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Symmetrical Three Phase to Ground Fault Detection and Localization Using Intelligent Systems
Case study : Misan - Kut Station 400 kV

A THESIS
SUBMITTED TO THE COLLEGE OF ENGINEERING -UNIVERSITY OF MISAN
IN A PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE IN ELECTRICAL ENGINEERING (POWER)

By

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بِسْمِ اللّهِ الرَّحْمَنِ الرَّحِيمِ

(قل لَّوۡ كَانَ ٱلۡبَحۡرُ مِدَادٗا لِّكَلِمَٰتِ رَبِّي لَنَفِدَ ٱلۡبَحۡرُ قَبۡلَ أَن تَنفَدَ كَلِمَٰتُ رَبِّي وَلَوۡ جِئۡنَا بِمِثۡلِهِۦ مَدَدٗا)

صَدَقَ اَللهَ العلي اَلَعَظَيَمَ

سورة الكهف – الآية119

DEDICATION

To my mother …

To my father …

To my husband …

To my brothers…

To my sisters…

To my sons…

And all my friends

With entire my honorary and respect

Statement of Authorship

This thesis was completed as part of the MSc. (**Electrical Engineering**) at **College of Engineering -University of Misan-**. This is my own unaided work. Where the work of others has been used or drawn on then it has been fully attributed to the relevant source.

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ABSTRACT

The importance of the study on advanced fault detection, and localization in transmission lines is to enhance the accuracy and efficiency of fault detection and localization in power transmission systems. The study aims to take advantage of advanced technologies such as adaptive neuro-fuzzy inference systems (ANFIS), neural networks, and hybrid methods to improve fault detection and its localization in transmission lines, where the work was compared using a model based on artificial neural networks (ANN), and the proposed system was preferred. The study emphasizes the benefits of ANFIS compared to alternative approaches, such as its ability to manage uncertainties and non-linear systems and the possibility of its integration with other preventive migration strategies for using power networks. Subsequent studies focus on improving the accuracy and reliability of the model used. This study shows the implementation of ANFIS technology for the automatic identification and localization of fault disturbances in transmission lines using data measured from a single transmission line station. The goal of designing and implementing this technology is high-speed processing that can provide fault detection and localization in real-time. It has been proposed to use the approach to identify faults and locations for digital distance protection systems in addition to detecting all shunt faults. Where a transmission line with a voltage capacity of 400 kV was used, with a distance of 200 km, connecting from Maysan Governorate to Wasit Governorate. The ten different forms of switching errors that may occur in a transmission line have been carefully identified by the stage(s) involved using the proposed technique. Different field data sets have been used to train and test the system of the used techniques. Using computer programs built on the Matlab platform, field data are extracted from simulations of faults at different locations along the transmission line. This study addresses a variety of fault scenarios,

including fault types, fault locations, and fault resistance. Measurement of the phase current and voltage available at the relay position based on the RMS values are the inputs of the ANFISs. When it comes to fault detection and fault type, the used technique outputs are either 1 or 0. The results of the simulation process show that the speed and selectivity of the approach are very reliable for the ANFIS as compared with ANN. The results of fault detection for a transmission line length of 20 km in ANFIS is (19.99821) km , whereas for an ANN transmission line of the same length is (19.0988) km. This clearly shows that ANFIS is more accurate and faster than ANN. Testing and comparison of two techniques models in defect identification and localization show that ANFIS outperforms ANN in terms of prediction accuracy, consistency of outcomes, and training duration. But still provide sufficient performance for applications involving transmission and distribution monitoring, control, and protection. Performance for applications including monitoring, control, transmission, and distribution protection.

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List of Symbols

Symbol	Definition
$O^1{}_i$	The membership function
Oi^2	Output of the rule layer
$O^3{}_i$	The output of the normalization layer
$O^4{}_i$	Output of the defuzzification layer
O_5 i	The actual output of ANFIS
$\mu_{Ai}(X)$	The fuzzy membership grade of the inputs
µx and µy	Membership degrees of each membership function
Wi	Firing strengths for the rules
Ŵi	The output of the normalization layer
{pi, qi,ri}	The parameter set, the consequence parameters

List of Abbreviations

ANFIS	Adaptive Neural Fuzzy Inference System
ANN	Artifitial Neural Network
AFCIS	Arc Fault Circuit Interrupters
BS	British Standard
DWT	Discrete Wavelet Transform
FRA	Frequency Response Analysis
(trimf)	The triangle function
Gbell	The generalized bell function
IQS	The Iraqi Standards
FIS	Fuzzy Inference System
ReLU	Rectified Linear Unit
MLR	Multi Linear Regression
W	Weighted vector
RNN	Recurrent Neural Network
LSTM	Long Short Term Memory
IOC	Insulated Overhead Conductor
LCC HVDC	Line Commutated Conductor High Voltage Direct Current

List of Publications

Alhashemi, B., & Hussein, A. R. " A Line to Ground Fault Detector in 400 KV Transmission Line by Using Intelligent System", Misan Journal of Engineering Sciences, vol.3, no.1, pp. 84-99,2024.

CHAPTER ONE

INTRODUCTION

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1.1 Introduction

For electrical power systems to remain highly reliable and to guarantee service continuity, power transmission lines' efficiency and dependability are essential. However, some causes, including aged equipment, the environment, and human mistakes, can cause transmission line failures, which can result in serious financial losses and disruptions to the provision of power[1].

To guarantee the dependability and effectiveness of electricity transmission lines, fault localization and detection are crucial processes. Conventional techniques for localizing and detecting faults depend on manual testing and inspection, which can be labor-intensive, time-consuming, and prone to human mistakes[2].

More sophisticated methods for defect localization and detection have been developed as a result of recent developments in machine learning and artificial intelligence. A method like this is called Adaptive Neuro-Fuzzy Inference. system (ANFIS), which offers a reliable and flexible method for defect localization and detection by fusing the advantages of fuzzy logic and artificial neural networks[3].

The purpose of this thesis is to look at the use of ANFIS methods for power transmission line fault detection. The goals of this research are to build an ANFIS model to identify power transmission line faults. Analyze the ANFIS model's performance with both simulated and actual data. Examine how well the ANFIS model performs in comparison to more conventional approaches for fault localization and detection. Examine the possibilities of ANFIS methods for localizing and detecting faults in real-time. The suggested ANFIS model will be assessed using performance metrics like accuracy, consistency, and recall after being trained on a dataset of simulated and real data. accuracy as well as memory.

The findings of this study will help to develop more dependable and effective strategies for guaranteeing service continuity and upholding high-reliability levels in electrical power systems. They will also shed light on the potential of ANFIS techniques for fault detection and localization in power transmission lines. The ANN network was constructed by the study to compare the ANFIS and ANN findings. Although they are both effective techniques for localizing and detecting faults, ANN and ANFIS have distinct advantages and disadvantages. While ANN is more adept at identifying patterns and generating forecasts based on past data, ANFIS is more trustworthy at forecasting efficiency and can handle language input factors. The particular requirements of the application determine which of the ANFIS, ANN, in brief, Fault detection and localization are crucial aspects of power system protection, ensuring the reliable and efficient operation of electrical grids.

The primary objectives are to quickly identify the occurrence of a fault and precisely pinpoint its location along the transmission or distribution lines. This enables prompt isolation of the faulty section, restoration of the power supply, and minimization of customer impact.

1.2 Problem Statement

Fault detection and localization in power systems are critical for maintaining the reliability and stability of electrical networks. The primary problem is to quickly and accurately identify the occurrence of faults, such as short circuits or open circuits, and to determine their precise location along transmission or distribution lines. This is essential for minimizing downtime, ensuring safety, and reducing economic losses associated with power outages.

The suggested approach uses an adaptive network-based fuzzy inference system to locate transmission line faults. This innovative technology provides precise fault location in real-time, overcoming the drawbacks of conventional techniques. The technique uses MATLAB to extract fault signatures from phase current and voltage values, stores the data in a file, and trains ANFIS to locate faults accurately. Simulation results are used to assess the performance of the suggested ANFIS-based approach, showing its efficacy in real-time fault detection, and accurate fault location estimate in transmission lines. The requirement for an accurate and effective way to locate and detect faults in transmission lines is the study challenge for the publication "Fault Detection and Localization in Transmission Lines Using Adaptive Neural Fuzzy Inference System". ANFIS can achieve high accuracy in fault detection and localization, often with low error percentages. This reliability is crucial for maintaining the stability and security of power systems.

1.3 The Research Objectives

The following are the study's research goals regarding enhanced fault localization and detection in transmission lines:

- Develop ANN and ANFIS models that achieve high accuracy and precision in detecting and localizing three-phase to-ground faults in transmission lines. This includes minimizing faults and ensuring reliable identification of faults.

- Develop methodologies for accurately determining the location of faults along the transmission line using voltage and current measurements from different points in the system.
- Utilize MATLAB and Simulink to simulate fault conditions and validate the performance of the Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) models. This includes generating synthetic fault data for training and testing the models
- Assess the performance of the developed models based on metrics such as detection speed, accuracy, and robustness against various faults.
- State the main differences in the training algorithms used by Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and the accuracy of each method.

1.4 Aim of the study

Using adaptive neuro-fuzzy inference system (ANFIS) methodologies, the project aims to design an intelligent fault detection and localization system for power transmission lines. The purpose of the study is to evaluate ANFIS's performance in terms of fault identification, localization, and localization in transmission lines in comparison to other machine learning algorithms, including neural networks and hybrid techniques. By putting the suggested method to the testing data transmission lines and contrasting its results with those of other approaches now in use, the study also seeks to show how effective it is.

The project is to aid in the creation of a different, highly accurate, and high-performing method for fault diagnostics in transmission lines. The project also seeks to locate and precisely diagnose defects to increase power systems' reliability in transmission lines, which can enhance power system stability and help avoid false trips.

1.5 Contribution of study

The application of ANFIS and ANN for fault detection and localization in power systems marks a significant contribution to the field of electrical engineering in Misan City by employing this technique in the 400 Kv transmission line between Misan and Kut 200 Km (south-west networks).ANFIS provides a robust framework for accurately detecting and localizing faults in transmission lines. By integrating fuzzy logic with neural networks, ANFIS can effectively process imprecise and uncertain data, which is critical in real-world power system scenarios.

The effectiveness of ANFIS has been validated through simulations using software like MATLAB and Simulink. By simulating various fault scenarios, train ANFIS models on diverse field data, ensuring that the system is well-equipped to handle real-world conditions and achieve very low error percentages in fault detection and localization, demonstrating its reliability. This high level of accuracy is crucial for maintaining the stability and security of power systems.

1.6 Outline of study

The following steps are commonly involved in the outline of this study of employing ANFIS for fault detection and localization in transmission lines:

- Chapter one: this chapter discusses the problem of the thesis the objectives of the research and how to deal with this problem using the technology of (Adaptive

Neuro-Fuzzy Inference System) ANFIS technology used first time in Misan –-Kut station. the background and requirement for ANFIS in fault localization and detection stem from the need to improve the efficiency and accuracy of fault detection in a variety of systems, especially electrical networks and power transmission lines.

- Chapter two: Includes the studies that provide valuable insights into the application of ANFIS in fault detection and localization, showcasing its effectiveness in improving fault diagnosis accuracy, classification, and localization in power transmission systems.

- Chapter Three: The first part of this chapter is The research technique, the modeling for the network, data analysis, and result interpretation presented in these sections of Chapter Three of a thesis are essential to gaining a thorough knowledge of the study's findings and their implications. Explain the methods and resources for data analysis that were utilized to evaluate the gathered information. Outlines the analysis's findings and talks about their ramifications. Incorporates figures, tables, and other visual aids to bolster the conclusions. the second part is this chapter is to build an ANN network and train the data used in ANFIS. Using the testing program in Matlab to compare the results between the two techniques.

- Chapter four: summarizes the study's conclusions based on the data analysis that was done. Contains graphs, tables, and figures to help visually represent the results. Gives a thorough explanation of the findings concerning the study topics.

- Chapter Five: explains the main conclusions and how important they are for answering the study questions. Summarizes the study's key findings and how they relate to the topic of study. provides suggestions for more research based on the findings of the study. Offers recommendations for useful uses or additional research based on the study's conclusions. Provides advice on how to apply the research's findings in practical situations. Identifies areas in the discipline that require further research or improvement. Makes recommendations for how to expand on the results of the current study in future research.

CHAPTER TWO

THEORETICAL BACKGROUND

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THEORETICAL BACKGROUND

2.1 INTRODUCTION

Faults in power systems refer to abnormal conditions that disrupt the normal operation of electrical equipment, leading to potential damage, safety hazards, and service interruptions. These faults can arise from various causes, including insulation failures, physical damage, environmental factors, and human errors. Understanding the nature and types of faults is crucial for effective power system design, operation, and protection[4]. Faults in power systems can be categorized into several types, symmetrical Faults These involve all three phases equally and are relatively rare but can cause significant damage. An example is a three-phase short circuit. Asymmetrical Faults: These involve one or two phases and are more common. Types include Single Line-to-Ground Fault (SLG) Occurs when one phase makes contact with the ground. Line-to-Line Fault (LLG) Involves two phases short-circuiting each other Double Line-to-Ground Fault (DLG) Involves two phases making contact with the ground [5]. There are many Causes of Faults Common causes of faults include deterioration of insulation materials can lead to short circuits. Physical Damage like Accidents, weather events, or wildlife can damage power lines. Excessive current can cause overheating and subsequent faults. Mistakes during maintenance or operation can lead to faults[6]. Faults can be characterized by their effects on the power system, including current and voltage Changes. faults typically cause abrupt changes in current and voltage levels, which can be monitored for detection. Fault currents can generate heat, leading to equipment damage, and can exert mechanical forces on conductors and components. Importance of fault detection prompt detection of faults is essential to Prevent damage to transformers, generators, and other components [7]. Maintain reliability and reduce the duration and frequency of outages by enabling quick isolation of faulty sections. Fault detection techniques various techniques are employed for fault detection in power systems, including Impedance-Based Methods, These methods measure the impedance seen from the relay location to determine fault conditions. They are effective but can struggle with accuracy in complex systems [8]. Traveling Wave Methods These techniques analyze high-frequency signals generated by faults, providing rapid detection and location capabilities. Techniques such as Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are increasingly used for their ability to learn from data and adapt to changing conditions. They can effectively classify faults and estimate their locations based on real-time measurements[7]. Understanding the theoretical background of faults in power systems and their detection is critical for developing effective monitoring and protection strategies. As power systems evolve and become more complex, advanced detection techniques, including AI-based methods, are essential for ensuring reliability, safety, and efficiency in electrical networks[9].

2.2 Electric Transmission Power System Faults

Transmission lines should transmit power over the required distance economically and satisfy the electrical and mechanical requirements prescribed in particular cases. It would be necessary to transmit a certain amount of power, as a given power factor, over a given distance and be within the limit of given the regulation, efficiency, and losses. The lines should stand the weather conditions of the locality in which they are laid. This would involve wind pressures and temperature variation at the places and the lines should be designed for the corresponding mechanical loading. The regulation would give the voltage drop between the sending-end and the receiving-end. The possibility of a corona formation and corresponding loss would be another consideration. The charging current of the line depends on the capacity of the line and should not exceed the limit. As far as the general requirements of transmission lines are concerned, the lines should have enough capacity to transmit the required power, should maintain 3 continuous supply without failure, and should be mechanically strong so that there are no failures due to mechanical breakdowns also[10].

2.2.1 Shunt faults (short-circuit faults)

2.2.1.1 Unsymmetrical faults

The most common type of shunt fault is Single Line-to-ground fault (SLG) see Figure 2.1, which is one of the four types of shunt faults, which occur along the power lines. This type of fault occurs when one conductor falls to the ground or contacts the neutral wire [10], Fault line to ground 75–80% of short circuits between a phase and the ground that result from physical contact are line-to-ground faults. (Ex. lightning and other influences). The second most common type of shunt fault is the Line-to-Line fault (LL). It is the result of two conductors being short-circuited. or if a tree branch falls on top of the two of the power lines. This type could be represented in Figure 2.2 with an occurrence percentage reaching 10-15% and the Third type is double-line-to-ground faults (DLG) see Figure 2.3. This can be a result of a tree falling on two of the power lines, or other causes with a 5-10% occurrence percentage[10].

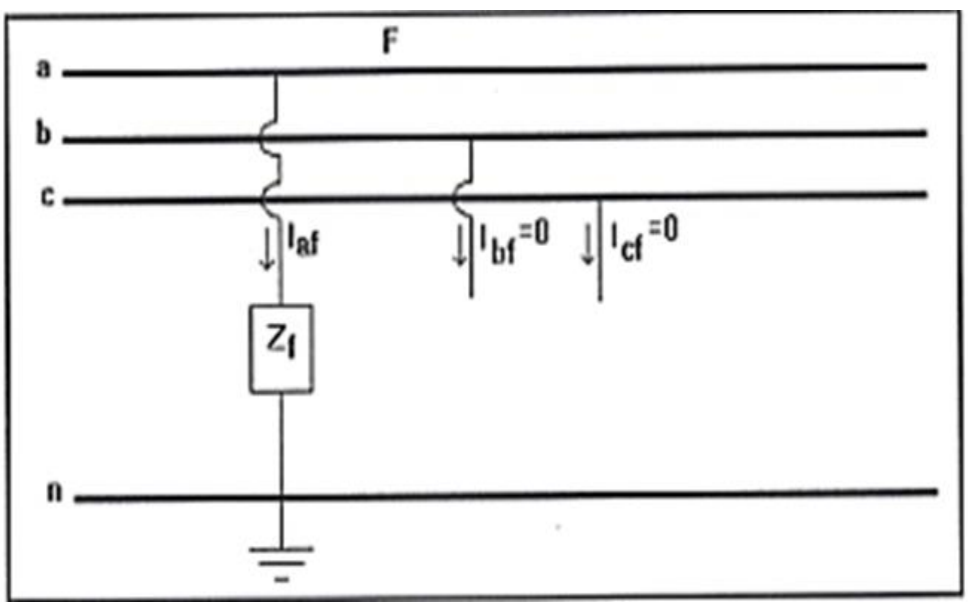


Figure 2.1 Single line to a ground fault[10]

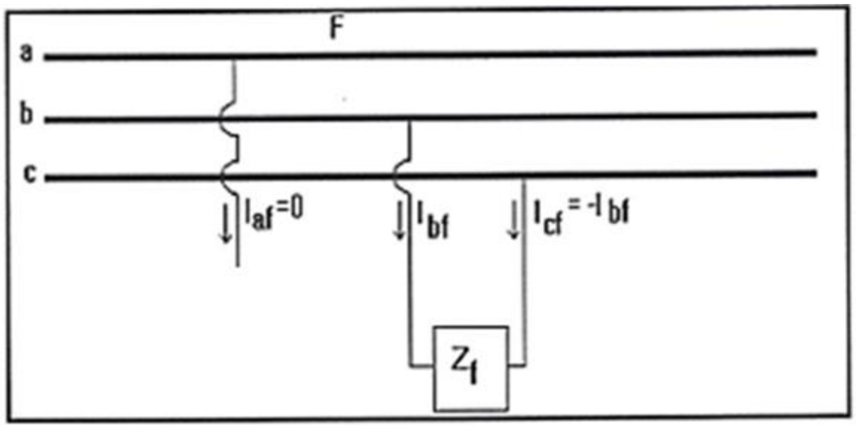


Figure 2.2 line to line fault ([10])

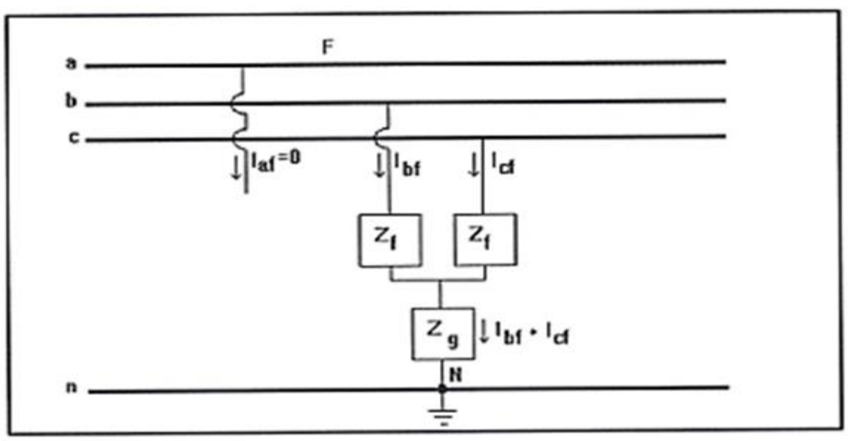


Figure 2.3 Line to line to ground fault [10].

2.2.1.2 Symmetrical faults (Three-Phase Faults).

The least common but most severe type of fault occurs when all three phases come into contact with each other or with the ground see Figure 2.4. It causes very high, symmetrical fault currents in all three phases [10]. A simultaneous short-circuit fault that results in a symmetrical current and happens in all three phases is referred to as this kind of fault.[11] It's the most severe kind, yet it happens rarely. The internal emf of the machine in the system, internal impedances, and the impedance in the network between the machine and the problem all influence this fault current. Asymmetrical three-phase faults may be studied using per-phase basis analysis or an equivalent single-phase circuit. Although the fault may be asymmetrical, using symmetrical components might help minimize computation complexity in cases of asymmetrical three-phase faults because transmission lines and other components are typically symmetrical. Because fault analysis provides answers that are roughly consistent across a range of voltage and power ratings and operates on values of order unity, it is typically performed in per-unit numbers.

