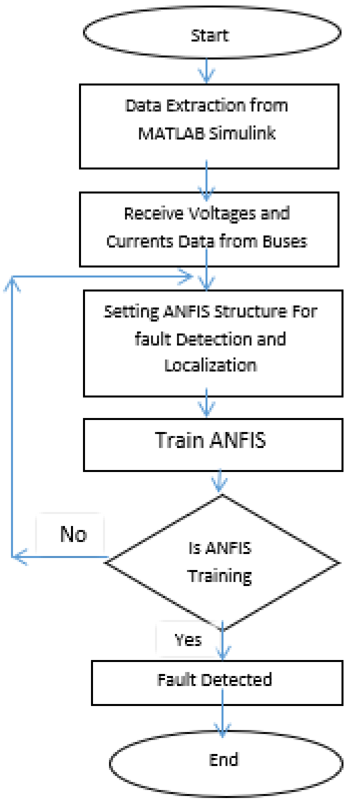


Figure 4. The Data processing model for ANFIS in MATLAB.

Table (2) The constant of 400 KV,200 Km transmission line (Overhead lines).

Conductor (400 KV single line)			R_O (Ω/Km)	R_1(Ω/Km)	X_O(Ω/Km)	X1(Ω/Km)	Thermal power (MVA)		Current (Amp)	
Type	C.S Area (mm^2)	Code					Rated	Max.	Rated	Max.
Twin ASCR	2*(490/ 65)	ASCR	.150	.03610	0.69	0.314	970	1154.3	1400	1666

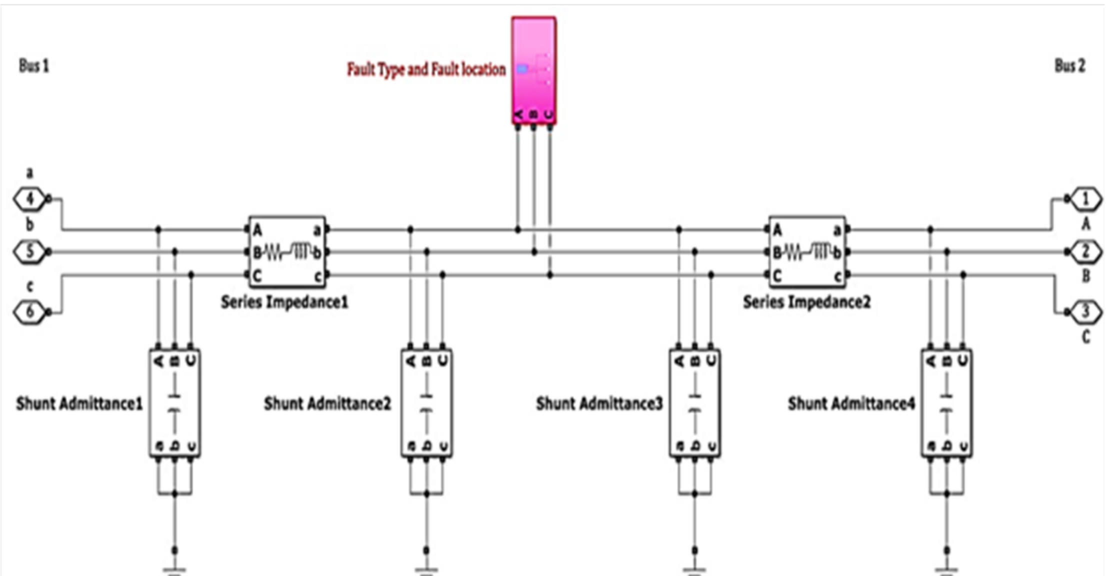


Figure 5. The Simulink- the model of (400 KV), 200 km lines between Misan –Wasit stations.

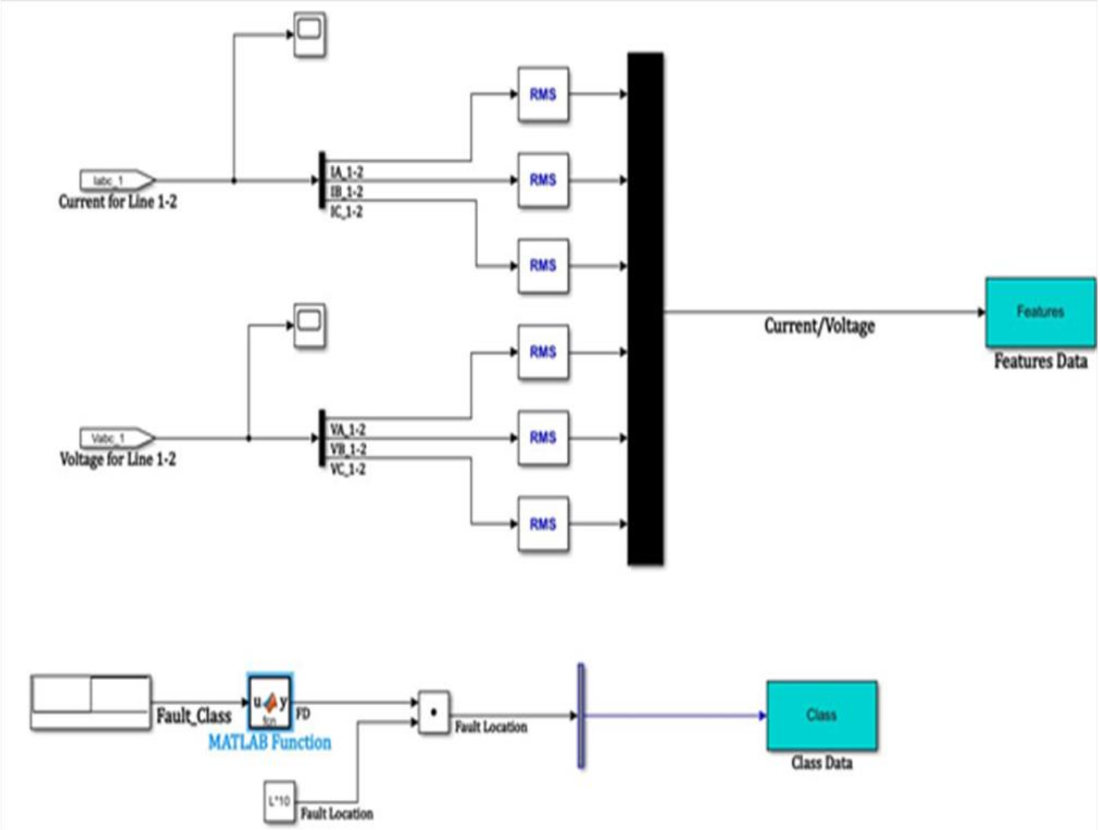


Figure 6. Data extraction in Matlab Simulink model.

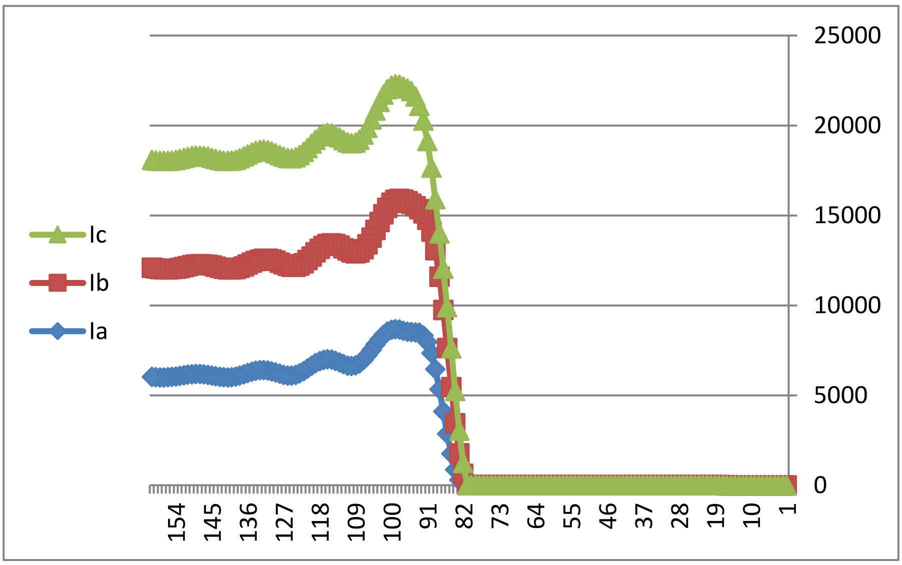


Figure 7. The data extraction (Three phase currents) from buses 1 & bus 2 when fault at 10% of the line length.

4. RESULTS AND DISCUSSION

After applying The fault in this work is a symmetrical, three-phase fault. At each bus bar in the Simulink model (bus 1, bus 2), these buses are measurement units that read the voltages and currents of the three phases after the fault occurs (each fault will take 0.05 sec.). The buses will collect the data at this moment, so we collect the data from two sides of the network: Misan station and Kut station. The data will be collected in feature data in matrix form. The feature data will transfer to the workspace in Matlab after the simulation. Fig.6 shows the shape of data of the three-phase currents measured by the two buses when the fault is at 10% of the line length. By using a Matlab function condition to compare the values of the feature data, if the input is larger than zero, the output will be logic1, and there is a fault. If the input is less than zero, that means the output is equal to zero, so no fault is detected.ANFIS model performance can be assessed using several metrics. The efficacy of fault detection and location is measured by these measures. It is also possible to evaluate ANFIS's computational efficiency in terms of memory usage and training time. A program in Matlab programmed to test the accuracy of the ANFIS file work to used it in the networks by using another Simulink network but with an unknown length and by giving any length the result will appear as shown in table (1) that illustrates the different values of transmission line length and the output appears with very low error percentage. The results in the table show the output value and the accuracy of locating the distance of fault points with different values of length and the final five results show the values of the output when there are no faults detected For fault detection the result will give logic one or zero for the detect the fault or not as shown in table (1)

For fault categorization, location, and detection in power systems, ANFIS has some benefits. It can give real-time analysis, adjust to shifting system conditions, and manage ambiguous and inaccurate data. Nevertheless, managing large-scale systems with a lot of variables and rules could be difficult for ANFIS. Additional requirements for the training process include a large volume of labeled data.

In summary, ANFIS is an effective technique for locating and detecting faults in power systems. It is an invaluable tool for preserving the stability and dependability of the electrical grid because of its capacity to learn from data and approximation of complex functions. Power system operators can improve fault management tactics, reduce downtime, and guarantee a steady supply of electricity by employing ANFIS. Locating and detecting errors The waveforms are essential for evaluating electrical signals and locating transmission line faults using ANFIS algorithms in MATLAB. Based on the given search results, the following is a description of the waveforms in MATLAB for fault identification and localization using ANFIS techniques:

Obtaining Data: To capture fluctuations brought on by faults or disturbances, waveforms representing voltage and current measurements are obtained from sensors or monitoring devices along the transmission lines.

Before processing: Before entering the obtained waveforms into the ANFIS model for fault identification and localization, they undergo preprocessing to eliminate noise, filter out undesired signals, and guarantee data quality.

Feature extraction: By applying wavelet transforms to the obtained waveforms, pertinent features that aid in locating fault signatures and patterns in the electrical signals can be extracted.

Training of ANFIS Models: The ANFIS model in MATLAB is trained with the preprocessed waveforms as input data for fault localization and detection.

Based on the properties of the input signals, the model learns from these waveforms to identify anomalies, categorize defects, and pinpoint the sites of faults.

verification as well as Testing: To evaluate the trained ANFIS model's effectiveness in precisely identifying and localizing transmission line faults, it is validated and tested using additional waveform sets. To ensure the precision and dependability of defect identification and localization, adjust the model's parameters and evaluate the outcomes. Optimize the model by making adjustments based on the outcomes of the simulation.

Table (3) Shows the results of the testing on the ANFIS file giving the different values of transmission line length.