Generally, this is a balanced state, and fault analysis just requires knowledge of the positive-sequence network. Additionally, since all three phases carry identical currents displaced by 120°, the single-line diagram can be utilized. Three-phase faults, with or without earth, account for only 5 percent of initial faults in a power system on average. Of the unbalanced faults, 15% are double-line faults with or without earth, and 80% are line-earth faults. These faults frequently worsen to become three-phase faults. The remainder is due to malfunctioning conductors. A fault is the equivalent of the structural network change brought about by the increase of impedance at the fault site. The defect is known as a fastened fault or a solid fault if the fault impedance is zero.[11]

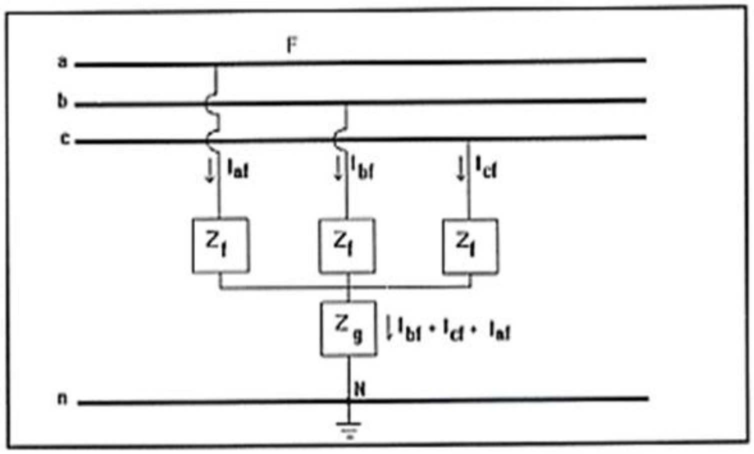


Figure 2.4 Three-phase fault[10]

Table .2.1 Types of faults with occurrence percentage *[12]*

Types of faults	Symbols	% Occurrence	Severity
Line to Ground	L-G	75-80 %	Very less severe
Line to Line	L-L	10-15 %	Less severe
Double Line to Ground	L-L-G	5-10 %	Severe
Three phase	3-ϕ	2-5 %	Very severe

2.2.2 Series faults or open circuit faults

These kinds of failures are caused by the lines' imbalanced series impedance situation. This might happen when circuits are controlled by fuses or any other mechanism that only opens one or two of the three phases. It can also happen from one or more lines breaking or from impedance being introduced into one or more lines. One or more line phases being open while the other phase or phases are closed could result in such faults figure 2.5 shows one open conductor [13].

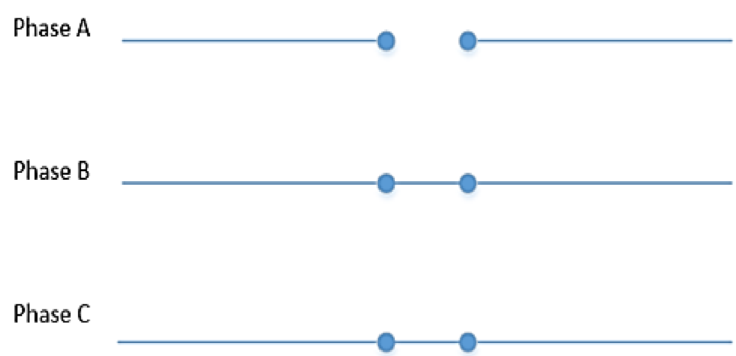


Figure 2.5 One open conductor.[13]

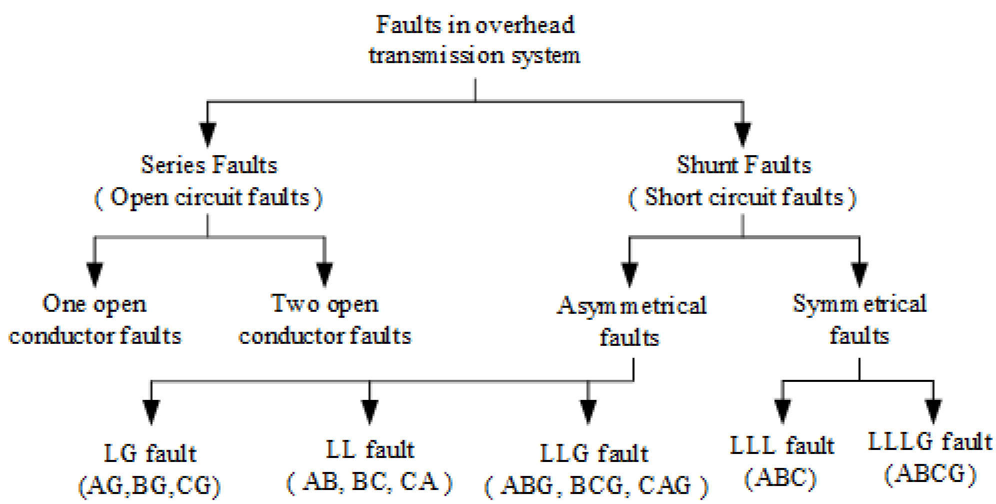


Figure 2.6 Three-phase power transmission systems can have several kinds of challenges [14].

The classification of faults in overhead transmission networks is depicted in Fig. 2.6; phases A, B, C, and G, respectively, represent these stages.

2.2.3 Arcing Faults

arcing faults are distinct from other electrical faults due to their unique characteristics, detection challenges, and potential hazards[15]. Understanding these differences is crucial for implementing effective electrical safety measures and protection strategies. An arcing fault is characterized by a high-power discharge of electricity that occurs between two conductors or between a conductor and a conductive surface[16]. This discharge generates intense heat and can create an electric arc that can ignite surrounding materials, leading to fires. Arcing faults can occur due to loose connections, damaged insulation, or physical obstructions like nails or staples piercing wires[17]. The current levels in arcing faults can be variable and may not always be high enough to trip standard circuit breakers, making them harder to detect. The current can range from a few amps to thousands of amps, and the behavior of the arc can be unpredictable[18]. Detection of arcing faults requires specialized devices, such as Arc Fault Circuit Interrupters (AFCIs), which are designed to recognize the unique signatures of arcing faults and respond quickly to interrupt the circuit. Traditional thermal breakers may not effectively detect arcing faults due to their lower current levels and variable nature. Common causes include loose wire connections, degradation of insulation due to age or environmental factors, and physical damage to wiring. The presence of moisture or dirt can also contribute to the occurrence of arcing faults [19].

2. 2.4 External Faults

Transient faults are temporary faults that occur briefly and then disappear, often caused by external factors like lightning strikes or falling branches. While common, they do not result in permanent damage to the system and are less impactful than the other fault types[20]. Overhead lines experience resistive losses, which result in what seems to be a series of resistance at the ends of the lines[21]. Line reactance is the term used to describe the magnetic field that is created around a conductor in overhead lines by current flow. An electrical field is produced by reactance between the phases of the wire and to ground; this phenomenon is known as capacitance. A lightning strike can occur in different locations besides the direct strike of a phase conductor, which is where a lightning fault often manifests, based on the magnitude of the lightning's voltage and the earth's resistance. A lighting problem on an overhead line will cause an arcing over the phases, insulators, and insulator brackets. A ground fault occurs if the isolator bracket is linked to the ground[22]. Depending on how many phases are involved, a ground fault might be single- or multiphase. When all three phases are involved, ground fault voltages into a properly grounded network have low values; if the ground fault voltage phase voltage reaches a high level, an earth fault has occurred. Almost every lighting strike on a 400 kV network is a single-phase fault, lighting strikes often happen on all phases simultaneously if the grid has two or more phase inductors[23]. One conductor may have been implicated if the voltage is mild and the insulation strength is more than the typical voltage level. Other kinds of problems can happen on overhead lines in the transmission system besides lightning strikes. Phase failure, faulty insulators, and failure from snow and ice, salt, or other contaminants are a few examples of these external defects[24].

2.2.5 Fault Resistance

A fault resistance consists of two major components. Arc resistance and ground resistance [25], [26]. It is either constant for the duration of a fault or it varies with time due to the elongation of the arc and its ultimate extinction. In phase-to-phase faults. Fault resistance is entirely due to the arc. However, for faults involving the ground. Fault resistances are composed of both arc and ground resistances. Ground resistance includes the resistance of the contact between the conductor and the ground and the resistance of the ground path for the flow of current in the ground in situations where the snapped conductor touches the ground. In situations where a broken conductor touches the tower, the ground resistance includes the resistance of the contact between the conductor and the tower and the resistance of the ground path for the flow of current in the ground and tower footings[19].

2.2.5.1 Arc Resistance

Arc resistance is a function of both the arc's length and current. The length of an arc is originally equal to the distance between two conductors or the conductor and the tower, but it grows as a result of arc elongation brought on by convection, electromagnetic propagation, and a crosswind. It has been proposed that the conductor spacing, wind speed, and duration can all be used to express arc resistance[27].

2. 2.5.2 Ground resistance

If overhead ground wires are insulated or not used, the ground resistance is the total of the tower footing resistance at the fault location and the resistance of the current path through the ground from the fault to the source[28]. Ground resistivity and tower footing resistance are measured and recorded by electric utilities. The resistances of the tower footings, the ground wires, and the ground path form lattice networks if above-ground wires are utilized. The resistance of the contact between the conductor and the current's passage through the ground if a conductor breaks and falls to the ground is the fault circuit's dominant resistance[29]. The type and moisture content of the soil determines the ground-contact resistance. The conductor voltage affects the contact resistance as well since surface insulation can only degrade at a certain voltage. Resistances to ground contact are typically greater than resistances to tower footing. For inter-phase short circuits, fault resistances are tiny and don't go above a few ohms. However, because tower footing resistances can reach 10 ohms or greater, fault resistances for ground faults are substantially larger[30]. When contact is made with trees or broken conductors that are laying on dry pavement, fault resistances are unusually high. There is a range of a few ohms to hundreds of ohms in the fault resistance. maximum weight [19].

2.2.3 Protection of transmission lines

Many essential transmitting issues that are relevant to the safety of various kinds of power systems can be found in the research on transmission line protection. While each electrical element will inevitably have its own set of issues, transmission line protection considerations include the ideas of selectivity, zones of protection, local and remote backup, coordination, speed, and dependability—all of which may be relevant in safeguarding one or more other electrical systems[31]. Transmission line protection needs to work with the other elements' protection as well since transmission lines serve as connectors to other lines or related equipment. Setting up, timing and feature synchronization is necessary for this. Power system protection is designed to identify malfunctions or unusual operating circumstances and to start the necessary repair action. To determine whether corrective action is necessary, relays need to be able to assess a wide range of parameters. A relay cannot stop the error. Finding the problem and taking the appropriate steps to reduce the harm to the system or equipment is its main goal. When a fault is present, the voltages and currents at the protected apparatus's terminals or the designated zone limits are the most frequent indicators. The definition of values capable of distinguishing between normal and abnormal situations is the core issue in power system protection. The current definition of "normal" is defined as existing outside the zone of protection, which exacerbates the issue. All protection systems are designed with this factor in mind since it is the most important one when creating a secure relaying system. [32]. Transmission line protection is essential in maintaining the dependability, security, and effectiveness of electrical power systems. Drawing from the sources cited, the following are salient issues reinforcing the need for transmission line protection. Dependability of transmission line protection is essential for preserving power systems' dependability because it stops errors, interruptions, and outages that could affect customers' access to electricity. Reducing Damage and Downtime with Effective Transmission Line Protection Reducing equipment and infrastructure damage minimizes downtime and ensures that homes, companies, and industries have a steady supply of electricity[33]. Security and System Robustness in Transmission line protection devices improve safety by quickly identifying and isolating faults to avert dangerous situations and preserve system stability. Keeping the Environment Safe Transmission line protection lowers the possibility of errors leading to equipment damage or fires, which helps to preserve biodiversity and the natural world. Efficient Energy Transmission by The seamless movement of electricity from generation sources to distribution centers and end customers is made possible by well-protected transmission lines. Economic Repercussions By preventing expensive repairs, equipment replacements, and downtime, transmission line protection helps reduce the financial losses brought on by power outages and other problems. To sum up, transmission line protection is crucial to guaranteeing the dependable and secure operation of power systems, reducing failures, protecting the environment, and assisting in the effective transfer of electricity[34]. Consumers and the overall operation of the power grid can both benefit from maintaining the integrity and resilience of electrical networks through the use of strong protection mechanisms. As seen in Fig. 2.7, many protection device types are employed in transmission systems. That protection device's job is to detect anomalous signals that indicate problems with a power transmission system.

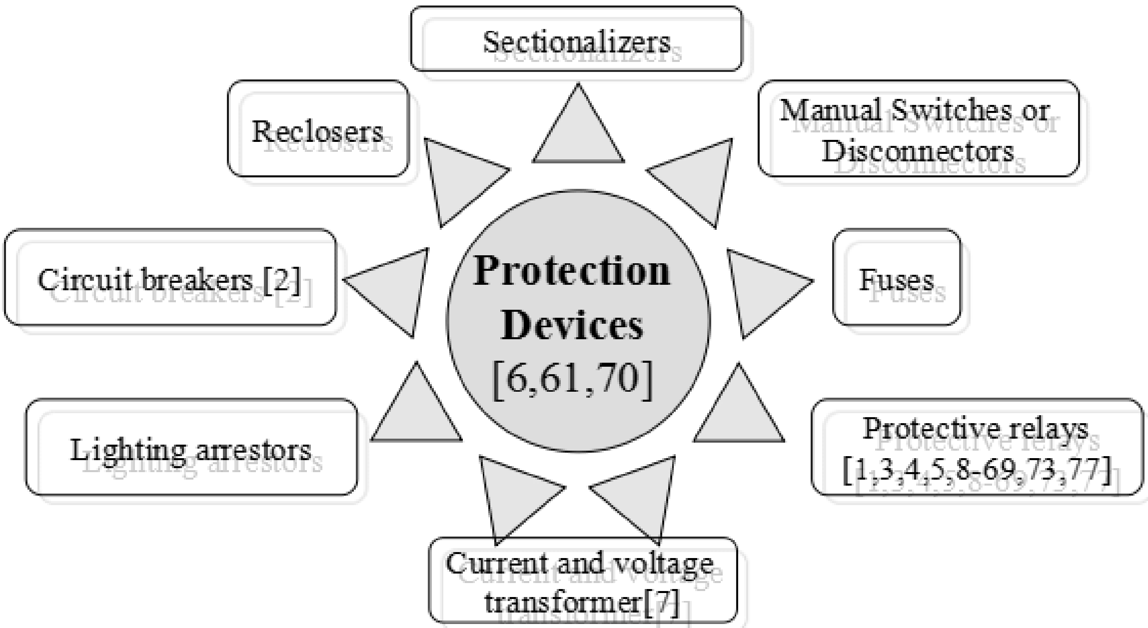


Figure 2.7 Protection devices of transmission lines and related work [35]

These numbers shown in fig 2.7 are based on a system that is adopted as a standard for automatic switchgear by the Institute of Electrical and Electronics Engineers (IEEE), and incorporated in American Standard(Allen Bradley, n.d.).Transmission line protection systems come in the following primary types differential protection, overcurrent protection, directional protection, phase comparison protection, and distance protection the most related type of protection with the thesis is distance protection :

2.2.3.2 Distance Protection

Distance protection is an essential component of power system security. Distance protection is a critical method used in power systems to detect and isolate faults on transmission lines. It operates by measuring the impedance of the line and comparing it to predefined settings to determine whether a fault has occurred. Distance protection relays measure the electrical impedance of the transmission line, which changes during a fault condition. When a fault occurs, the impedance decreases, indicating the presence of a fault. The relay calculates the distance to the fault based on this impedance measurement and compares it to pre-set values to determine if the fault is within the protection zone. Distance protection is primarily used for phase-fault protection, including single line-to-ground, line-to-line, double line-to-ground, and three-phase faults. It is particularly effective for long-distance transmission lines where traditional overcurrent protection may not be reliable due to reduced fault currents. Distance protection is typically implemented in multiple zones see figure 2. , zone 1 covers the area closest to the relay, providing primary protection.

Zone 2 Provides backup protection for the next section of the line. Zone 3 Offers further backup protection, often extending beyond the line to cover adjacent lines.

The effectiveness of distance protection can be influenced by several factors, including, fault Resistance higher fault resistance can lead to underreaching of the relay, source impedance ratio the relationship between the source impedance and the line impedance affects the relay's ability to detect faults accurately, and measurement errors voltage and current transformer errors can impact the accuracy of impedance measurements. The advantages of Distance Protection are

Speed can operate quickly, often within a few cycles, minimizing damage to equipment and maintaining system stability, selectivity by measuring impedance, distance protection can discriminate between faults and normal operating conditions, reducing unnecessary tripping, simplicity the principle of measuring impedance simplifies the protection scheme compared to more complex methods.

Distance protection is widely used in high-voltage transmission lines, sub-transmission lines, and as part of teleportation schemes. It is essential for ensuring the reliability and safety of power systems, especially in areas with high fault occurrence. Distance protection is a vital tool in the protection and control of electrical transmission systems. By measuring impedance and utilizing multiple protection zones, it provides fast, reliable, and selective fault detection, ensuring the stability and security of power delivery. Understanding its principles and applications is crucial for protection engineers and operators in maintaining efficient power system operations.

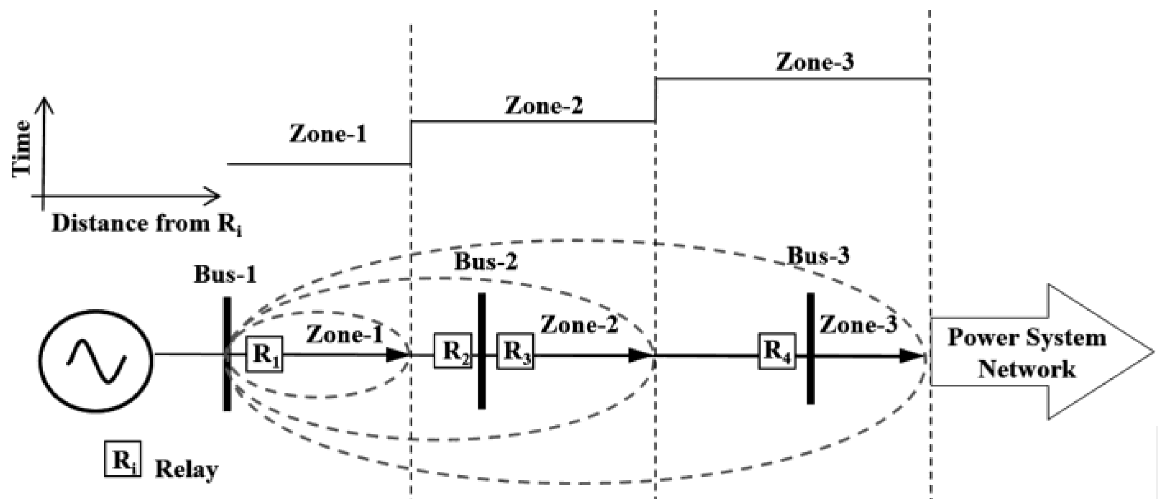


Figure 2.8 Relay R1's stepped distance protection characteristics[37].

2.2.4 The intelligent Techniques Used in Transmission line protection

2.2.4.1 Artificial Neural Network (ANN) Techniques

Artificial Neural Networks (ANNs), or simply neural networks, are novel computational techniques and systems for machine learning, knowledge demonstration, and, ultimately, applying learned principles to optimize complicated system output responses. A data processing model called an Artificial Neural Network (ANN) is based on how biological nervous systems, like the brain, handle information. On a much smaller scale, they are concentrated on the neuronal architecture of the mammalian cerebral cortex. Artificial neural networks are regarded by many experts in artificial intelligence as the greatest, if not the only, option for creating intelligent machines[38]. The divisions and segments of the computational techniques. Artificial neural networks are regarded by many experts in artificial intelligence as the greatest, if not the only, option for creating intelligent machines. The divisions and segments of the computational techniques. Artificial neural networks are constructed with neuron nodes connected in a manner akin to that of the human brain The billions of cells that comprise the human brain are called neurons. The cell bodies that make up each neuron are responsible for processing information as it enters and exits the brain. The primary concept behind these networks is derived from the way the organic nervous system processes information and data to enable learning and knowledge creation [39]. The primary notion of this concept is to establish new frameworks for the information processing system figure 2.11 Artificial neural network architecture. One popular technique for training artificial neural networks (ANNs) is the backpropagation algorithm. This is a high-level summary of how it functions:

Moving forward Propagation: The input layer of the neural network receives the input data. The information is routed through the hidden layers, where each neuron processes the weighted total of its inputs employing an activation function. The network's prediction for the supplied input is the last layer's output.

Calculating Errors: A loss function, such as mean squared error or cross-entropy, is used to compare the projected output to the desired (target) output.

The difference between the target and expected outputs is quantified by the loss function.

Backpropagation: Beginning at the output layer, the error spreads backward through the network. The method determines the gradient of the loss function relative to each network weight. To prevent unnecessary computations, the gradients are efficiently computed layer by layer using the chain rule.

Weight Update: To minimize the loss function, an optimization procedure, like gradient descent, is used to update the weights. The gradient's negative value and learning rate are directly correlated with the update. Because it computes the gradients one layer at a time, iterating backward from the last layer, the backpropagation algorithm is efficient. By doing this, the chain rule's intermediate terms are not calculated twice. With the help of the potent technique known as backpropagation, neural networks may learn complicated relationships drawn from inputs to outcomes. It is extensively employed in many different applications, including speech recognition, image recognition, and natural language processing.

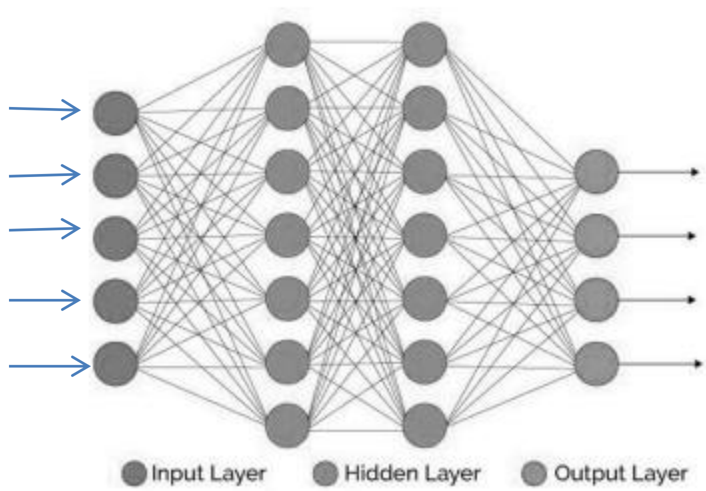


Figure 2.9 Artificial neural network architecture [40]

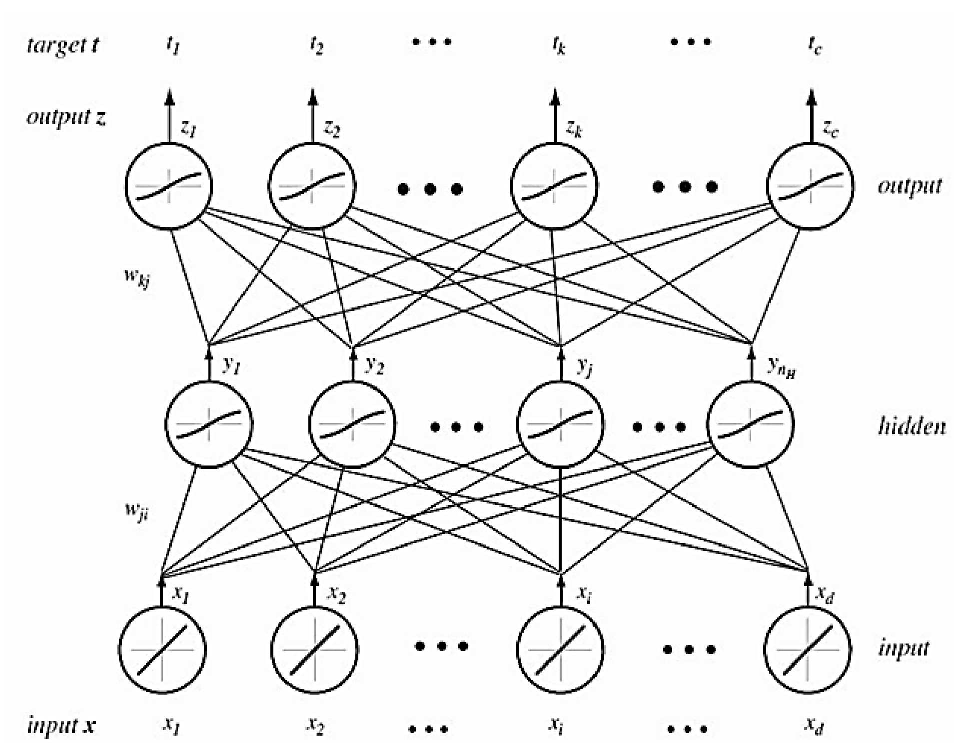


Figure 2.12 A fully connected network of ANN [41]

Backpropagation Algorithm: The most popular technique for training artificial neural networks is backpropagation. Figure 2.12 shows a fully Connected Network where every neuron in one layer is connected to every other layer's neuron in a fully connected artificial neural network (ANN).

The following equations are crucial for output units

$$\beta j = (tj - xj)\, xj\, (1 - xj) \qquad 2.8$$

For hidden units:

$$\beta j = xj\, (1 - xj) \Sigma\, \beta kwjk \qquad 2.9$$

ANN Output Equation:

$$yn = B1 + LW * \tanh(B2 + IW*xn) \qquad 2.10$$

is the output equation for a single hidden layer ANN. where IW and LW are the input and layer weights, B1 and B2 are the biases, and xn and tn are the normalized input and target values. A tangent hyperbolic function is another name for the tanh function. In actuality, it is a sigmoid function that has been mathematically shifted. Both are derived from and comparable to one another. unit j is a typical unit in the output layer and unit i is a typical unit in the previous layer. xj = activity level of the jth unit in the top layer tj = is the desired output of the jth unit[41].In general Layers of ANN are:
Input Layer: After obtaining the input features, the input layer forwards them to the hidden layer.
Hidden Layer(s): The output layer receives the results of computations made by the hidden layer(s) on the input features. The activation functions sigmoid, tanh, and ReLU (The RELU Function For Rectified Linear Unit, it stands. The most

popular activation function is this one. mostly used in a neural network's hidden layers).

Output Layer: The output layer generates the ANN's final forecasts or outputs

2.2.4.2 ANFIS Technique

Neural networks and fuzzy logic concepts are used in the hybrid computational model known as the Adaptive Neuro-Fuzzy Inference System (ANFIS), with five layers, the fuzzification layer, rule layer, normalization layer, defuzzification layer, and output layer are the five layers that construct the ANFIS. Using membership functions, the first layer transforms input values into fuzzy values. Firing strengths for rules are generated by the second layer, normalized by the third, defuzzified values are computed by the fourth, and the output is returned by the final layer. To identify and learn patterns, ANFIS employs a training algorithm that combines a least squares approach with backpropagation 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)[42]. 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 [42].

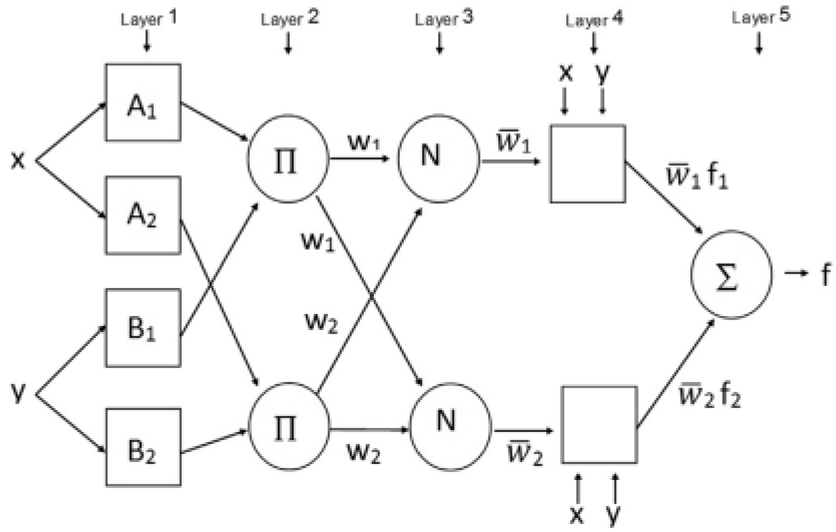


Figure.2.11 The structure of the ANFIS [43].

where x and y are the crisp inputs to the first layer, fi (f_1,f_2) is the output within the fuzzy region specified by the fuzzy rule. wi represents the firing strength of the rule. The quantity w is known as $\overline{w_i}$ the normalized firing strength. Ai and Bi are the fuzzy sets in the antecedent.

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 [2.1] and [2.2] 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:

$$\mu_{Ai}(x) = \text{gbellmf}\ (x;a,b.c) = \frac{1}{1+|\frac{x-c}{a}|^{\wedge}(2b)} \qquad 2.1$$

$$O^{1}{}_{i} = \mu_{Ai}(X) \qquad 2.2$$

where O^{1}_{i} is the membership function. $\mu_{Ai}(X)$ Every MF made a change to this layer parameter. 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. The nodes are fixed nodes denoted as π, indicating that they perform as a simple multiplier.[44] Each node in this layer calculates the firing strengths of each rule by multiplying the incoming signals and sending the product out. The equation (2.3) can be represented as:

$$Oi^{2} = w_{i} = \mu_{Ai}(x) \cdot \mu_{Bi}(x) = 1\ \mu_{Ai}(X) \quad i = 1, 2, \ldots \qquad 2.3$$

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:

$$O^{3}_{i} = \hat{w}_{i} = \frac{wi}{w1+w2+w3+w4} \qquad i = \{1,2,3,4\} \qquad 2.4$$

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

This layer's nodes are all adaptive, and their parameters for output are changed. Usually, this output is a linear function of the input. The output was calculated using a first-order [44] polynomial and normalized firing strength for every node in the layer. ŵ is the output of the normalization layer. Therefore, this layer's outputs are provided by:

$$O^4_i = y_i = \hat{w}_i f_i = \hat{w}\,(p_i x_1 + q_i x_2 + r_i)\ ,\ i=1,2,3,\ldots \qquad 2.5$$

Output layer: Provides the system's final output. ANFIS uses a least squares approach in conjunction with a backpropagation gradient descent technique to learn and improve its behavior. Through these principles, ANFIS may adjust to new data and gradually get better at making predictions. All of the signals combine to form a single node, denoted as Ÿ, which performs the following functions for the model[45]:

$$O^5{}_i = \text{overall output} = \sum_i \hat{w}i\ fi = \frac{\sum_i wifi}{\sum_i wi} \qquad 2.6$$

A least squares approach can be used to solve for the consequent parameters in this final layer. To make this final equation more practical, let's rewrite it as follows:

$$y = [\ w_1x_1 \quad w_1x_2 \quad w_1 \quad w_2x_2 \quad w_2x_2 \quad w_2\ ] * \begin{bmatrix} p1 \\ q1 \\ r1 \\ p2 \\ q2 \\ r2 \end{bmatrix} = XW \qquad 2.7$$

Regression analysis can be used to find the weight vector (W), which is made up of the resulting parameters when input-output training patterns are present[45].

2.3 Previous Studies

2.3.1 The Traditional Studies

The main part of the power system is the overhead transmission lines. 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.[46] . 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[10]. The fault must be identified to prevent the transmission line from damage[47], However, fault detection input may considerably aid problem localization for faster fault clearing and power restoration [21] Identifying the location of a transmission line failure in a power system is crucial for rapid response and power supply dependability [21]. The fault location must be precise for speedy line isolation different types of fault location algorithms are presented. In the beginning, older technologies laid the foundation for modern protective relaying systems. While they have been largely replaced by more advanced digital and microprocessor-based devices that offer improved speed, accuracy, and functionality, understanding these traditional methods is essential for appreciating the evolution of transmission line protection. Modern systems now incorporate advanced algorithms and communication technologies to enhance reliability and performance in fault detection and localization[48]. The oldest methods used in transmission line protection primarily include electromechanical and solid-state relay technologies. Electromechanical relays are slower and less accurate compared to modern digital relays. They also require manual resetting after operation, which can lead to longer downtime[49]. While more reliable than electromechanical relays, solid-state relays still lack the advanced functionalities and adaptability of modern microprocessor-based relays[50]. Distance protection can be affected by load conditions and fault resistance, which may lead to misoperation under certain circumstances. Pilot protection requires reliable communication channels, which can be a challenge in some environments[49]. By measuring the impedance at different points along the line, utilities can estimate the location of faults .The accuracy of impedance-based methods can be compromised by variations in line characteristics and load conditions[51]. Digital relays represent a significant advancement over analog relays in transmission line protection, offering improved speed, accuracy, and functionality. Their ability to adapt to changing conditions and communicate with other devices makes them essential for modern power systems, enhancing reliability and efficiency in fault detection and localization[52].

Conventional methods were used for transmission line protection. The impedance measurement-based method and traveling wave method are the conventional methods broadly used for the detection, classification, and localization of the fault in a transmission line[53]. In impedance-based methods, the distance relay operation is accurate and reliable on the low value of fault impedance but does not rely upon high fault impedance[54]. Based on some current and voltage signals collected from a terminal of a transmission line, single-end or two-end impedance methods are proposed. The concept of the single-ended impedance-based method is to identify the location of the fault by calculating the apparent impedance seen from one termination of the line. Impedance-based method fault position error is high due to high fault path impedance, load on the line, source parameters, and shunt capacitance.[55][56]. 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[12]. The two-ended impedance-based method is implemented to locate the fault to eliminate the above-said problems. The disadvantage of this method is a high computational burden due to the measurement of current and voltage signals at two ends of the line. However, improves the accuracy of locating the fault[1][57]. Traveling wave-based methods are used to determine the distance of fault by using the correlation of forward and backward waves traveling in a transmission line. This method has less error in locating faults in high resistance faults. However, the main difficulties are computational burden, expensive and high sampling frequency, and difficulty in practical application[58][59]. based on the fact that any disturbance on a transmission line generates traveling waves that travel along the transmission line. These waves are the consequence of charging and discharging the line capacitance and line inductance of the transmission line. Each wave, with a frequency anywhere from a few kilohertz to several megahertz, travels at a rate that is almost as fast as the speed of light[60].

2.3.2 Intelligent Methods

A similar hybrid technique is used in [61] to predict the fault's location using the three-line impedances of the three phases as input to the ANFIS. Approximation coefficients are used to compute line impedances. The maximum error of fault location is found to be 1.5%. A comparative study of ANN and ANFIS fault detection and fault location has been done by [62] the percentage error in both techniques is found to be 0.25%. However, the mean error of ANFIS is less than ANN. The accuracy for the fault classification for both techniques is found to be 99.9%. Wavelet-based ANN is used for fault detection in ultra-high transmission lines [63]. High-frequency details of the local current signal at one end of the transmission line are used to classify transients, categorize transients and faults, and detect the causes of the transients on the protected and adjacent lines. DWT is used to extract high-frequency components. A feature vector is developed and used to train ANN. (ANN) and a fuzzy expert system called an Adaptive Network-Based Fuzzy Inference System (ANFIS) is proposed. First, three-phase transmission lines are modeled and various types of faults are generated using MATLAB/Simulink. Then, the faulted current signal is segmented from the faulted transmission. Next, feature extraction is performed to obtain information from the faulted current signal. In [64], the extracted features are mean, standard deviation, energy, peak-to-peak, and amplitude value. Feature selection is then applied to select important features that correlate with the fault location. Takagi-Sugeno fuzzy control system algorithm was used to detect High Impedance Faults. The tuning algorithm is performed off-line employing the concept of Adaptive Neuro-Fuzzy Inference System (ANFIS). In [64] magnitude and phase angle of 3rd harmonics were used to detect the HIF. The controller algorithm is developed in the Matlab. The experimental results show that the proposed controller can provide an adequate performance for detecting HIF. Modern AI techniques have affected almost all scientific disciplines. Businesses and industries are already being disrupted and transformed by it. The top economies and IT firms in the world are competing to enhance modern AI learning. It has already outperformed humans in many fields, including disease diagnosis and disaster prediction. Hutcher et al introduced the LSTM in 1997 as a powerful, recurrent neural network (RNN) architecture for time series modeling and forecasting. Experiments with artificial data have shown that LSTM leads to more successful runs and learning faster compared to other recurrent network methods[8]. LSTM is also capable of solving complex long and time-consuming tasks, that previous methods were unable to solve. LSTM (Long Short-Term Memory) network has been able to overcome major limitations and shortcomings of recurrent neural networks, such as the problem of vanishing gradient, by allowing gradients to pass unaltered. While traditional neural networks focus on learning the static relationship between inputs and outputs of the network, LSTM can retain knowledge or information of previous modes and is trained for high-dimensional data that requires memory or needs previous knowledge [65]. The use of the frequency response analysis (FRA) approach to locate and categorize transmission line problems according to their impedance is covered in [66]. The FRA technique is employed to evaluate the effects of fault location and impedance on frequency-domain voltage and current data. Authors [67] propose a new relaying scheme for bipolar line commutated converter high voltage direct current ((LCC HVDC) transmission lines that detect faults, identify the pole of fault, and estimate the fault's location using features from rectifier end DC and voltage signals. The scheme uses LSTM, a deep learning method. In [68], a novel method for identifying insulated overhead conductor (IOC) faults following partial discharge is described. It is based on discrete wavelet transform (DWT) and long short-term memory network (LSTM). First, DWT denoises the raw signal. Second, DWT decomposes the denoised signal and extracts characteristics on several layers. Another study on fault classification in transmission lines using a Long Short-Term Memory (LSTM) network is presented in [69]. The research entails simulating a 400 kV, 100-kilometer transmission line and generating fault signals for ten different types of failures. The fault signals are pre-processed, and the post-fault current signals are supplied into the LSTM network, which has been trained to recognize various sorts of defects. The suggested model is tested with white Gaussian noise with Signal-to-Noise Ratios (SNR) of 20 dB and 30 dB, and it achieves a promising classification accuracy of 100%, 99.77%, and 99.55% for ideal, 30 dB, and 20 dB noise, respectively. The results are compared with four different methods, and the LSTM network outperforms them with the highest classification accuracy. Modern AI learning techniques particularly LSTM have gained significant attention worldwide in modern artificial intelligence approaches. The approach has been widely used in a variety of power system applications and has yielded remarkable results. Several attempts have been made to classify transmission line faults using various deep-learning approaches[8] . Overall, each method has its strengths and weaknesses, and the choice of the appropriate method depends on the specific application and the characteristics of the data. A combination of these methods may be used for fault detection in transmission lines to improve the accuracy and robustness of the system. ANFIS can give advantages in terms of accuracy, efficiency, and training speed in many scenarios, making it a competitive choice for modeling 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 (2.2) that it can provide advantages in terms of accuracy, efficiency, and training speed in many cases, making it a competitive choice for modeling 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 2.2 Comparing different approaches to fault categorization

Ref.	Name of approach	Techniques used	Advantage	Dis advantages
[70]	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.
[71]	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.
[72]	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
[73]	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	Investigating faults in these banks requires significant time and human resources.

			and two capacitor banks connected in a back-to-back topology can be resolved.	
[23]	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
[74]	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.
[75]	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 of 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
[76]	PARTICLE SWARM	the Particle	-Simple Idea	-Premature Convergence

	OPTIMIZATION ALGORITHM-BASED FAULT LOCATION USING ASYNCHRONOUS DATA RECORDED AT BOTH SIDES OF TRANSMISSION LINE	Swarm Optimization (PSO)	-Easy Execution. -Robustness to Control Parameters -Computational Efficiency	-Limited Exploration -Sensitivity to Parameters -Lack of Guaranteed Global Optimum
[77]	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.
[78]	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
[79]	Transmission Line Fault Location Using Deep Learning Techniques	Convolutional neural network (CNN) Long short-term memory (LSTM)	Emphasizing the potential for improved accuracy and efficiency in fault detection and localization.	-The complexity and computational resources required for training and implementation.
[80]	Intelligent Fault Detection and Identification Approach for Analog Electronic Circuits Based on Fuzzy Logic Classifier	Fuzzy logic classifier	-Utilizes the frequency response of the circuit along with simple statistical feature extraction techniques. -allows for a better description of circuit behaviors in various conditions.	-May not be as robust or adaptable to complex fault patterns compared to more advanced machine learning algorithms. -the complexity of such optimization-based approaches

2.5 Summary

A brief overview of the many techniques used to investigate faults in the power system, especially in transmission lines. The experimental results of ANFIS-based fault location. The key advantages and disadvantages of the several techniques created by different researchers for the localization, classification, and detection of transmission line faults are briefly discussed. A review of the literature reveals that models for fault analysis, like the wavelet transform, fuzzy inference system, and artificial neural network, have a big influence on fault analysis approaches. Because ANN and other models using supervised learning approaches need to be extensively trained using a wide range of data, their analyses are more complicated. The FIS method may lead to complexity and inaccurate analysis. As a strong rule-based system, FIS does not require precise inputs. Hybrid models are the preferred method used by researchers to optimize technique benefits. Before using ANN-supervised learning techniques, researchers frequently used WT to extract fault features in fault analysis. When all of these tactics are used together, fault analyzers become precise and effective. Researchers have recently presented novel methodologies, like fault analysis techniques based on LSTM. When updating each weight, LSTM is less complicated than the backpropagation approach. ANFIS-based approach; performs best for fault detection and classification, while it can still be improved in terms of location by ANFIS. Because it expresses a hybrid technology that combines the discrimination ability of artificial neural networks with the control technique represented by the visual, it was noted from the results that it is a more efficient technique than the neural networks alone and the physical technique alone.

CHAPTER THREE

MATHEMATICAL MODEL

Chapter Three

Mathematical Model

3.1 Introduction

Electrical grid stability and efficiency are based on the dependability of electricity transmission lines. On the other hand, several factors can cause defects like short circuits or line breakage, which can disrupt the power supply and perhaps harm equipment. Ensuring the integrity and resilience of the electrical grid requires prompt detection and precise localization of these disturbances. In this chapter, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has proven to be an effective instrument for fault location and detection. Modeling complicated nonlinear systems such as power grids is a good fit for ANFIS because it combines the understanding of fuzzy logic systems with the flexibility of neural networks. Through the utilization of ANFIS, engineers may create effective algorithms for fault detection and location. Compared to traditional methods, this methodology has several advantages, such as being robust to noise, able to manage nonlinearities, and flexible enough to adjust to changing operating conditions. In this study, we will use the MATLAB (R2022 a) Simulink program to identify and localize transmission line issues using the ANFIS technique. To construct ANFIS-based fault detection and localization algorithms, MATLAB Simulink offers an extensive platform for modeling, simulating, and evaluating dynamic systems. Our goal in undertaking this study is to show how well ANFIS can precisely and quickly locate and identify the faults. Through the integration of ANFIS models into MATLAB Simulink, we can simulate multiple fault scenarios and assess how well the suggested solution performs in different circumstances. In the end, this study advances the creation of sophisticated methods for improving the electricity transmission networks' dependability and robustness.