Ia (A)	Ib(A)	Ic (A)	Va (Volt)	Vb(Volt)	Vc(Volt)	L (length)/Km	OUTPUT	fault (1)no-fault(0)
6518.458	6545.002	6540.482	19098.55	19113.5	19090.96	0.5	7.01098	1
5991.413	6018.652	6017.298	35044.43	35061.09	35036.29	1	10.00059	1
5542.813	5570.075	5570.946	48629.18	48647.01	48620.87	1.5	14.98088	1
5156.407	5183.311	5185.77	60334.64	60353.25	60326.36	2	19.99821	1
4820.132	4846.465	4850.069	70522.76	70541.86	70514.61	2.5	25.00792	1
4524.849	4550.498	4554.931	79468.97	79488.33	79461.01	3	30.00606	1
4263.508	4288.419	4293.453	87386.23	87405.72	87378.49	3.5	35.00173	1
4030.581	4054.739	4060.207	94441.71	94461.22	94434.21	4	39.99619	1
3821.68	3845.089	3850.868	100768.4	100787.8	100761.1	4.5	45.0086	1
3633.27	3655.951	3661.948	106473.3	106492.7	106466.3	5	50.03395	1
3462.476	3484.458	3490.602	111643.7	111662.9	111636.9	5.5	55.05578	1
3306.937	3328.251	3334.488	116351.1	116370.1	116344.5	6	60.05143	1
3164.689	3185.372	3191.662	120655.1	120673.9	120648.7	6.5	64.48385	1
3034.094	3054.182	3060.494	124605.3	124624	124599.1	7	69.79157	1
2913.766	2933.297	2939.608	128243.8	128262.3	128237.8	7.5	74.76349	1
2802.53	2821.542	2827.833	131606.1	131624.4	131600.2	8	79.85554	1
2699.377	2717.911	2724.168	134722.6	134740.8	134716.9	8.5	84.98052	1
2603.437	2621.533	2627.749	137619.7	137637.7	137614.1	9	89.80761	1
2.526418	2.526418	2.526418	216310.8	216310.8	216310.8	1	9.67E-08	0
2.524973	2.524973	2.524973	216310.8	216310.8	216310.8	2	-2.26E-06	0
2.52354	2.52354	2.52354	216310.9	216310.9	216310.9	3	-3.79E-06	0
2.522125	2.522125	2.522125	216310.9	216310.9	216310.9	4	-3.79E-06	0
2.520732	2.520732	2.520732	216311	216311	216311	5	-3.79E-06	0

A Comparison with other techniques

ANFIS can give advantages in terms of accuracy, efficiency, and training speed in many scenarios, making it a competitive choice for modelling and prediction tasks, according to comparisons of ANFIS with other techniques across different research and applications. Comparisons of ANFIS with other techniques across various research and applications shown in Table (4) that it can provide advantages in terms of accuracy, efficiency, and training speed in many cases, making it a competitive choice for modelling and prediction jobs.

To evaluate ANFIS's relative effectiveness in fault identification and localization in power transmission lines, a direct comparison of its training time with these particular algorithms is required. The particular techniques employed, the intricacy of the data, and the application all affect how accurate ANFIS is to other machine learning algorithms for fault detection and localization in power transmission lines. While several research has revealed that ANN is generally better than ANFIS, ANFIS has demonstrated promising results in fault classification and real-time detection.

Table (4) Analyzing the ANFIS technique in comparison to other artificial intelligence (AI) techniques

	Ref.	Name of approach	Techniques used	Advantage	Dis advantages
1	[32]	Eliminating the Dependence of GPS or Communication Latency Estimation in Traveling Wave Based Double-Terminal Fault Location	double-terminal traveling wave	independence from GPS or communication latency estimation, accurate fault distance calculation, and applicability to various fault circumstances.	needs for GPS or communication latency estimation for data synchronization, making it independent of these external factors.
2	[33]	Transmission Line Fault Location Using MFCC and LS-SVR	the Mel-Frequency Cepstral Coefficients (MFCC) as inputs for fault location in Transmission Lines (TL).	accurate fault location in TLs, robustness to noise, and efficient representation of signal information.	limited application in Electrical Power Systems EPS, lack of detailed technique information, the assumption of noiseless signals, and the need for further investigation to enhance the approach.
3	[34]	Fault Location in Transmission Lines based on LSTM Model	LSTM Model	- does not require explicit feature engineering by a domain expert, making it more accessible and less dependent on expert knowledge. -allows for capturing temporal dependencies in the data, which can improve the accuracy of fault location estimation	-the method is applied in appropriate conditions and with careful consideration of the data quality and computational resources. -the effectiveness of the method heavily relies on the quality and availability of the data. If the data is incomplete or contains noise

4	[35]	Analyzing the Characteristics of Faults in a Transmission Line and High Voltage Capacitor Banks in a 115-kV-Power System Using Discrete Wavelet Transform	The discrete wavelet transform (DWT)	-The use of DWT in fault analysis can improve the efficiency of power systems and ensure their protection. -the discrepancy between the system parameters in the case of faults occurring in a single capacitor bank and two capacitor banks connected in a back-to-back topology can be resolved.	investigating faults in these banks requires significant time and human resources.
5	[36]	Design and Implementation of Hybrid Transmission Line Protection Scheme Using Signal Processing Techniques	signal processing techniques (the Stock well transform), (the Wigner distribution function), and (the alienation coefficient)	a robust and efficient method for fault detection and classification, offering improved accuracy and reliability in power system protection	the complexities and computational requirements of integrating multiple techniques remain a potential drawback of the proposed transmission line protection scheme
6	**[37]**	Deep Neural Network Based Fault Classification and Location Detection in Power Transmission Line	Deep Neural Network (DNN)	- high accuracy achieved in fault identification -the reliability and efficacy of power systems -adaptability contributes to the robustness and efficiency of fault detection	-the requirement for a large amount of training data to achieve high accuracy. DNNs are data-hungry models. - the complexity and black-box nature of DNN models can make it difficult to interpret and explain the decision-making process behind fault classifications.
7	**[38]**	Study of Fault Detection on a 230kV Transmission Line Using Artificial Neural Network (ANN)	artificial neural network	-allows for quick decision-making in detecting system problems. -provides a reliable method for identifying various fault types. -adapt to changes in the power system network after intense training.	the need to make critical decisions regarding the type of network, network architecture, and termination standards the Back Propagation Neural Network (BPNN) used in -ANN programming requires feedback from the output to the

					input to evaluate weight changes, which can be a complex and time-consuming process
8	**[39]**	PARTICLE SWARM OPTIMIZATION ALGORITHM-BASED FAULT LOCATION USING ASYNCHRONOUS DATA RECORDED AT BOTH SIDES OF TRANSMISSION LINE	the Particle Swarm Optimization (PSO)	-Simple Idea -Easy Execution. -Robustness to Control Parameters -Computational Efficiency	-Premature Convergence -Limited Exploration -Sensitivity to Parameters -Lack of Guaranteed Global Optimum
9	**[40]**	A Fuzzy Logic System to Detect and Classify Faults for Laboratory Prototype Model of TCSC Compensated Transmission Line	Thyristor Controlled Series Capacitor (TCSC) compensated transmission line model	-Increased transmittable power. -Enhanced system stability. -Improved voltage control. -Minimized transmission losses.	-Conventional distance relays may experience overreach and mal-operation in the presence of TCSC devices. -Dynamic control action affecting relay performance.
10	**[5]**	The use of artificial neural network for low latency of fault detection and localization in transmission line	Artificial Neural Network(ANN)	Ability to extract patterns associated with the analyzed process or system, making them effective in fault analysis -handle internal network processing efficiently.	Inability to train on non-numerical data, making it challenging to interpret findings and match results with real-life circumstances

The waveforms in Matlab Simulink

The waveforms are utilized as input data to train the ANFIS model in MATLAB after they have been preprocessed and pertinent features have been retrieved. Based on the properties of the input signals, the model learns from these waveforms to identify anomalies, categorize defects, and pinpoint the sites of faults.

The accuracy, resolution, and signal-to-noise ratio of the obtained waveforms have a substantial influence on how well ANFIS performs in defect localization and identification. Accurate defect identification and dependable analysis depend on high-quality data

Finding fault signatures and patterns in the waveforms depends critically on how well feature extraction techniques work. The model's accuracy in fault detection and localization is directly impacted by the features chosen.

The ANFIS model's waveform training procedure is essential to its functionality. The model's capacity to learn and generate accurate predictions is influenced by various factors, including the choice of training data, model parameter optimization, and training method convergence. The performance of ANFIS can be impacted by the complexity and diversity of fault types and circumstances in transmission lines. Robust fault detection and localization depend on the model's capacity to generalize across many fault scenarios and adjust to changing fault characteristics.

The ability of the model to adapt to quickly changing fault circumstances can be impacted by how well waveforms are processed in real-time in MATLAB for fault detection and localization using ANFIS. Effective fault management requires fast analysis and decision-making based on incoming waveforms.

Fig. 8 illustrates the input signals from the buses (voltages and currents). The plot shown in the figure is taken from a plotting program in Matlab, where the x-axis is the time and the y-axis is the three-phase voltage signals. In the first part, the second part in Fig. 8 labels the y-axis with the three-phase current signals. By making a two-phase ground fault in the Simulink model to show the effect of the faults on the values of the current and voltages, we can see in Fig. The shape of the input waveforms for 10% of the line length shows that the high value of the current in two phases and the voltage will be reduced. The current in the third phase will be zero. So on, for all lengths, the currents will be higher when the fault point is nearest to the station, and the voltage will be lower.

The advantages of ANFIS (Adaptive Neuro-Fuzzy Inference System) in fault detection and localization.

The ones that follow are some advantages related to using ANFIS (Adaptive Neuro-Fuzzy Inference System) for defect localization and detection:

-Utilizes Illustrations Nonlinearity: Because ANFIS can capture a process's nonlinearity efficiently, it is a good fit for complicated systems where traditional approaches can have trouble[23].

-Automatic Adaptation Capability: ANFIS can automatically adjust to data changes, guaranteeing that the system continues to function properly even in dynamic situations[24].

-Rapid Learning Capacity: ANFIS can learn well and swiftly, which is critical in situations when quick learning is required[23].

-Excellent Generalization Capability: ANFIS can perform effectively on data that hasn't been seen because of its great generalization capability[25].

-High Flexibility: ANFIS's system design is very flexible, enabling a multitude of variations and making it appropriate for a broad range of applications.

-Interpretability: ANFIS is a useful tool for situations where it's critical to comprehend the decision-making process since it strikes a compromise between interpretability and accuracy[26.

-Fault Detection and Localization: The efficacy of ANFIS in locating and identifying faults has been demonstrated by its successful application in fault detection and localization along power transmission lines[27].

-Real-World Applications: The usefulness and efficacy of ANFIS have been demonstrated by its application in real-world settings, such as fault detection and localization in power transmission lines[28].

To sum up, ANFIS is an effective tool for defect identification and localization because of its many benefits, which include its capacity to capture nonlinearity, adjust to changing data, pick things up fast, and have a high degree of generalization ability.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) drawbacks

- Complexity in Parameter Tuning: The number of fuzzy sets and membership functions in ANFIS models, for example, may need to be carefully adjusted. This might take time and be difficult to optimize successfully.

- Dependency of Data Quality: The caliber and volume of training data that is provided greatly influences ANFIS performance. Results may be less than ideal if there is insufficient or noisy data.

- Computing Capabilities: Training ANFIS models can take a lot of time and computational power, particularly for large-scale systems with complicated failure scenarios.

- Accuracy vs. Interpretability Trade-off: It might be difficult to balance interpretability and accuracy in ANFIS models. Raising the model's complexity to achieve greater accuracy could make the system harder to understand.

- Overfitting: Similar to other machine learning models, ANFIS can overfit, particularly if the training dataset is small or the model is very complex[1].

- Limited Scalability: ANFIS's performance in fault detection and localization tasks may be impacted by scalability issues when used to very big or high-dimensional datasets.

- Expertise Requirement: Users lacking specialized knowledge may find it difficult to develop and fine-tune ANFIS models as they require an understanding of both fuzzy logic and neural networks.

- Model Interpretation: Although ANFIS provides interpretability, it can still be difficult to comprehend and interpret the deep correlations that the model learns, particularly in complex failure scenarios.

- Optimization Difficulties: ANFIS's optimization procedure, which includes changing membership functions and rule parameters, can be intricate and needs sophisticated optimization methods.

- Limited Robustness: The dependability of fault detection and localization results may be impacted by ANFIS models' limited capacity to withstand outliers, noisy data, or unanticipated fluctuations in fault patterns.

To effectively use ANFIS in fault detection and localization applications and to minimize potential difficulties during model building and deployment, it is imperative to be aware of these constraints.