In this work, the following are the steps needed to develop an adaptive neural fuzzy inference system (ANFIS) for localizing and detecting faults in transmission lines:

Data Collection: Measurements of voltage, current, and power may be obtained from the transmission lines in the first step of data collection.

Data Preprocessing: To ensure the quality of the data for fault identification and localization, the gathered data must be preprocessed to remove noise and outliers. Feature extraction is the process of removing pertinent features from the preprocessed data so that they can be used as ANFIS model inputs. Development of the ANFIS Model, the retrieved features are used to create the ANFIS model. To do this, the model must be trained to understand the connections between the input features and the transmission line fault states. Finding Faults by examining the input data and finding deviations that point to a problem, a trained ANFIS model is used to find transmission line failures. The ANFIS model can be used to pinpoint the precise place along the transmission lines where a fault has occurred once it has been identified. Evaluation of Performance By contrasting the fault localization and detection outcomes of the ANFIS model with real fault data, the model's performance is assessed. This stage aids in evaluating the ANFIS system's precision and efficacy. The ANFIS model may be subjected to optimization and fine-tuning to enhance its performance and guarantee the precise detection and localization of transmission line problems. These procedures allow engineers and researchers to Leverage the capabilities of ANFIS to improve the efficiency and reliability of power transmission systems by successfully implementing an adaptive neural fuzzy inference system for fault detection and localization in transmission lines. In the final part of this chapter to provide an innovative ANN-based method for the quick, dependable, and precise localization and diagnosis of faults in transmission lines. In addition, to compare the ANFIS and ANN findings and simultaneously minimize the fault detection time delay by detecting several fault situations, such as defective voltage and current. By simulating multiple errors and training them with the ANN model, the performance of the proposed technique was evaluated, and the outcomes were positive. Furthermore, power systems' transmission line fault management and protection will be developed using the proposed model. A notable drawback of the method is that the model cannot be trained on non-numerical data. As a result, evaluating the data is never easy because it involves tying the findings to the issue statements and actual situations.

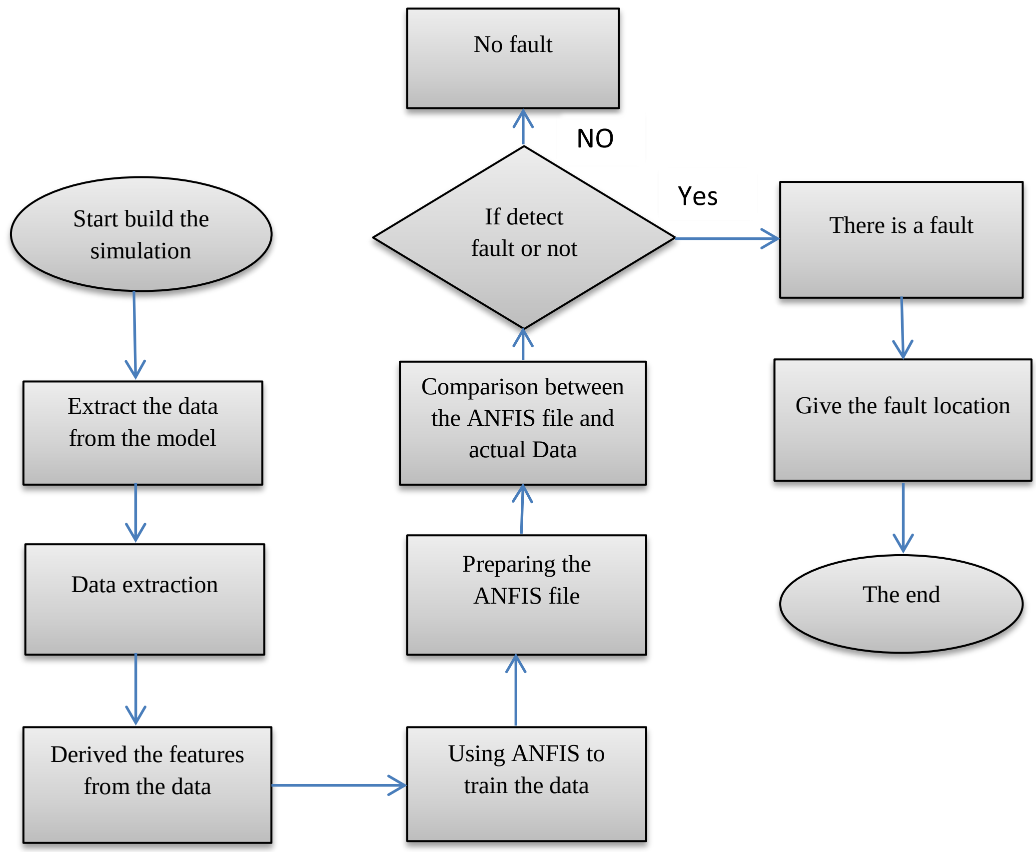


Fig. 3.1 The Data processing model for ANFIS.

3.2 Simulink in MATLAB

Modeling, simulating, and analyzing dynamic systems is possible with Simulink, a graphical programming environment in MATLAB. The following essential aspects are frequently included in Simulink models used for power system failure identification and detection the precise depiction of the elements of the power system, Practical error injection, Extensibility, online adaptability, visualization tools, integration of artificial intelligence, and advanced signal processing blocks. The machine learning method solves issues involving ambiguous or imprecisely defined data by fusing fuzzy logic with neural network concepts. ANFIS and

ANN a tools that Simulink can utilize to find and identify power system failures. Fig. 3.1 shows the data processing model for ANFIS Use the Library in Matlab for Simulink to build the model. It offers models for online, sample-by-sample training and operation.

Use MATLAB to develop a model for identifying and pinpointing faults between two stations that are 200 km apart.

- Gather and prepare data from the stations and adjacent areas that represent voltage, current, frequency, and other pertinent measures. Make sure there are enough illustrations of both ideal circumstances and problematic situations.
- Create training and testing datasets from the gathered data. Split the data for the input and target variables into different files.
- To train the ANFIS and ANN model using the training data, use the ANFIS function. Give details about the sort of fuzzy inference system (e.g., Sugeno or Takagi-Sugeno) and the quantity of input and output variables and using the algorithm's performance (Scaled Conjugate Gradient) in (ANN). To determine the ideal arrangement, you might need to try a few different configurations.
- Utilizing the test dataset, validate the trained ANFIS and ANN model. Analyze its performance indicators, such as mean absolute error (MAE), and root mean square error (RMSE).
- After you are happy with the model's performance, use the Matlab block library to implement the ANFIS and ANN models in Simulink. Assign the appropriate configuration to the ANFIS blocks after connecting the input signals to them.

- To ensure that the generated Simulink model can precisely identify and pinpoint errors between the two stations, test it with more data.
- Use the verified ANFIS and ANN models in real-time apps to keep an eye on the electrical grid and send out alerts for possible problems.

3.3 The Network Modeling (Modeling of 400 kV Transmission Line).

The two-terminal transmission line model's modeling details are presented in this part as an overview. The Simulink software version R2022a and MATLAB were used to create the transmission line model Fig. 3.2. The transmission line model's development goal was to produce a model that could measure voltage and current at both buses on each side of the transmission line. These measurement values will have relative magnitudes (RMS) that a practical utility could encounter. 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. Table 3.1 The constant of 400 KV,200 Km transmission line. Table 3.2 Fault parameters of the proposed model .The transmission line model consists of two stations as shown in Fig 3.2, each with a 400 KV and 5000 KVA modeling block. There are 200 kilometers between the two stations. This operation selects the 400 KV transmission line between the Kut and Misan stations. 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 line between two stations (the π model transmission line) as shown in Fig. 3.3 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 faults). 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. (see Appendix. K) .

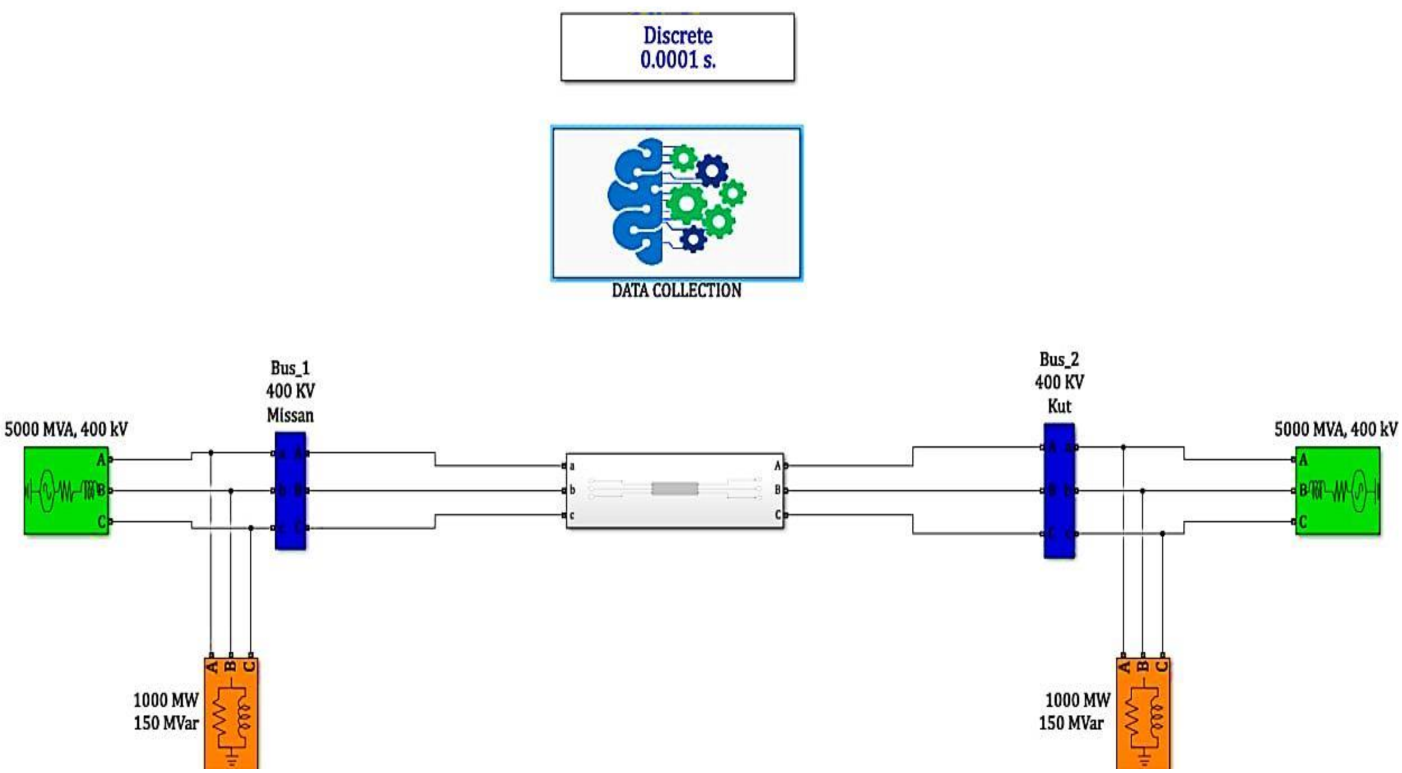


Figure 3.2 Transmission Line Simulink Model

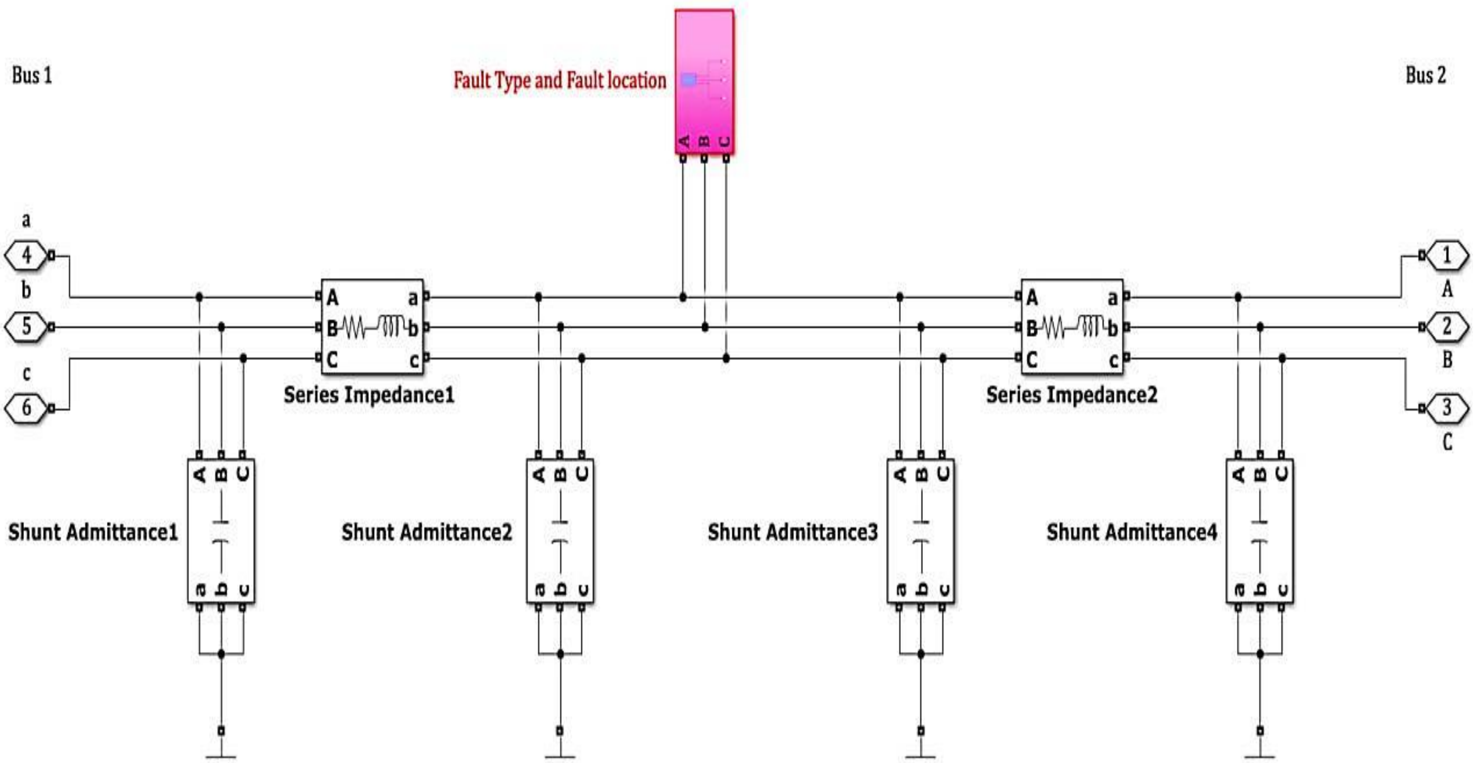


Figure .3.3 Transmission Line Construction (π model).

Table 3.1 The constant of 400 KV,200 Km transmission line (Overhead lines).

Conductor (400 KV single line)			R_O (Ω/Km)	R_1(Ω/Km)	Xo(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

Table 3.2 Fault parameters of the proposed model

System components	**Parameters /units**	**Value**
Short circuit level (S)	*$5000*10^6$*	MVA
Fault capacitance Cs	*F*	Infinite
Switching time	*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*	$150*10^6$

3.3.1 Data extraction

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) as shown in Figure 3.2, 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.). Figure .3.3 shows transmission line construction (π model) inside the transmission line. The buses will collect the data at this moment, figure (3.4) shows the data extraction Simulink model inside the buses (1 & 2)(The Training network). The data was collected from two sides of the network (Misan station and Kut station).

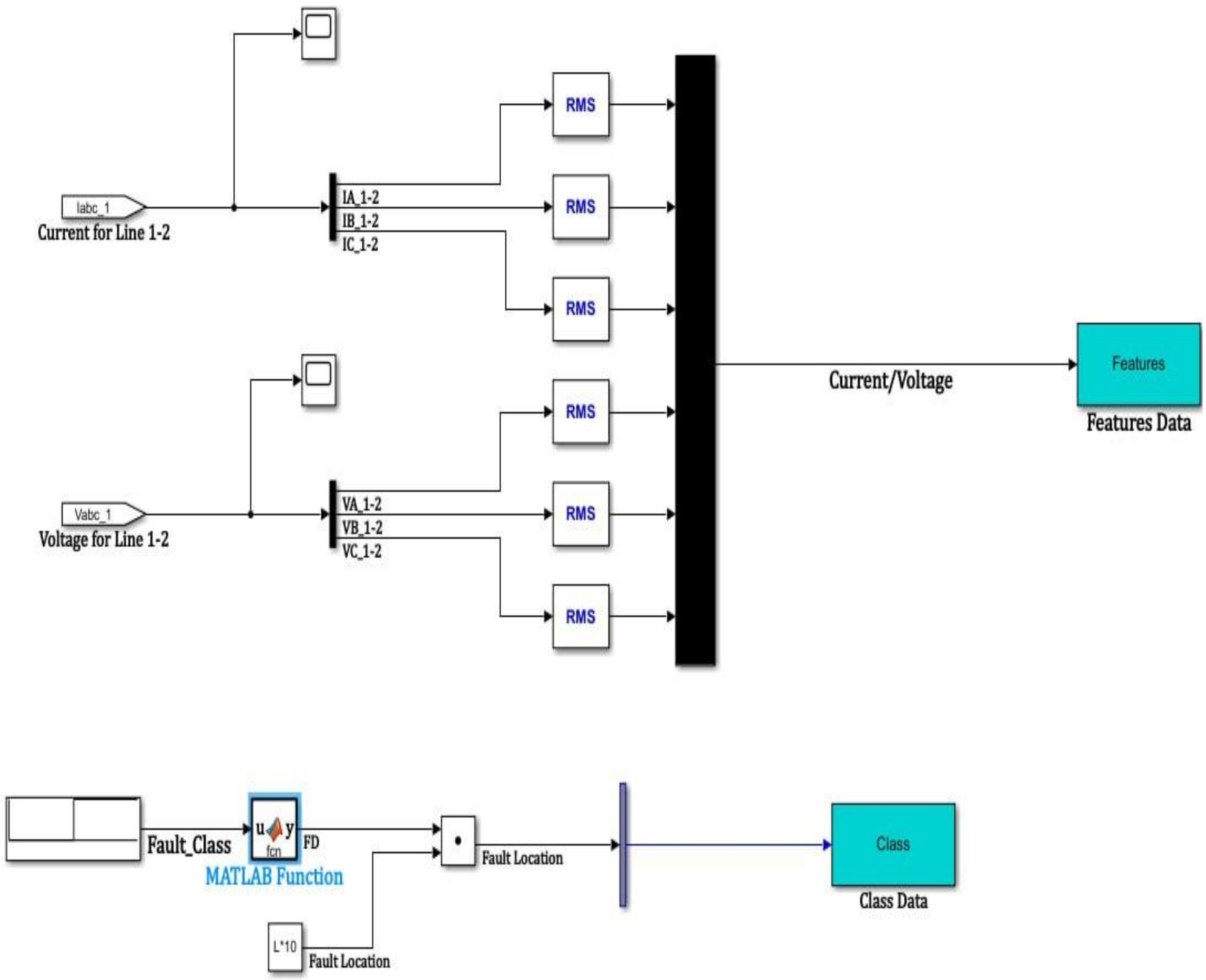


Figure 3.4 Data extraction Simulink model inside the buses (1 & 2)

The data will be collected in feature data in matrix form. The feature data will transfer to the workspace in Matlab after the simulation. 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 logic 1, 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. The waveforms of the input data (The three-phase currents) shown in the figures below 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 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

3.3.2 Training Data Using ANFIS Techniques

A large dataset with both normal and fault circumstances is needed to properly train ANFIS in this work are about 729 cases of data measurements along the transmission line between normal and fault cases collected in the data features block in Figure (3.4) and fault location in the class data block. Accurate fault labels and a broad range of problem scenarios should be included in this dataset. ANFIS performance can be improved by using data preprocessing techniques like scaling, normalization, and feature selection. So in this work, the data collected from the buses on the network that's built in the Simulink model in Matlab is the data collected from the line with a length of 200 km. Utilizing labeled fault data and extracted features from the Simulink model, train the ANFIS model. To enable the ANFIS model to accurately anticipate fault locations, train it with the labeled fault data and extracted characteristics from the Simulink model figure (3.2). Extract the FIS file (Fuzzy Inference System, or FIS for short, is a tool used in power, robotics, and control systems, among other fields. Fuzzy rules are used by FIS, a kind of fuzzy logic controller, to make decisions based on incoming data see appendix L to see the system that is used in the system to set up the ANFIS file. Fuzzy sets and fuzzy operators are used by the system to process input data and produce outputs. After that, the output is utilized to decide or operate the system) and located in the MATLAB program to compare this file with the real data that is taken from any network for the detection of faults and localization information. Figure(3.15) shows the surface of the ANFIS that appears during the data training Utilizing extra test datasets from the other Simulink model for data extraction from buses (1 & 2) With unknown locations (L is unknown), evaluate the performance of the trained ANFIS model to make sure it is accurate in defect detection and ANFIS file localization by comparing the trained data in the ANFIS file and the real data. In general, the testing and validation are illustrated in steps by using a test program in Matlab the ANFIS file will test the accuracy of the detection and localization at a specific time. the result of the high speed of the technique.