The Optimization techniques used in ANFIS (Adaptive Neuro-Fuzzy Inference System)

Several tactics can be used to get over ANFIS's (Adaptive Neuro-Fuzzy Inference System) limitations in practical applications:

- Optimize Parameter Tuning: Use cutting-edge optimization strategies to efficiently adjust the ANFIS model's parameters, cutting down on the complexity and time needed to do so[29].

- Boost Data Quality: To ensure improved performance and robustness in real-world scenarios, increase the quantity and quality of data used to train ANFIS models[30].

- Apply Ensemble Techniques: By combining several ANFIS models using ensemble techniques, you can increase prediction accuracy, decrease overfitting, and boost system dependability.

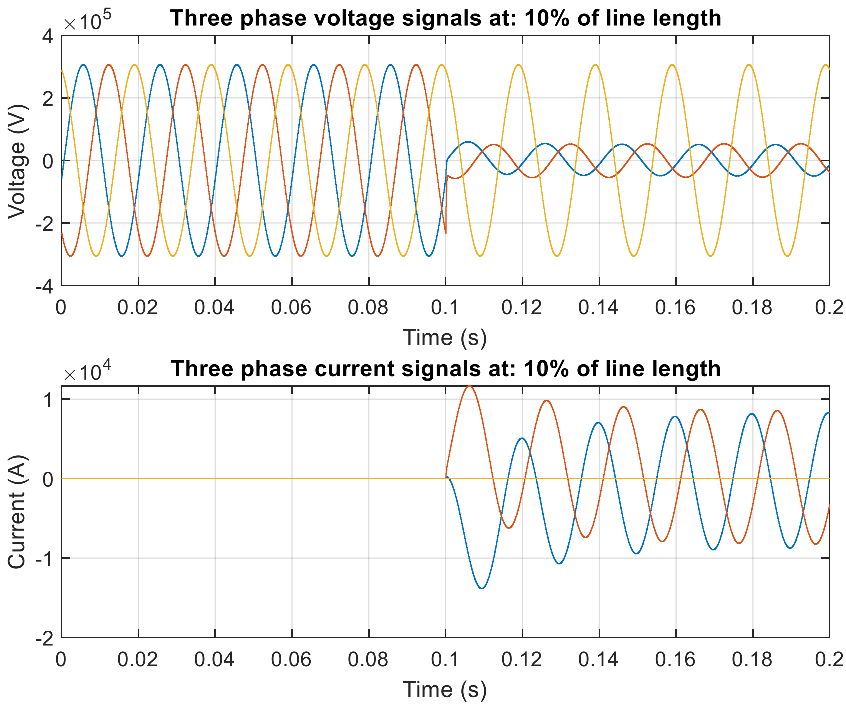
- Feature Engineering: To improve the model's capacity to recognize intricate correlations and patterns, and perform comprehensive feature engineering to extract pertinent and instructive characteristics from the data[31].

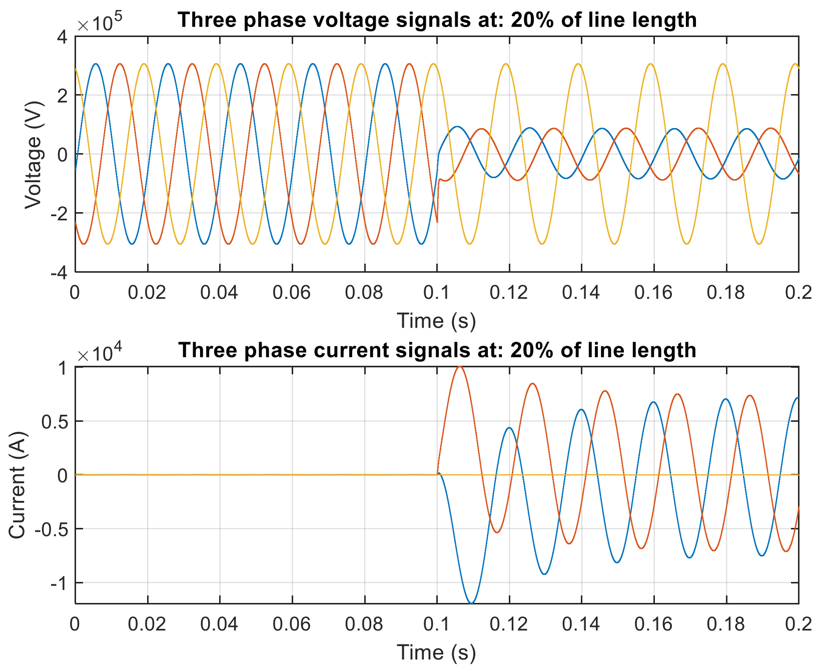
- Methods of Regularization: Use regularization strategies to enhance and avoid overfitting.

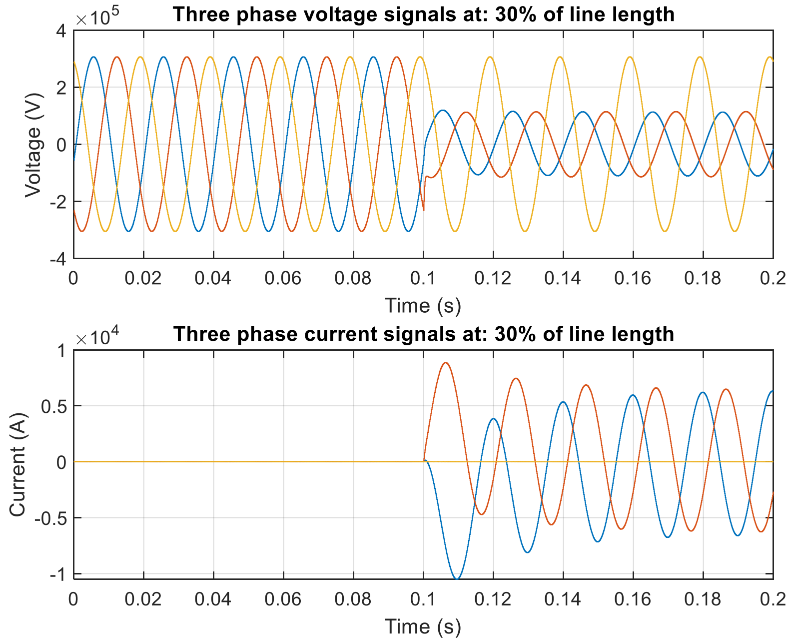
- Hybridization with Optimization Techniques: To improve the model's capacity for learning and efficiency, hybridize ANFIS with sophisticated optimization techniques like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO).

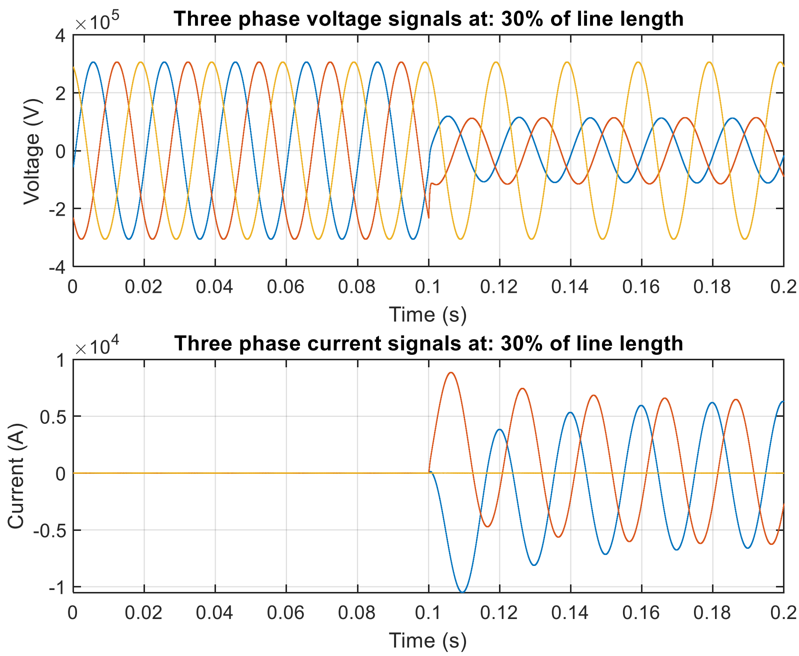
- Cross-validation: Use cross-validation techniques to evaluate the ANFIS model's performance on hypothetical data to make sure it is robust and able to generalize to real-world situations. Based on real-time data, continuously assess and update the ANFIS model to maintain optimal performance and adjust to changing circumstances.

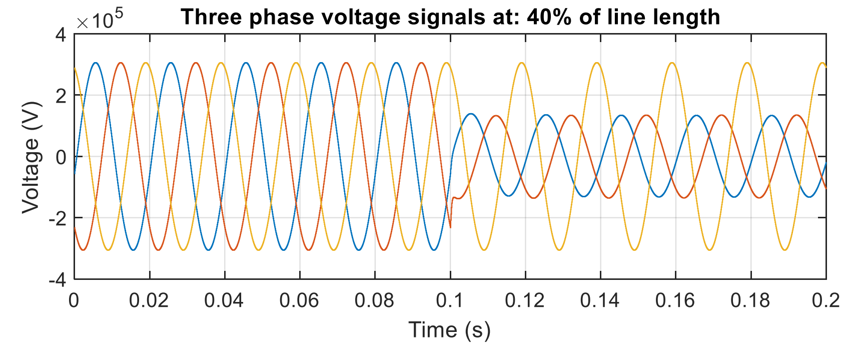
Collaborative Research: Encourage cooperation between researchers and domain professionals to address particular issues and modify the ANFIS model to successfully satisfy the needs of practical applications. These techniques can help overcome ANFIS's shortcomings in practical applications[31]

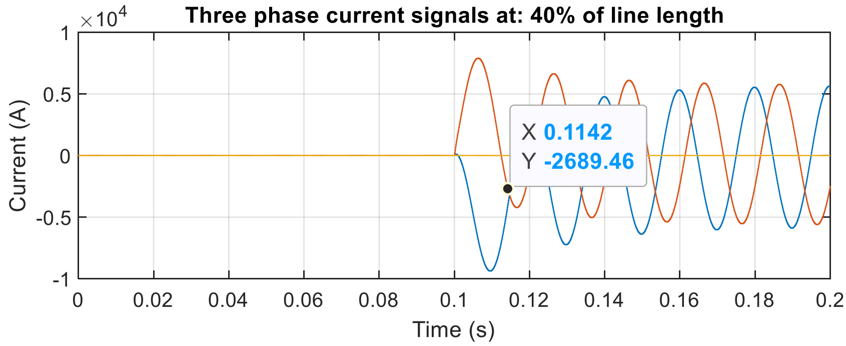

Three phase voltage signals at: 10% of line length
×10^5
4
2
0
-2
-4
Voltage (V)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)
Three phase current signals at: 10% of line length
×10^4
1
0
-1
-2
Current (A)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)

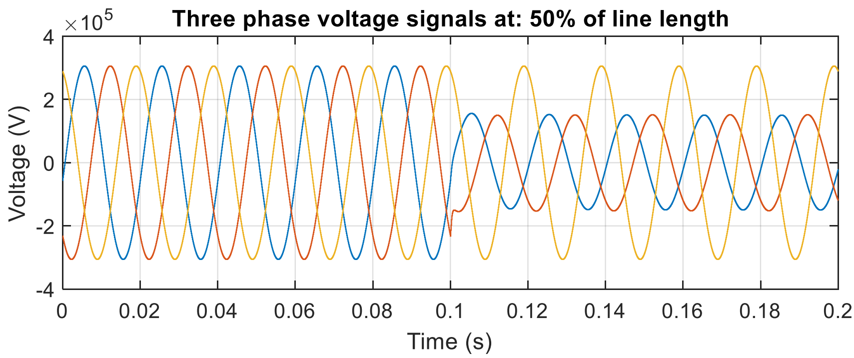

Three phase voltage signals at: 20% of line length
×10^5
4
2
0
-2
-4
Voltage (V)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)
Three phase current signals at: 20% of line length
×10^4
1
0.5
0
-0.5
-1
Current (A)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)