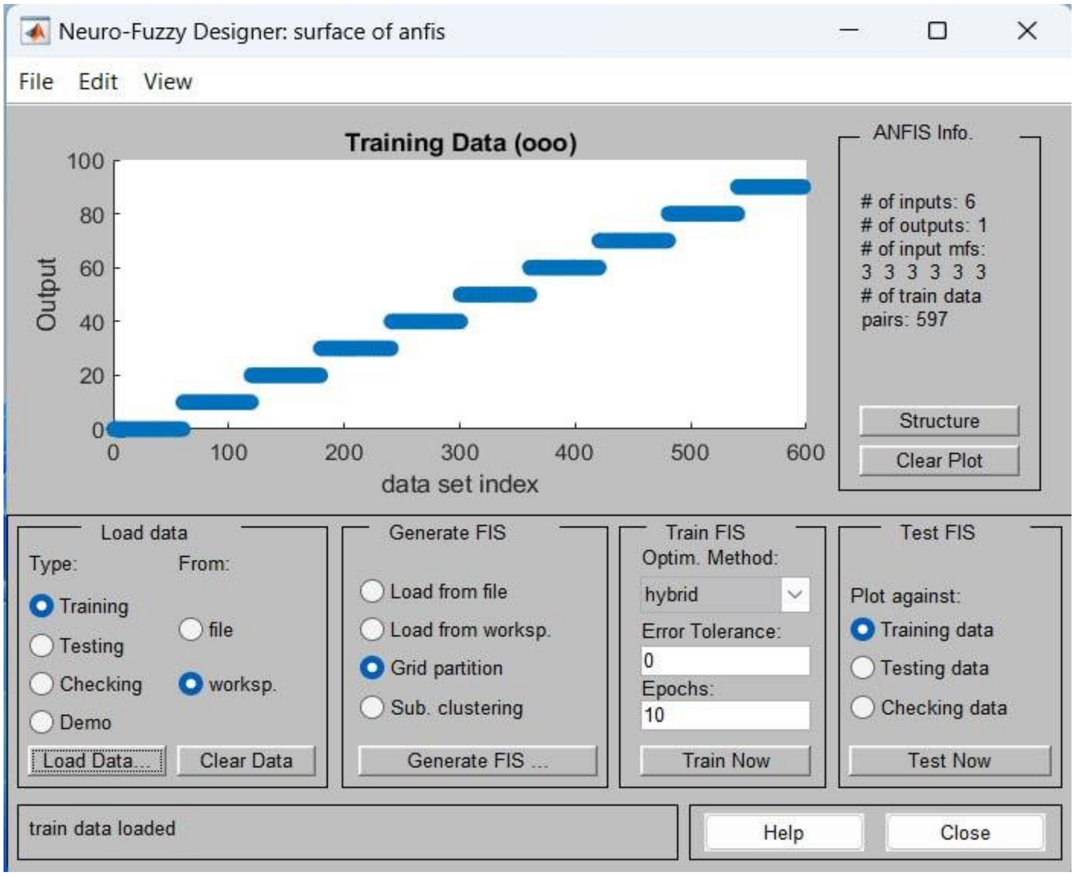


Figure 3.5 The window of the ANFIS program in Matlab.

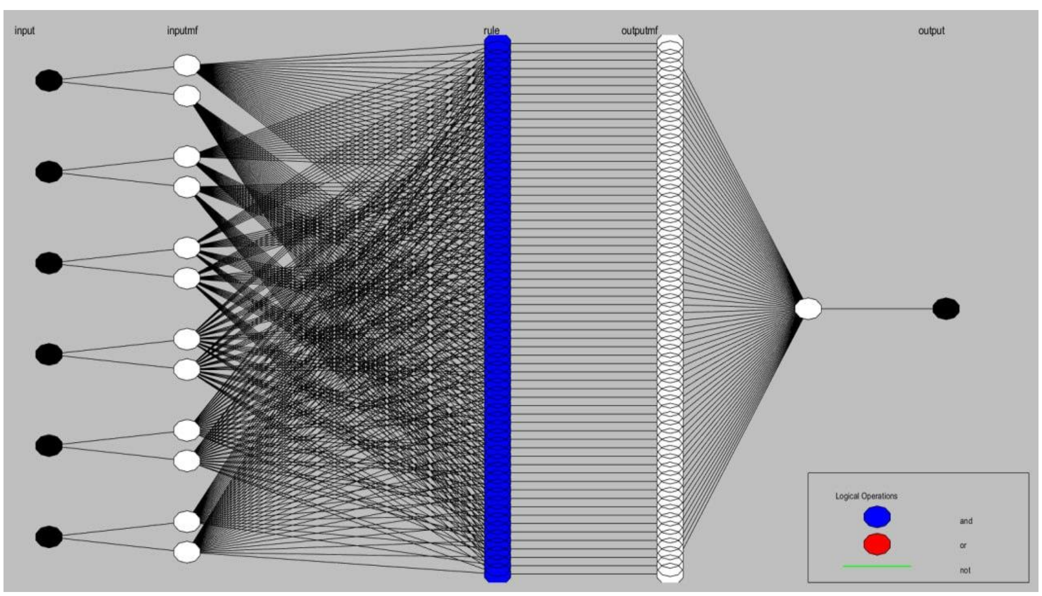


Figure 3.6 The structure of the ANFIS.

, the data trained in ANFIS, and the trained data extracted in a file Figure 3.16 shows the processing of training the ANFIS file with 10 epochs the resulting file will be used later in other networks to compare the real data and the trained file. The structure of the ANFIS with the trained data is shown in Figure 3.17.

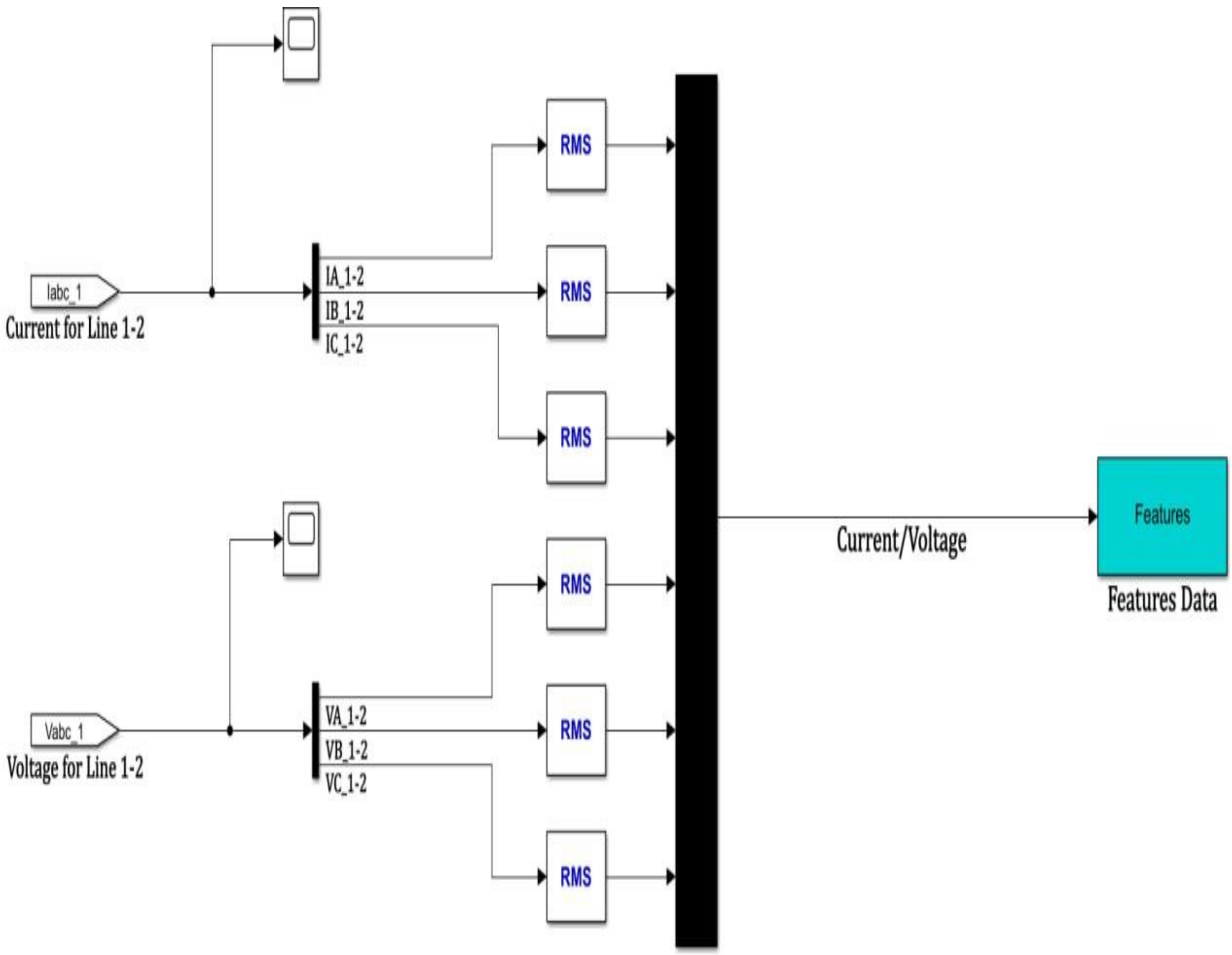


Fig 3.7 Shows the Simulink model of the features data collected from buses 1 and 2 (From any network)

3.3.3 Training Data in ANN (Artificial Neural Network)

An ANN model's ability to function properly and generalize successfully depends on both the representativeness and quality of the training data. In this section, the final data extract from the Simulink model shown in Fig 3.2 is the data taken from all nine sections along the transmission line (200 Km) between two stations as illustrated in previous sections in Matlab R2022a using the nnstart tool to build a neural network figure (3.19). and employed in the training of the algorithm. The voltage and current waveform's simulated fault results were used to determine the data size. To prevent over-fitting, the data is split into training, testing, and validation. The input layer consisted of the three-phase value, whereas the input data consisted of the phase value of the defective current and voltage. For the training, a total of six input parameters, ten input layers, and one output layer result are used. In addition to the Mean Square Error (MSE), 1000 epochs,

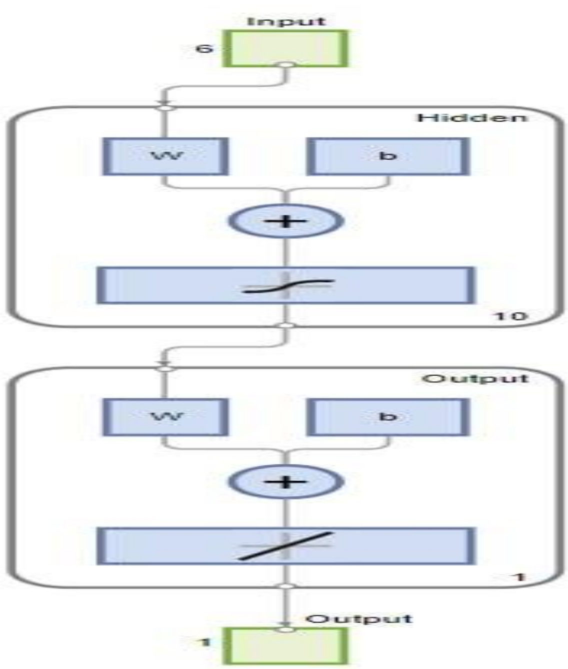


Figure (3.8) ANN network

and training time, the algorithm's performance (Scaled Conjugate Gradient) was examined. The model's performance was assessed using a confusion matrix, which contrasts the measured values obtained from the ANFIS result with the ANN result. It also provides a comprehensive picture of the model's functionality and the kinds of errors that the system has. The outcome also clarifies how ANNs are used in transmission line fault management system plans., and the optimal configuration was obtained by setting the hidden layer to 10. Six input data points three-phase current and voltage, Ia, Ib, Ic, and Va, Vb, Vc as well as about 729 fault data points were utilized in the training process, yielding 100% correctness and 0% confusion. In the meantime, the fault data was highly accurately validated and trained using 729 datasets. After the ANN network has been trained, the error between the target and predicted values is displayed in Fig. 3.23 's error histogram. With a zero error value of 2,08 for the difference between the target and the output, it is evident that the mistake is negligible. Fig. 3.22 illustrates the network's best validation performance, which was 0.0015335 at 341 epochs., this is an excellent performance because the network is fitted and the best-fit line is near the train, validation, and test lines due to shared features that enable efficient training. Based on Fig. 3.23, the model has a gradient of 18.08 and a maximum permissible failure level of 6 at 14 epochs. This graph demonstrates the effectiveness of the model due to the network gradient Additionally, the model is made to locate faults in transmission lines by creating a neural network with Simulink. ..Because it explicitly indicates the kind of defect and its position at any given time, this model is better than others. This is useful for the transmission line fault management system and will enable the maintenance team to promptly clear the fault. At various transmission line stations, By including noise in the input vector during training and training the noise vector using the tanH activation function, the model was tested for noise regularization. The accuracy dropped significantly to 88%, as Fig. 3.21 illustrates.

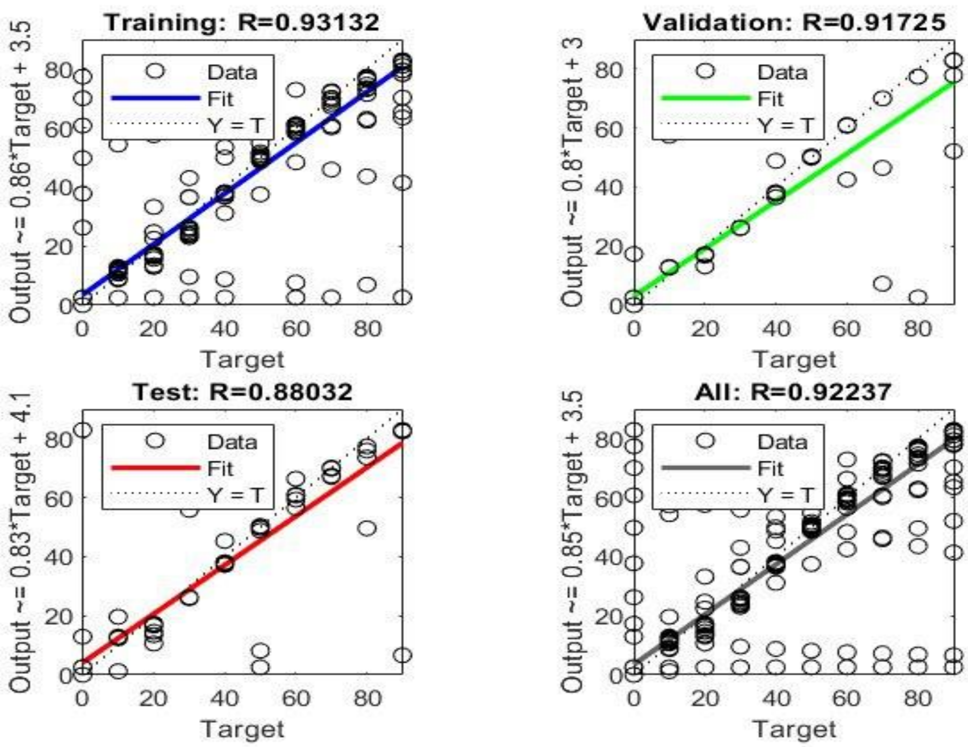


Figure 3.9 Regression Fit for the noise signal data.

Using ANNs for fitting a regression model to noisy signals leverages the flexibility and learning capabilities of neural networks. By carefully designing the network, training it on appropriate data, and evaluating its performance, ANNs can effectively model complex relationships and extract meaningful signals from noisy data. a perfect fit corresponds to a regression value of **1**. This indicates that the model explains all the variability in the data without any error. Conversely, a regression value of **0** indicates no explanatory power.

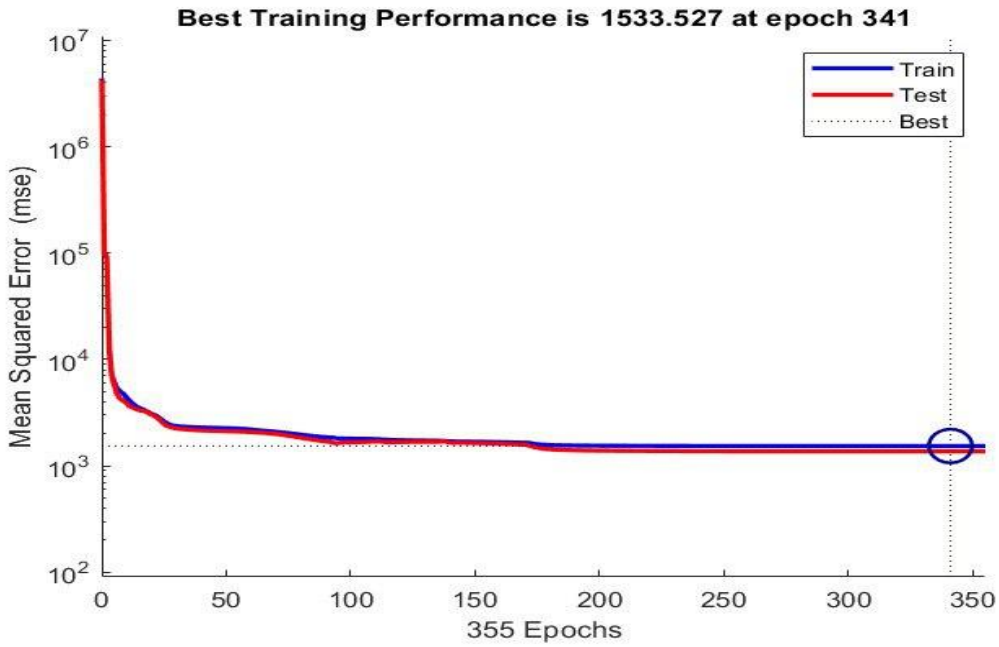


Figure 3.10 ANN network performance.

Measuring the performance of an ANN involves a combination of data splitting, selecting appropriate metrics, employing cross-validation, monitoring training progress, and tuning.

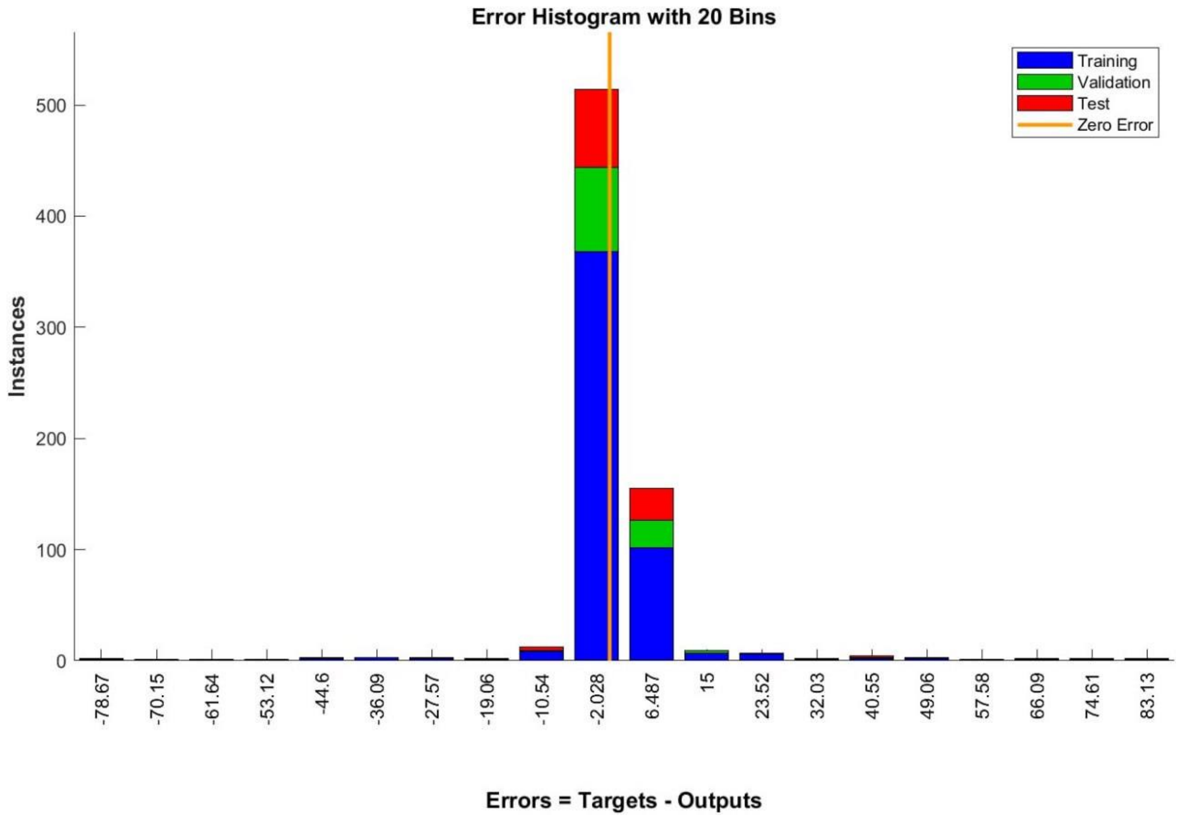
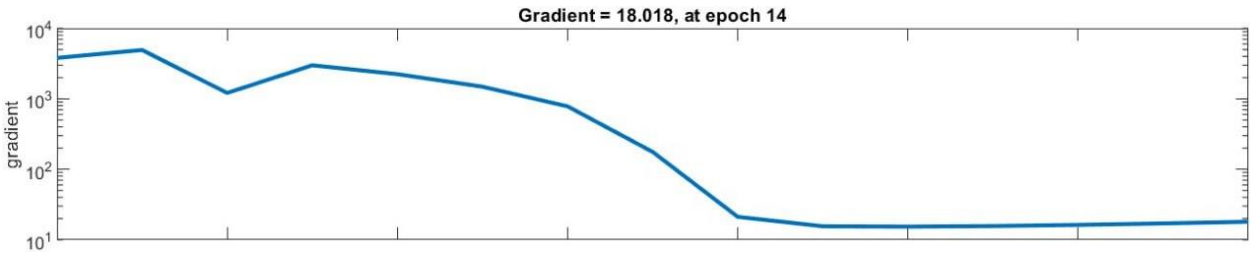


Figure 3.11 Error histogram for the ANN network.

The error values are then grouped into bins to create a histogram. The x-axis represents the error values (which can be positive or negative), while the y-axis indicates the number of samples that fall within each error bin. By analyzing the distribution of errors, practitioners can gain insights into the model's accuracy, identify biases, and assess the overall effectiveness of the training process. Understanding the characteristics of the error histogram can guide further improvements in model design and training. The perfect value for an error histogram in an ANN context is characterized by a distribution centered around zero.



3.12 Validation failures of faults in ANN training

Validation failures in ANN training highlight the importance of evaluating model performance on unseen data. They serve as critical indicators of potential issues such as overfitting or underfitting, guiding practitioners to make necessary adjustments to improve model generalization and reliability.

CHAPTER FOUR

RESULTS AND DISCUSSION

Chapter four

RESULTS AND DISCUSSION

4.1 Introduction

The power system is an essential component of the infrastructure that needs to be continuously maintained and monitored to guarantee a steady supply of electricity. Errors in the power system may result in equipment damage, blackouts, and safety risks. Thus, keeping the power system stable and reliable requires effective fault categorization, location, and detection procedures. The Adaptive Neuro-Fuzzy Inference System (ANFIS) has become a potent tool for fault analysis in power systems in recent years**.** ANFIS is a hybrid intelligent system that blends fuzzy logic's linguistic representation with neural networks' adaptive capabilities. It is capable of approximating complex nonlinear functions and learning from input-output data. ANFIS is composed of a learning algorithm that modifies the parameters of a set of fuzzy if-then rules according to training data. Faults in the power system malfunctions can be caused by several things, including human mistakes, lightning strikes, and malfunctioning equipment. Short circuits, open circuits, voltage sags, and harmonics are examples of common fault types. Accurately and quickly identifying and locating these flaws is necessary to save downtime and guarantee the security of the power system. In this work, the first step is to build a Simulink model in Matlab, as shown in Figure (3.2), which represents the (south-west) networks at Misan station (400 kV) and Kut station (400 kV) along 200 km distance between them. The block parameters of the Simulink model (the series and parallel impedances) values of the transmission line are selected approximately to the real value in the Misan station because these values are changed by any fault that occurs in the line. Later a comparison between the result of detection and localization of ANFIS with results in artificial neural network (ANN).

4.2 The Testing of the ANFIS file working in detecting and localization

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 (4.1) that illustrates the different values of transmission line length. A three-phase, symmetrical defect exists in this work. Bus 1 and Bus 2 are measurement units that are used in the Simulink model to read the voltages and currents of the three phases at each bus bar. Three phase faults will occur one at a time, each taking 0.05 seconds. Given that the buses are now collecting the data, we collected it from the stations in Misan and Kut for those two network locations. An attribute data matrix was used to collect the data. ANFIS will use the feature data to generate an ANFIS file that will be used to locate and identify faults in another network when the values of the feature data are compared using a Matlab function condition. Before employing the ANFIS file in networks, a Matlab application is created to validate its accuracy using an alternative Simulink network of unknown length. This program's output shows a very low error percentage along with different values of transmission line length. The output value of the fault detection and the fault location are shown in Table 4.1's results. The precision of the findings in determining the separation of fault locations with different length values. As the table illustrates, Before employing the ANFIS file in networks, a Matlab application is built to validate its accuracy using an alternative Simulink network of unknown length (L). This program's result, which shows an extremely low error percentage, of fault detection, will likely result in a logic one or zero for the identification of a fault or not, meaning that 100% of the faults were detected without any errors. The proportion of location mistakes in Table 4.1's column is extremely low, nearing 99.9%. For instance, when 45 km is entered into Matlab's test program to assess the ANFIS file's functionality, the result is 45.0088 km. When no errors are found, the output values are shown in the last five results. Ultimately, ANFIS provides several benefits for power system malfunction, localization, and detection. It can give real-time analysis, adjust to shifting system conditions, and handle imprecise and ambiguous data. Nonetheless, ANFIS can find it difficult to oversee intricate, expansive systems. with a great deal of variables and statutes. It takes a significant amount of labeled data to improve the training process. In conclusion, ANFIS is a helpful tool for discovering and identifying power system problems. Due to its capacity to learn from data and approximate complicated processes, it is an essential instrument for preserving the electrical grid's stability and reliability. Power system operators can improve their fault management tactics, reduce downtime, and guarantee a steady supply of electricity by utilizing ANFIS. locating and recognizing errors. The results in the table show the output value and the accuracy of locating the distance of fault points with different values of length 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.

Table (4.1) 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(V)	Vb(V)	Vc(V)	Length (Km)	Fault location (Km)	fault (1) no fault(0)
6518.458	6545.002	6540.482	19098.55	19113.5	19090.96	5	7.01098	1
5991.413	6018.652	6017.298	35044.43	35061.09	35036.29	10	10.00059	1
5542.813	5570.075	5570.946	48629.18	48647.01	48620.87	15	14.98088	1
5156.407	5183.311	5185.77	60334.64	60353.25	60326.36	20	19.99821	1
4820.132	4846.465	4850.069	70522.76	70541.86	70514.61	25	25.00792	1
4524.849	4550.498	4554.931	79468.97	79488.33	79461.01	30	30.00606	1
4263.508	4288.419	4293.453	87386.23	87405.72	87378.49	35	35.00173	1
4030.581	4054.739	4060.207	94441.71	94461.22	94434.21	40	39.99619	1
3821.68	3845.089	3850.868	100768.4	100787.8	100761.1	45	45.0088	1
3633.27	3655.951	3661.948	106473.3	106492.7	106466.3	50	50.03395	1
3462.476	3484.458	3490.602	111643.7	111662.9	111636.9	55	55.05578	1
3306.937	3328.251	3334.488	116351.1	116370.1	116344.5	60	60.05143	1
3164.689	3185.372	3191.662	120655.1	120673.9	120648.7	65	64.48385	1
3034.094	3054.182	3060.494	124605.3	124624	124599.1	70	69.79157	1
2913.766	2933.297	2939.608	128243.8	128262.3	128237.8	75	74.76349	1
2802.53	2821.542	2827.833	131606.1	131624.4	131600.2	80	79.85554	1
2699.377	2717.911	2724.168	134722.6	134740.8	134716.9	85	84.98052	1
2603.437	2621.533	2627.749	137619.7	137637.7	137614.1	90	89.80761	1
2.526418	2.526418	2.526418	216310.8	216310.8	216310.8	1	0	0
2.524973	2.524973	2.524973	216310.8	216310.8	216310.8	2	0	0

Ia(A)	Ib(A)	Ic(A)	Va(V)	Vb(V)	Vc(V)	Length (Km)	Fault location (Km)	fault (1) no fault(0)
2.52354	2.52354	2.52354	216310.9	216310.9	216310.9	3	0	0
2.522125	2.522125	2.522125	216310.9	216310.9	216310.9	4	0	0
2.520732	2.520732	2.520732	216311	216311	216311	5	0	0

4.3 The Testing of the ANN working in detecting and localization and comparing with the testing of ANFIS .

Using Simulink to create a neural network and forecast the fault position shown in Fig. 3.6, the model is also intended for fault localization in the transmission line. The fault voltage and current of a three-phase line measured at buses in the simulation model fig. 3.2 are the input parameters. Once the defect location has been identified, the input is sent to the classifier. For convenience, a screen display of these defect types and locations is provided. A quick and efficient fault management plan is implemented through potential action. By entering the same data of the currents and voltages in the testing program in Matlab (R2022a) with Simulink as shown in figure (4.1) Simulink Model of 400 kV, 200 km Transmission line illustrates the testing of the trained data in ANN the results and testing the lengths as shown in table (4.2) the output data of the fault detection shows the accuracy of the ANN with 100% in location the results show the results from ANFIS is nearest to the given value of transmission line length.

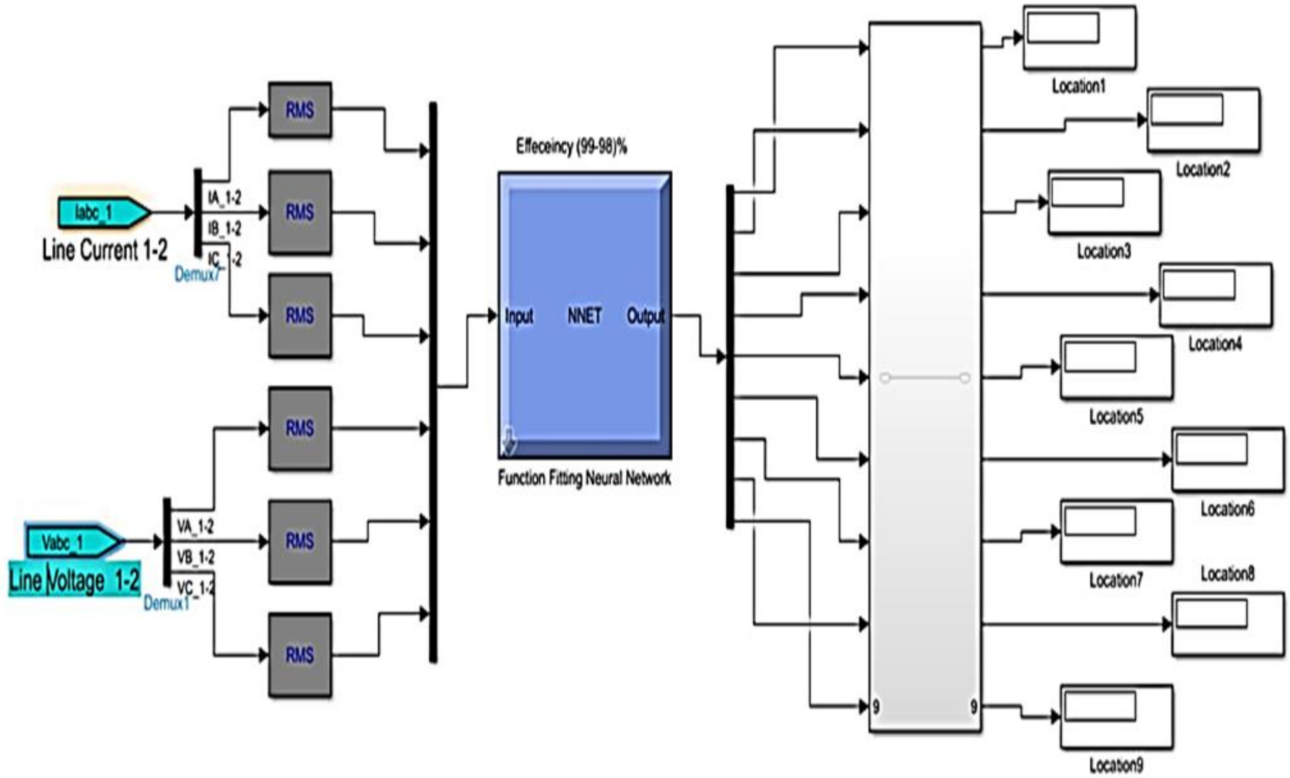


Figure. 4.1 Simulink Model of 400 kV, 200 km Transmission line (Testing the Trained Data in ANN).

Table (4.2) Shows the results of the testing on the ANN giving the different values of transmission line length.

Ia(A)	Ib(A)	Ic(A)	Va(V)	Vb(V)	Vc(V)	Length (Km)	Fault location (Km)	fault (1) no fault(0)
6518.458	6545.002	6540.482	19098.55	19113.5	19090.96	5	7.2012	1
5991.413	6018.652	6017.298	35044.43	35061.09	35036.29	10	10.1022	1
5542.813	5570.075	5570.946	48629.18	48647.01	48620.87	15	14.5600	1
5156.407	5183.311	5185.77	60334.64	60353.25	60326.36	20	19.0988	1
4820.132	4846.465	4850.069	70522.76	70541.86	70514.61	25	24.0123	1
4524.849	4550.498	4554.931	79468.97	79488.33	79461.01	30	29.0555	1
4263.508	4288.419	4293.453	87386.23	87405.72	87378.49	35	35.9821	1
4030.581	4054.739	4060.207	94441.71	94461.22	94434.21	40	39.0087	1
3821.68	3845.089	3850.868	100768.4	100787.8	100761.1	45	44.0446	1
3633.27	3655.951	3661.948	106473.3	106492.7	106466.3	50	49.04495	1
3462.476	3484.458	3490.602	111643.7	111662.9	111636.9	55	55.9843	1
3306.937	3328.251	3334.488	116351.1	116370.1	116344.5	60	61.06344	1
3164.689	3185.372	3191.662	120655.1	120673.9	120648.7	65	64.9666	1
3034.094	3054.182	3060.494	124605.3	124624	124599.1	70	68.71111	1
2913.766	2933.297	2939.608	128243.8	128262.3	128237.8	75	73.6722	1
2802.53	2821.542	2827.833	131606.1	131624.4	131600.2	80	79.0002	1
2699.377	2717.911	2724.168	134722.6	134740.8	134716.9	85	83.65552	1
2603.437	2621.533	2627.749	137619.7	137637.7	137614.1	90	89.01002	1

Ia(A)	Ib(A)	Ic(A)	Va(V)	Vb(V)	Vc(V)	Length (Km)	Fault location (Km)	fault (1) no fault(0)
2.526418	2.526418	2.526418	216310.8	216310.8	216310.8	1	0	0
2.524973	2.524973	2.524973	216310.8	216310.8	216310.8	2	0	0
2.52354	2.52354	2.52354	216310.9	216310.9	216310.9	3	0	0
2.522125	2.522125	2.522125	216310.9	216310.9	216310.9	4	0	0
2.520732	2.520732	2.520732	216311	216311	216311	5	0	0

4.4 The waveforms in Matlab Simulink

The waveforms can be used as training data for ANFIS models in MATLAB, allowing researchers to evaluate electrical signals, identify defects, categorize faults with effectiveness, and identify issues in transmission lines with exceptional precision and dependability. 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 waveform. Voltage and Current Measurements reading from Amara Bus-Bar for 9 fault positions when we have

three phases to ground fault at each position as shown in the figures below .

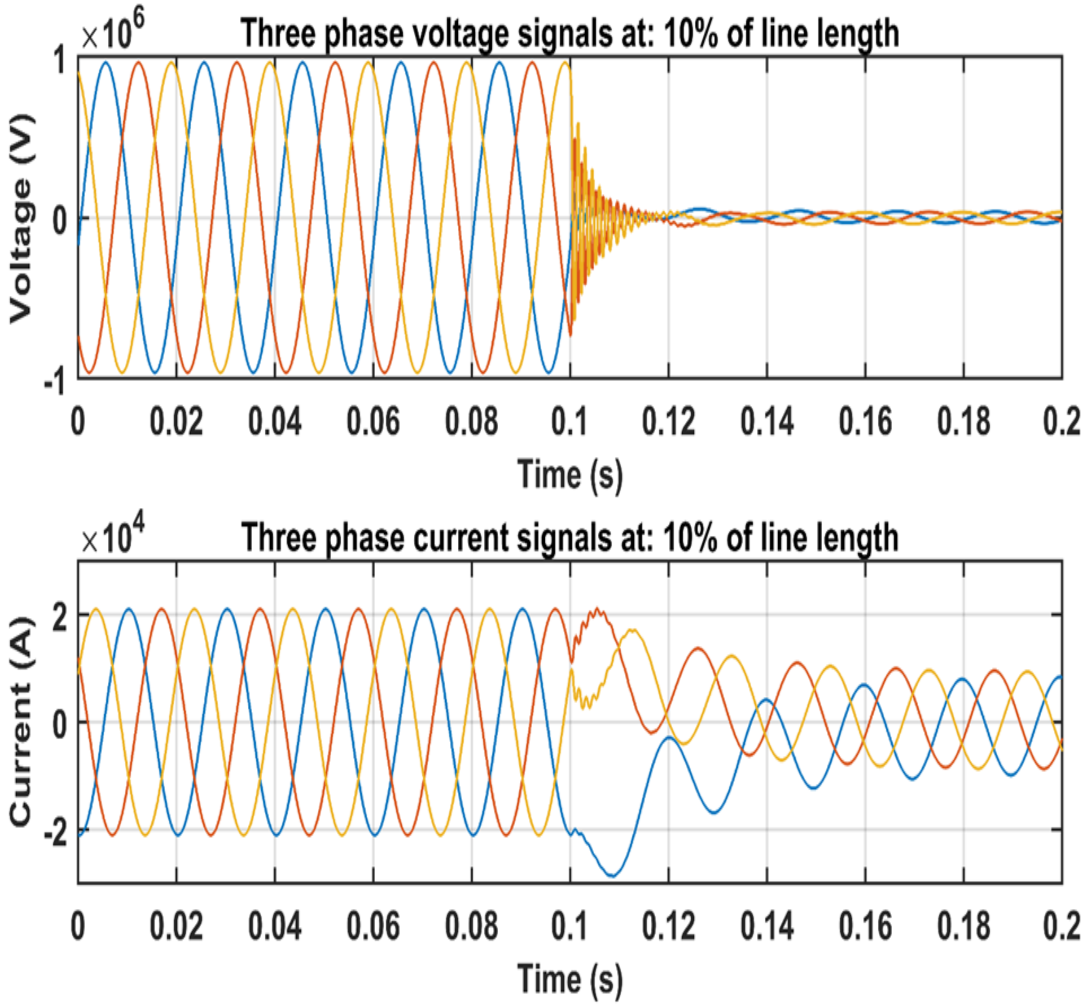


Figure 4.2 The Matlab waveform of current and voltage signal at 10 % of the transmission line length .

Fig. 4.2 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. 4.14 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.

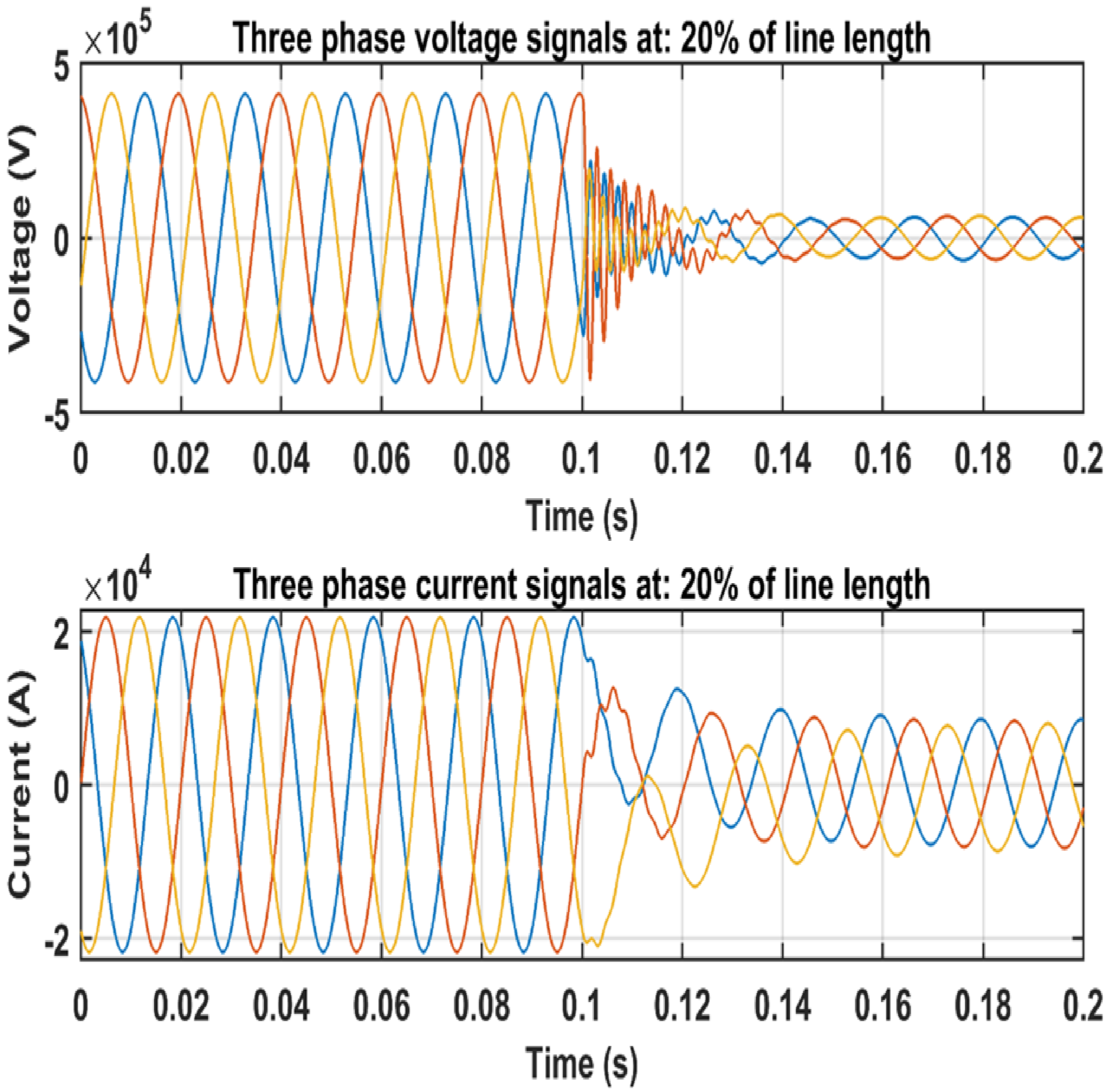


Figure (4.3) The Matlab waveform of current and voltage signal at 20 % of the transmission line length.