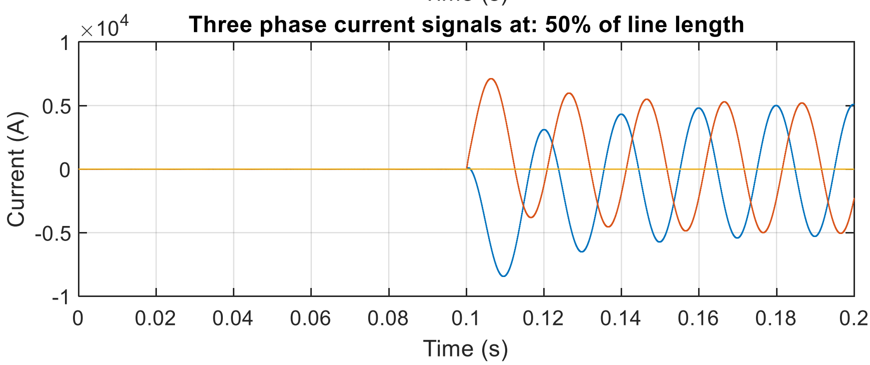

Three phase voltage signals at: 30% of line length
×10^5
Voltage (V)
Time (s)
Three phase current signals at: 30% of line length
×10^4
Current (A)
Time (s)

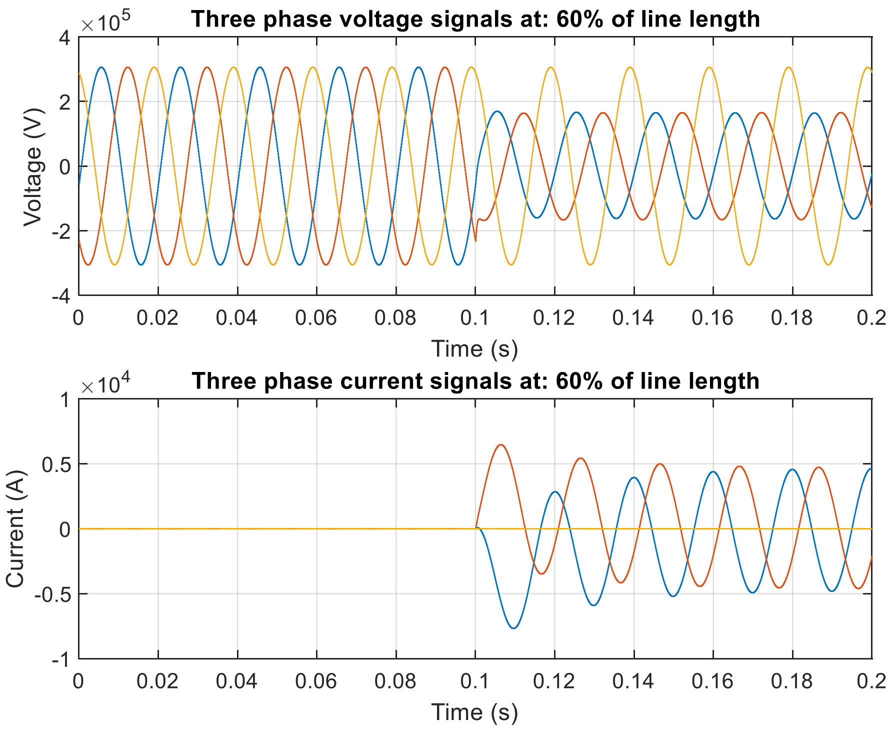

Three phase voltage signals at: 30% of line length
×10^5
Voltage (V)
Time (s)
Three phase current signals at: 30% of line length
×10^4
Current (A)
Time (s)

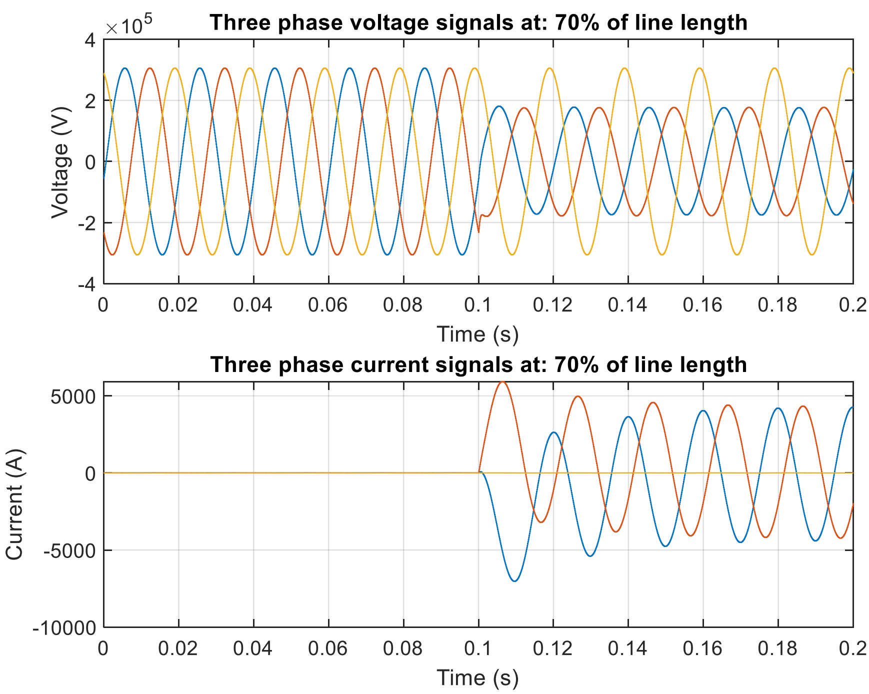

Three phase voltage signals at: 40% of line length
×10^5
4
2
0
-2
-4
Voltage (V)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)