In Fig. 4.3, the shape of the input waveforms for 20% of the line length shows that the high value of the current in two phases and the voltage will be reduced. The current will be lower than in the previous state. The voltage is higher due to the distance.

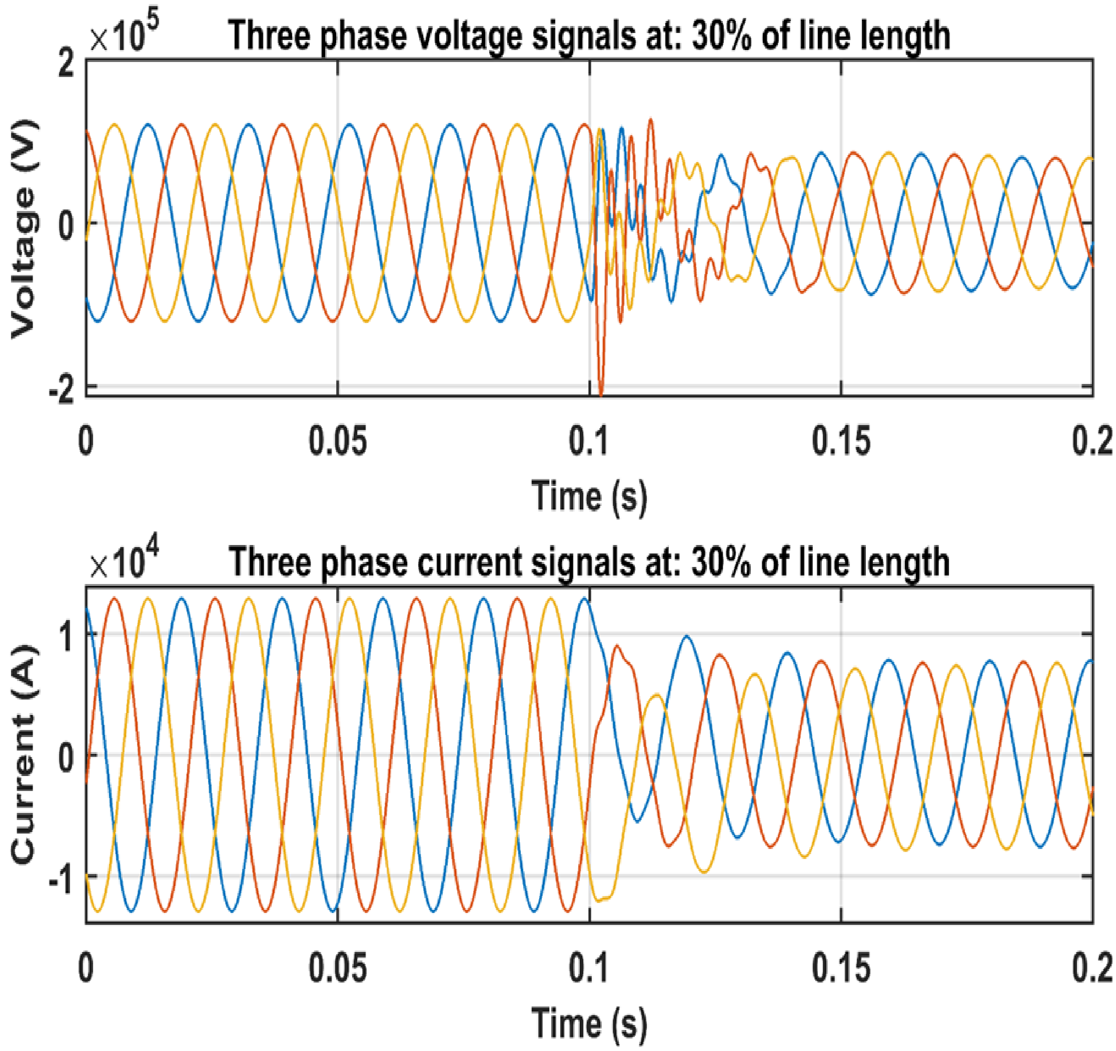


Figure (4.4) the Matlab waveform of current and voltage signal at 30 % of the transmission line length.

In Fig. 4.4, the shape of the input waveforms for 30% of the line length shows that the high value of the current in two phases and the voltage will be reduced. The current will be lower than in the previous state. And the voltage is higher due to the distance

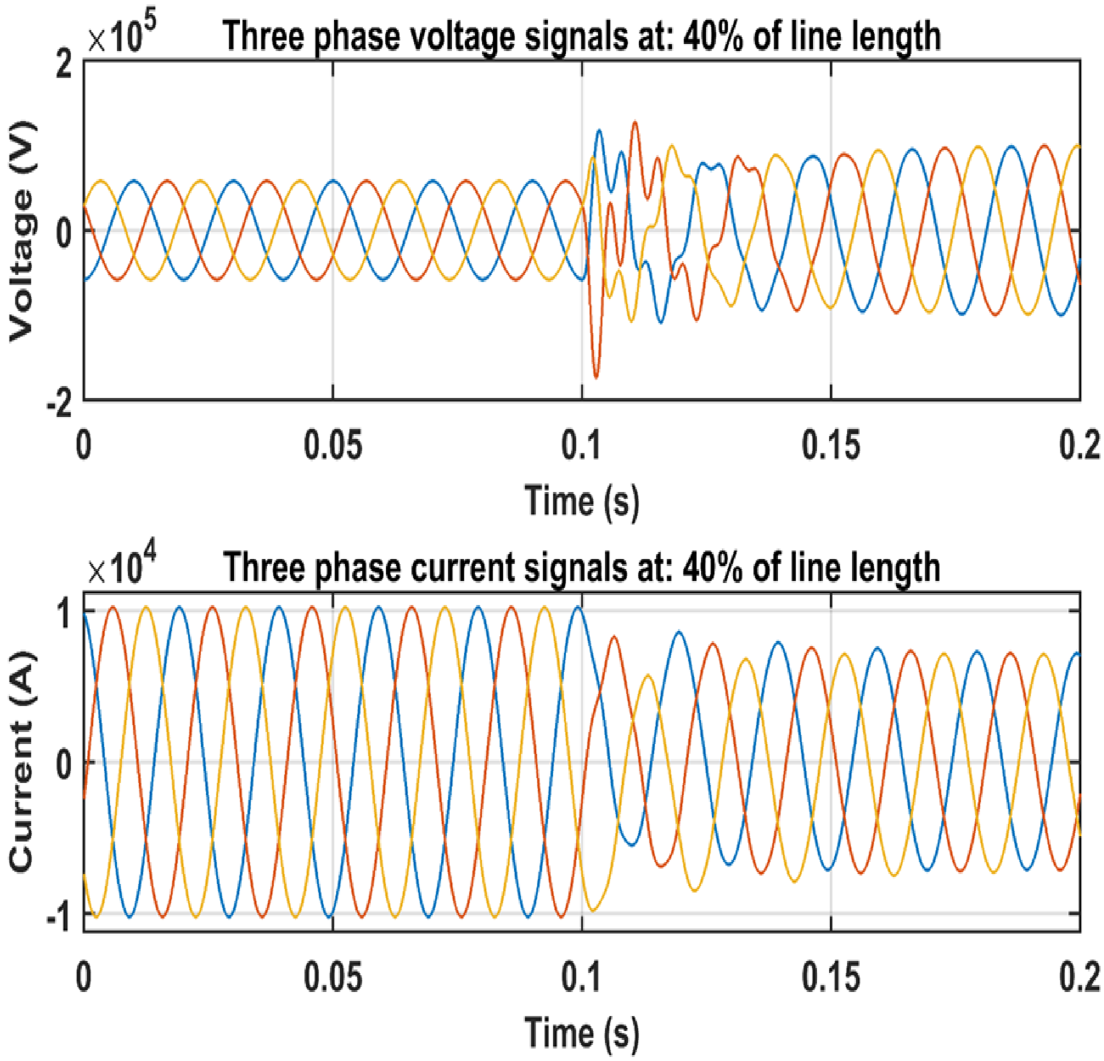


Figure (4.5) the Matlab waveform of current and voltage signal at 40 % of the transmission line length .

In Fig. 4.5, the shape of the input waveforms for 40% of the line length shows that the high value of the current in two phases and the voltage will be reduced. The current will be lower than in the previous state. And the voltage is higher due to the distance.

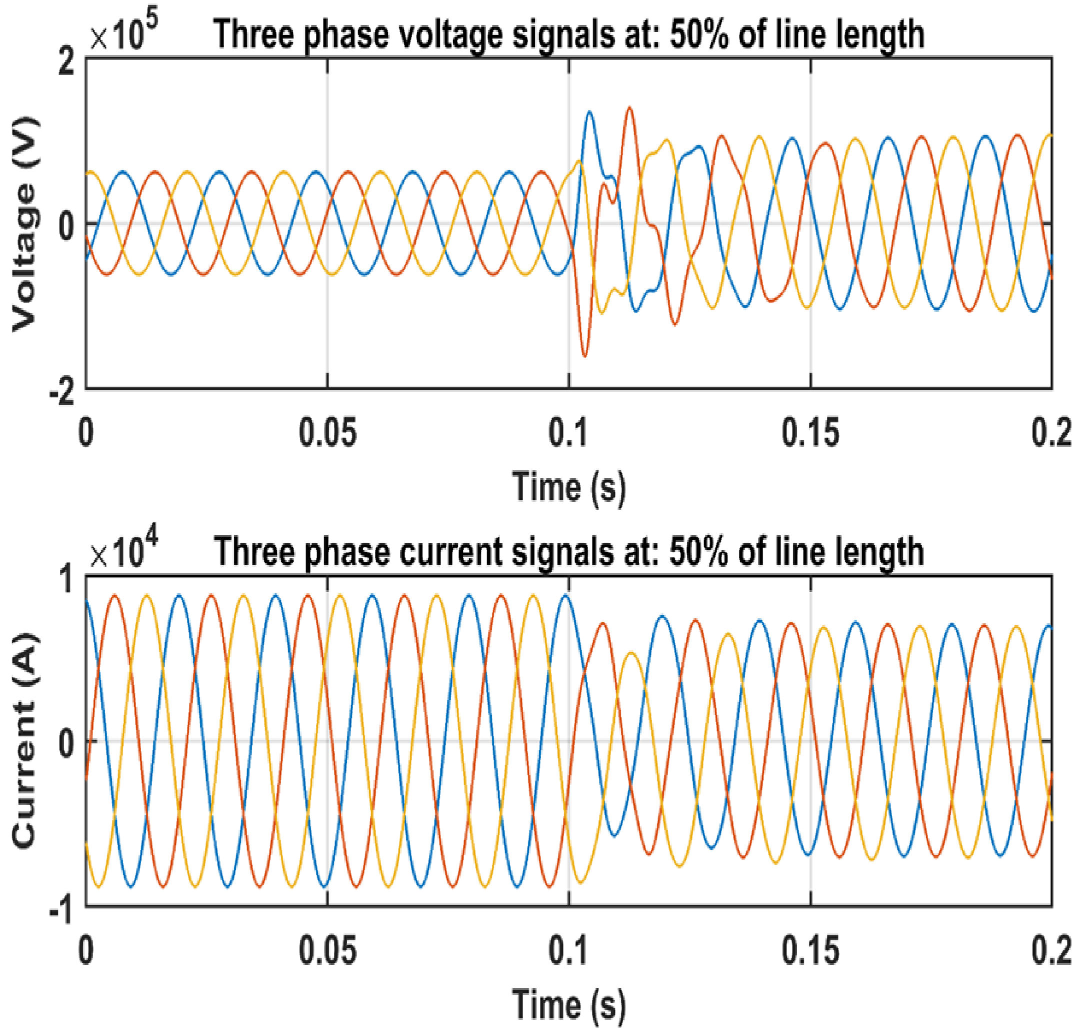


Figure (4.6) the Matlab waveform of current and voltage signal at 50 % of the transmission line length.

In Fig. 4.16, the shape of the input waveforms for 50% of the line length shows that the high value of the current in two phases and the voltage will be reduced. The current will be lower than in the previous state. And the voltage is higher due to the distance. Other locations of fault in transmission lines 60%,70%,80%, and 90%) of the line length in appendices (A, B, C, D).

4.5 The Comparison between Artificial Neural Network (ANN) and Adaptive Neural Fuzzy Inference System (ANFIS).

In the field of artificial intelligence and machine learning, Adaptive Neuro-Fuzzy Inference System (ANFIS) vs Artificial Neural Network (ANN) contrast is essential. Although they both have strong modeling and prediction capabilities, ANFIS and ANN have different underlying architectures and methods. ANFIS is a kind of fuzzy logic system that builds a strong and flexible model by fusing the powers of fuzzy logic and neural networks[81]. It is especially helpful for managing uncertainty and simulating systems with non-linear connections. ANN, on the other hand, is a kind of neural network that draws its inspiration from the composition and capabilities of the human brain. It is renowned for its capacity to pick up on and adjust to intricate data patterns[82]. Given that both ANFIS and ANN have advantages and disadvantages, a comparison of the two models is necessary. Although ANFIS is renowned for its capacity to manage uncertainty and non-linear interactions, training it may need a substantial quantity of data and be computationally demanding. ANN, on the other hand, is renowned for its capacity to identify intricate patterns in data; yet, its performance may be adversely affected by the caliber of the training set and may not be optimal in scenarios with non-linear correlations between variables[83]. This comparison is crucial since it can assist in determining which model is appropriate for a certain situation and enhance the system's overall performance. In conclusion, it is critical to compare ANFIS with ANN in the context of machine learning and artificial intelligence. Each model has advantages and disadvantages, and the best model to use will rely on the particular application and the kind of data that is accessible.

Table 4.3 The Characteristics as a comparison between ANN and ANFIS

Feature	Artificial Neural Network (ANN)	Adaptive Neuro-Fuzzy Inference System (ANFIS)
Basic Structure[84]	Composed of layers of interconnected neurons (input, hidden, output).	Combines neural network structure with fuzzy logic principles.
Layers[82]	Typically consists of an input layer, one or more hidden layers, and an output layer.	Consists of five layers: input layer, fuzzification layer, rule layer, normalization layer, and output layer.
Functionality of Nodes[85]	Neurons perform weighted sums and apply activation functions.	Nodes perform specific functions related to fuzzy logic and inference.
Learning Mechanism[85]	Uses backpropagation and gradient descent for weight adjustment.	Employs a hybrid learning approach combining gradient descent and least squares estimation.
Handling of Inputs[85]	Accepts numerical inputs and processes them through activation functions.	Accepts both numerical and linguistic inputs, converting them into fuzzy sets.
Output Type[86]	Produces continuous outputs based on learned patterns.	Produces fuzzy outputs that can be defuzzified into crisp values.
Interpretability[86]	Often considered a "black box"; difficult to interpret outputs.	More interpretable due to fuzzy rules, providing human-readable outputs.

Feature	Artificial Neural Network (ANN)	Adaptive Neuro-Fuzzy Inference System (ANFIS)
Adaptability[81]	Adapts well to large datasets but may require extensive retraining.	Adapts to changing conditions by updating fuzzy rules and parameters.

4.6 Discussion of the Results

Power transmission lines have seen the successful application of ANFIS for fault localization and detection. The method enhances the efficiency of finding and identifying faults in voltage distribution power system networks by utilizing ANFIS. With the least amount of error, the approach can locate and detect faults, as well as determine their distance and major and minor branches. the result shown in Table (4.1) illustrates the accuracy of detection reached 100% and the localization to 99.99% which is considered a very effective and reliable technique.

Comparison of ANN and ANFIS Models: To characterize the generation of polygalacturonase, the ANN approach was contrasted with the ANFIS. While the ANFIS model and the ANN model both showed comparable predictions, the ANFIS method more accurately forecasted and fit the testing data. Compared to ANN, ANFIS Performs Better and Learns More Quickly when it comes to forecasting particle ratios, the ANFIS models outperformed the ANN system and other theoretical models in terms of performance and training speed. Whereas ANN Results Vary, ANFIS Results Are Consistent, the ANFIS system will yield the same result in every iteration of the experiment when employing it in place of the ANN system, whereas the ANN system will yield a new result each time. ANN Needs Longer Training Time Than ANFIS, To reach optimal performance, the ANN system needed an overly long training period compared to the ANFIS system. ANN results in table (4.2). Table 4.3 shows the Characteristics as a comparison between ANN and ANFIS and the comparison between ANFIS and ANN is clear in the table the result of fault detection in ANFIS for the length (20 Km) of the transmission line is (19.99821 Km) and for ANN for the same length of the transmission line is (19.0988 Km) so ANFIS is more accurate and faster. In summary, ANFIS performs better than ANN in terms of prediction accuracy, consistency of outcomes, and training duration, according to testing and comparison of ANN and ANFIS models in defect detection and localization. However, the application and caliber of the training data determine each model's performance.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATION

Chapter five

CONCLUSIONS AND RECOMMENDATION

5.1 CONCLUSION

It's essential to realize that an examination of fault identification can be done by ANFIS. The data that may be utilized to train the ANFIS, the time required to design and test the ANFIS, and the required accuracy of the ANFIS predictions are all important considerations. The application of ANFIS for fault detection and localization in 400 kV transmission lines has shown promising results in terms of accuracy, speed, and reliability. ANFIS can accurately detect and locate different types of faults (Three-Phase Faults), with very low error percentages. The proposed ANFIS-based approach demonstrates high-speed processing capabilities, enabling real-time fault detection and localization within less than 0.05 cycles of time. This is crucial for minimizing downtime and preventing cascading failures in the power system. ANFIS effectively handles uncertainties and imprecisions in measurement data, such as voltage and current signals, by combining the strengths of neural networks and fuzzy logic. This makes it suitable for practical applications where data quality can vary. The interpretability of ANFIS is enhanced by its fuzzy rule-based structure, which allows for linguistic representation of the fault conditions. This can help power system operators better understand and diagnose fault cases. Simulation results using MATLAB/Simulink demonstrate the effectiveness of ANFIS in localizing faults along the transmission line, with estimates within 200 Kilometers meters of the actual fault location. This level of accuracy is essential for isolating and repairing faults. The hybrid learning approach of ANFIS, combining gradient descent and least squares estimation, enables more accurate training compared to traditional ANN models. This is beneficial for adapting the system to changing network conditions and evolving faults in different locations. In summary, the integration of ANFIS into transmission line protection schemes can significantly enhance the reliability, stability, and security of power systems by providing accurate, real-time fault detection and localization capabilities.

5.2 The Recommendations and Future works

The intricacy of the recommendations made on the use of ANFIS for transmission line fault detection ANFIS models can be complicated and challenging to implement, requiring a large number of computational resources and expertise; training and testing the choice of membership functions can significantly impact By implementing these recommendations and pursuing future works, the effectiveness of ANFIS in fault detection and localization in transmission lines can be significantly enhanced. This will contribute to the reliability and stability of power systems, ultimately benefiting both operators and consumers by reducing downtime and improving service quality.

- Incorporate ANFIS with smart grid systems to enhance real-time monitoring and fault management capabilities. This integration can leverage data from smart meter devices for improved accuracy in fault detection.

- Explore hybrid models that combine ANFIS with other machine learning techniques, such as deep learning or support vector machines, to improve fault classification and localization accuracy.

- Build user-friendly interfaces for operators to interact with the ANFIS system, making it easier to visualize fault detection results and understand the decision-making process.

-Adaptive and Self-Tuning ANFIS: Create adaptive and self-tuning ANFIS architectures that can automatically adjust their parameters based on systems of detection. Integrate with Other Protection Schemes: Examine how ANFIS-based fault detection can be integrated with other protection schemes, including communication-based, overcurrent, and distance protection. This might result in the creation of fault management systems that are more thorough and dependable .