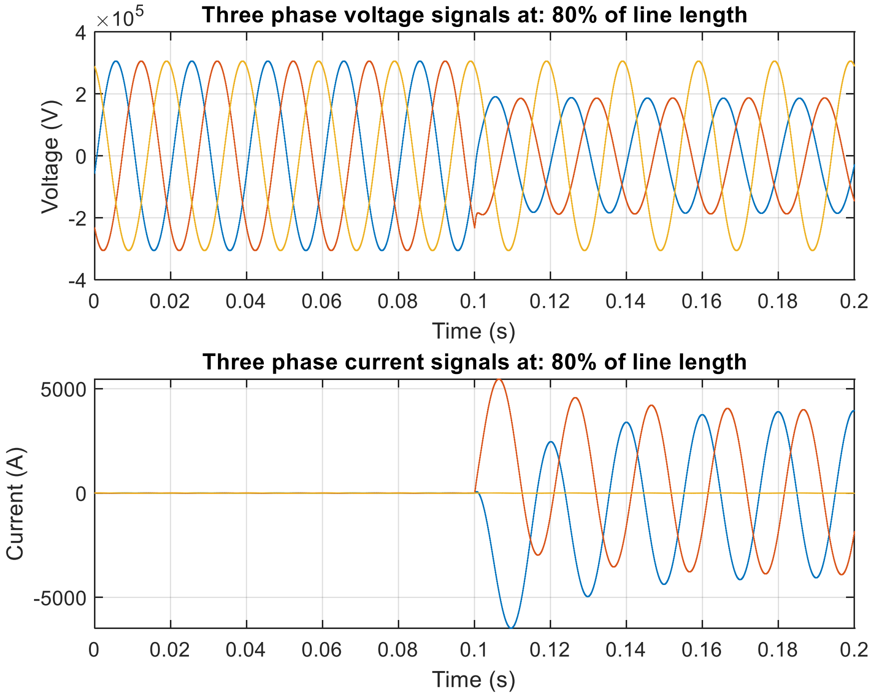

Three phase current signals at: 40% of line length
×10^4
1
0.5
0
-0.5
-1
Current (A)
X 0.1142
Y -2689.46
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)

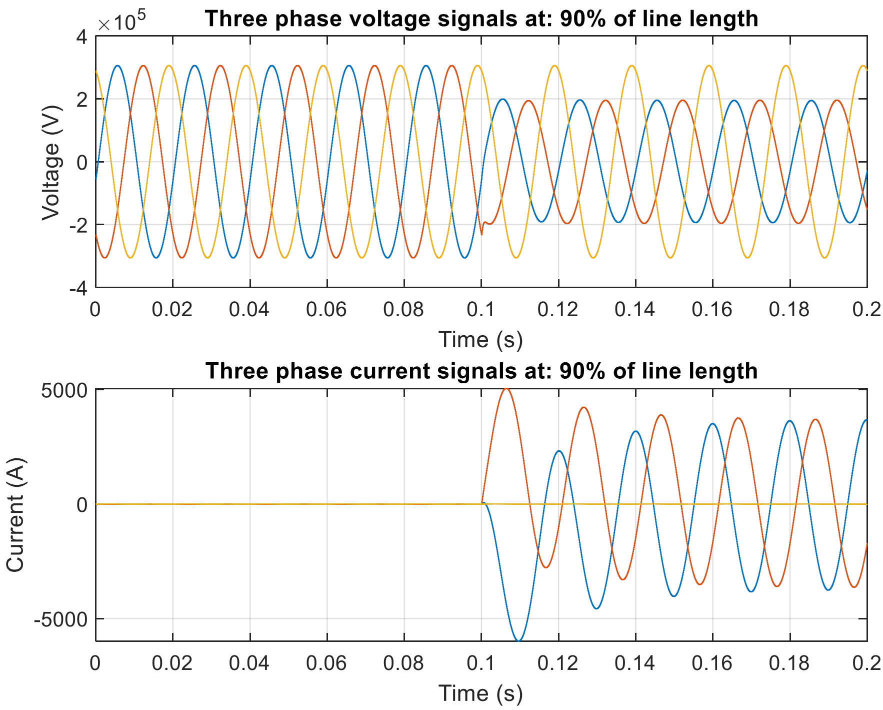

Three phase voltage signals at: 50% of line length
×10^5
4
2
0
-2
-4
Voltage (V)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)


Three phase current signals at: 50% of line length
×10^4
1
0.5
0
-0.5
-1
Current (A)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)


Three phase voltage signals at: 60% of line length
×10^5
4
2
0
-2
-4
Voltage (V)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)
Three phase current signals at: 60% of line length
×10^4
1
0.5
0
-0.5
-1
Current (A)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)


Three phase voltage signals at: 70% of line length
×10^5
4
2
0
-2
-4
Voltage (V)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)
Three phase current signals at: 70% of line length
5000
0
-5000
-10000
Current (A)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
Time (s)


Three phase voltage signals at: 80% of line length
×10^5
Voltage (V)
Time (s)
Three phase current signals at: 80% of line length
Current (A)
Time (s)


Three phase voltage signals at: 90% of line length
×10^5
Voltage (V)
Time (s)
Three phase current signals at: 90% of line length
Current (A)
Time (s)

5. CONCLUSION

This work presents an ANFIS-based application for localizing and detecting faults in a transmission line protection scheme. Three steps make up the suggested system: data extraction, data testing, and location accuracy checking using the table. 3. Using the recorded RMS currents and voltages, the transmission line faults are discovered and detected in this study. The following are the key findings from this research that can be inferred from the results above: A new application for computers has been created to do voltage and current calculations for three-phase faults used in ANFIS training and testing, as well as to resemble a transmission line. Although the ANFIS technique requires more processing, it offers superior accuracy in the detection of defects and localization. Numerous tests conducted under various transmission line fault conditions show that this technology is precise and has an error rate of less than 0.01%. The findings collected indicate that the suggested strategy provides accurate estimations. ANFIS simulations have demonstrated that the real values produced using the suggested technique meet the intended data.

The transmission line protection mechanism can make use of the suggested output methodology based on ANFIS .

This work has examined the application of adaptive neural fuzzy inference (ANFIS) as a transmission line fault localization and detection method. A 400 kV, 200 km, the Matlab/Simulink model aimed to determine the mean absolute value of the erroneous voltage and current signals from the 50 Hz three-phase transmission line. 600 data samples of defective current and voltage were collected from different locations along the transmission line to use the module for fault localization and to identify defects using ANFIS. The faults are distributed along the route in nine locations (10%-90%). The topic was raised, specifically the three-phase. Table 3 shows the speed, reliability, and sensitivity training of the data. Defect identification was completed with 100% accuracy, and problem localization at several sites was completed with 99.9% accuracy. This work has focused on the speed of execution to enable rapid fault detection, which is important because fault identification time is a critical factor in fault protection. In general, improving fault management techniques and guaranteeing the stability and dependability of power systems may be accomplished with the help of the ANFIS application for fault detection and localization in transmission lines. It is a dependable, accurate, and effective solution.

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