For future research in multi-objective optimization techniques to balance various computational efficiency in performance metrics, such as detection speed, accuracy, and fault detection and localization, foster collaborative research efforts between academic and industry to advance the application of ANFIS in power systems, facilitating knowledge exchange and practical implementation of findings

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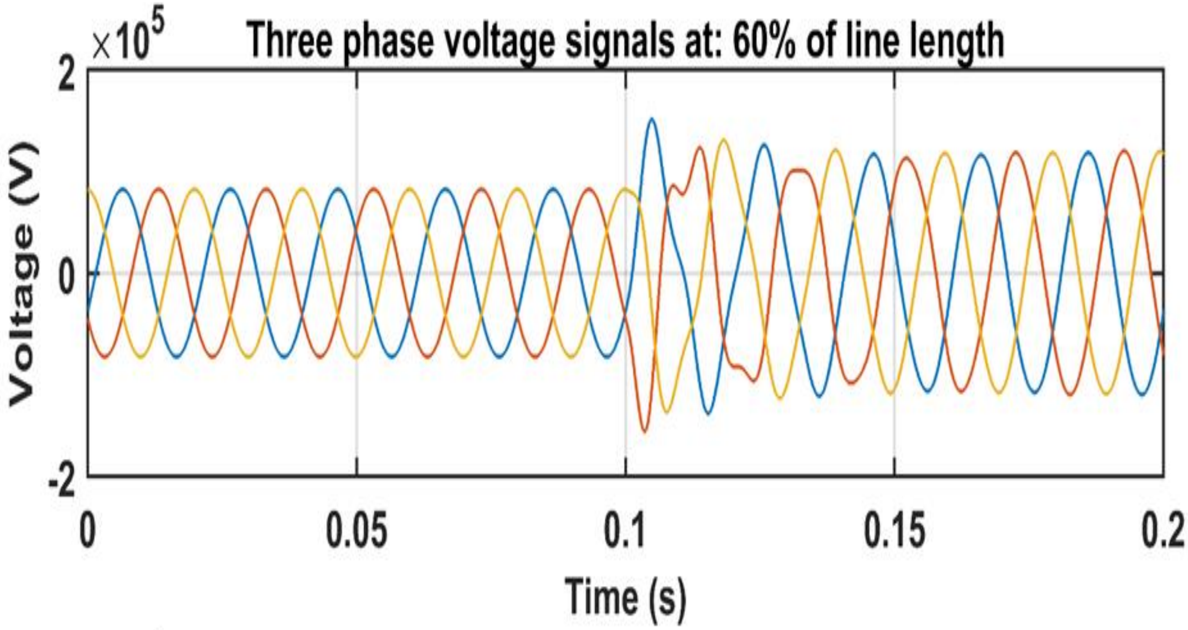
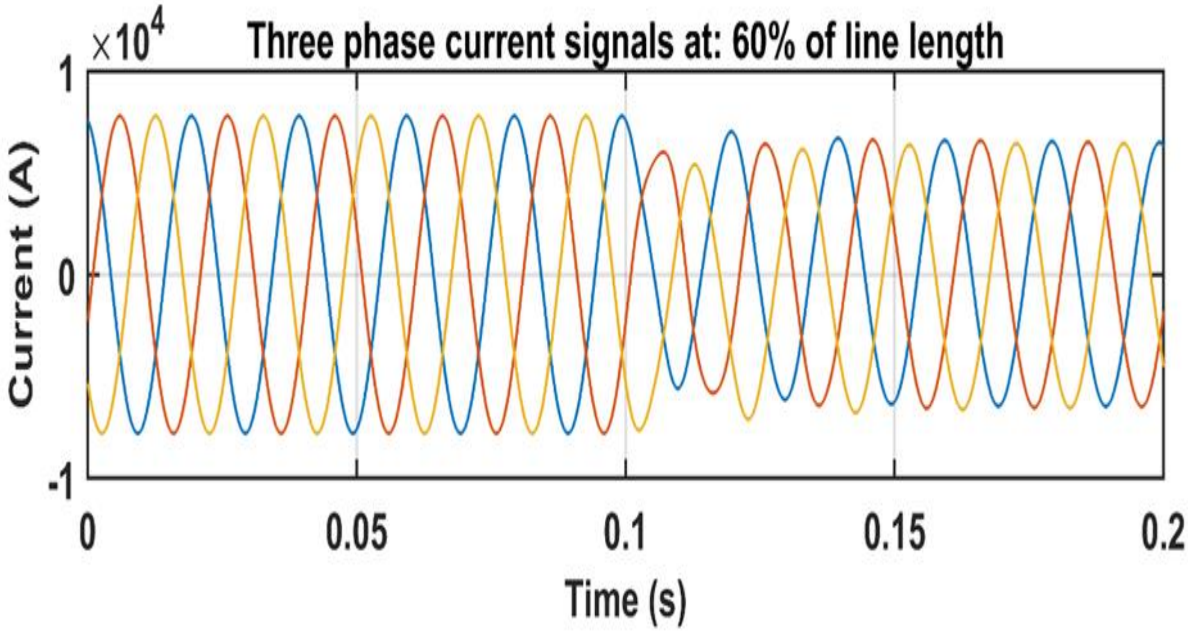
APPENDICES

APPENDIX A

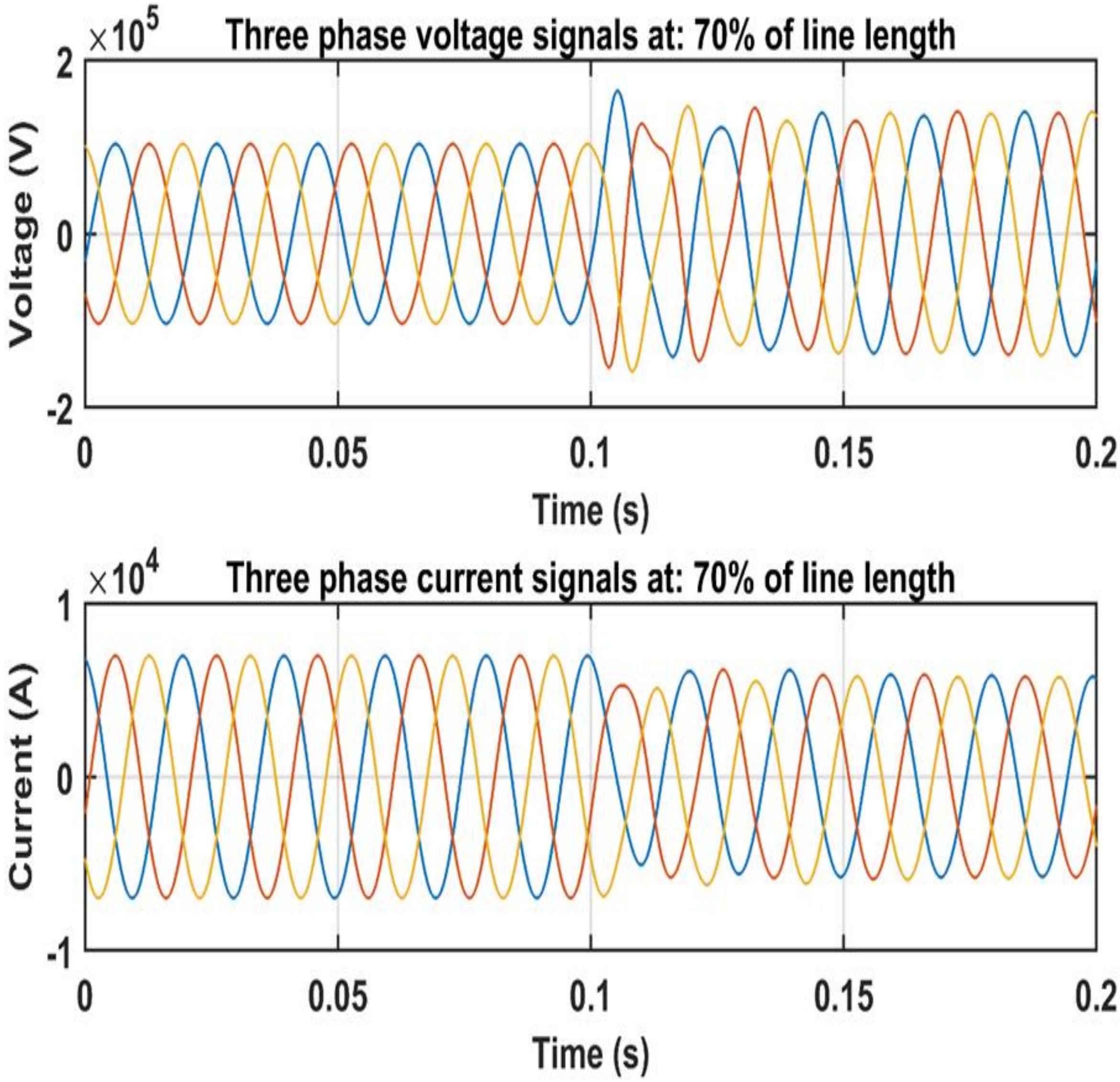


×10^5
Three phase voltage signals at: 60% of line length
Voltage (V)
2
0
-2
0
0.05
0.1
0.15
0.2
Time (s)

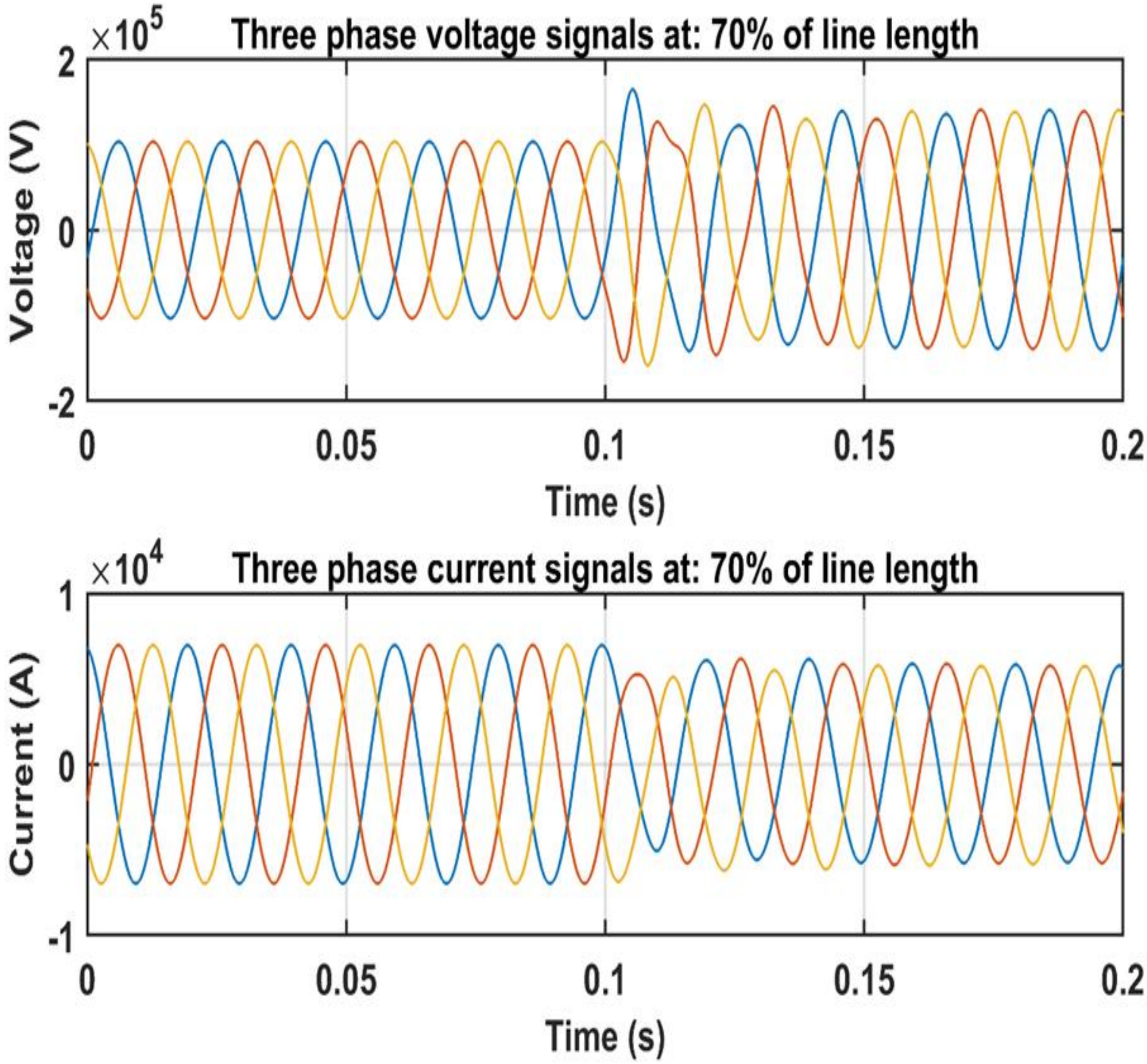


×10^4
Three phase current signals at: 60% of line length
Current (A)
1
0
-1
0
0.05
0.1
0.15
0.2
Time (s)

Appendix B

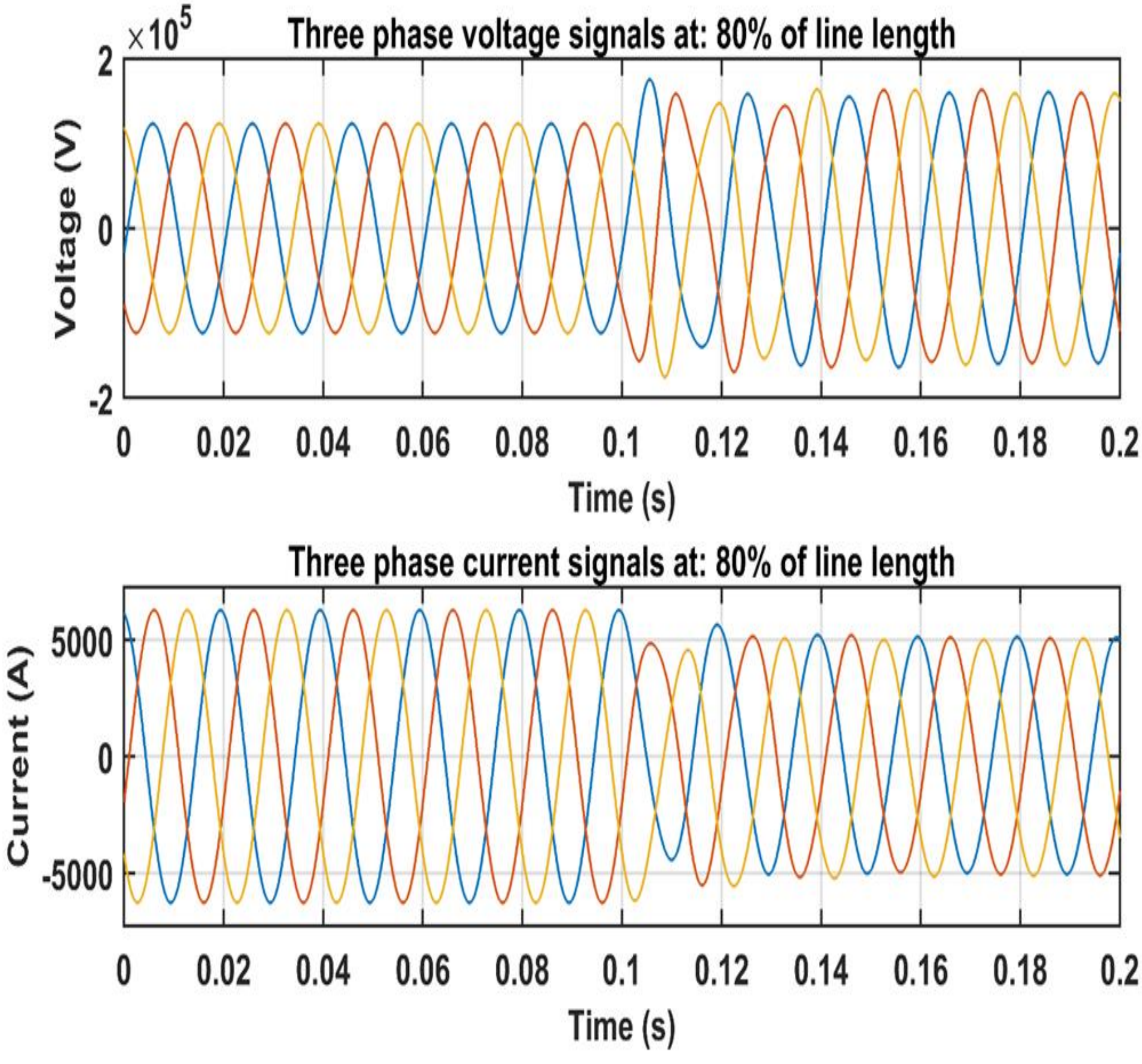

×10^5
Three phase voltage signals at: 70% of line length
2
0
-2
Voltage (V)
0
0.05
0.1
0.15
0.2
Time (s)
×10^4
Three phase current signals at: 70% of line length
1
0
-1
Current (A)
0
0.05
0.1
0.15
0.2
Time (s)

APPENDIX C

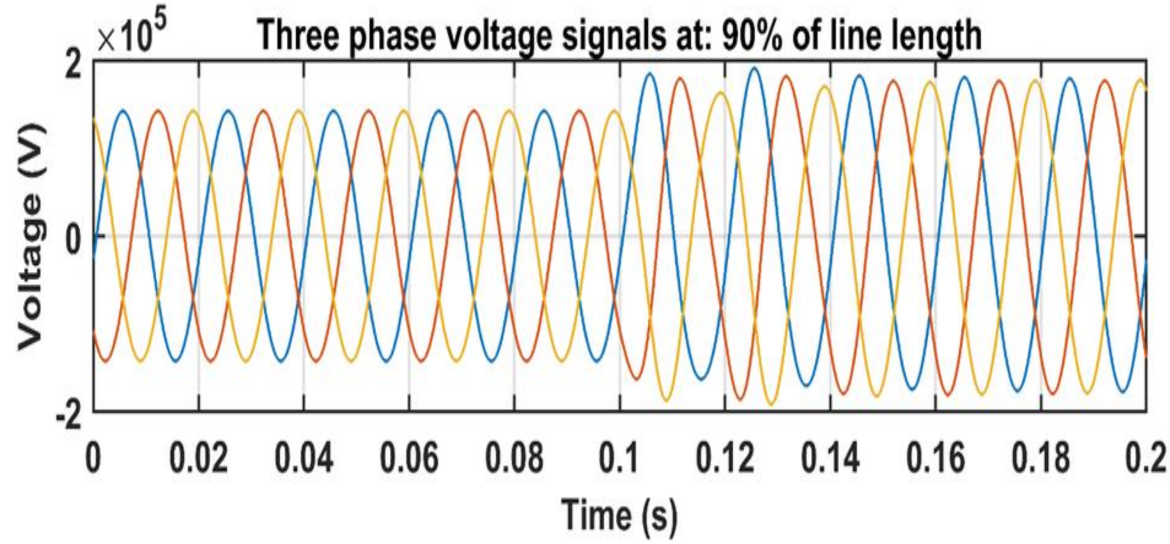


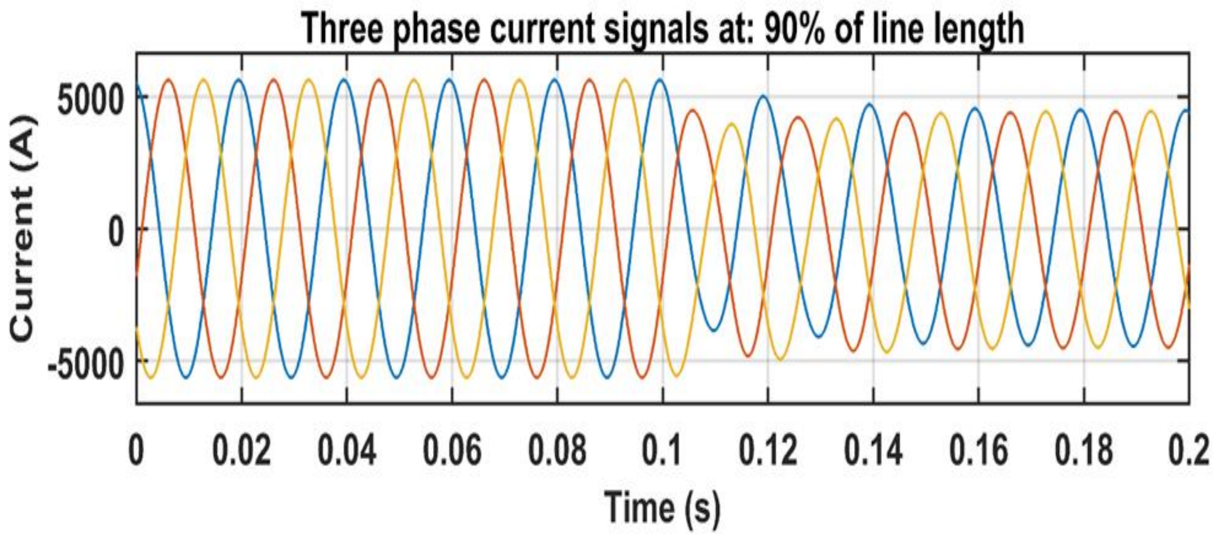
×10^5
Three phase voltage signals at: 70% of line length
Voltage (V)
2
0
-2
0
0.05
0.1
0.15
0.2
Time (s)
×10^4
Three phase current signals at: 70% of line length
Current (A)
1
0
-1
0
0.05
0.1
0.15
0.2
Time (s)

APPENDIX D



APPENDIX D


Three phase voltage signals at: 90% of line length
×10^5
Voltage (V)
2
0
-2
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: 90% of line length
Current (A)
5000
0
-5000
0
0.02
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.18
0.2
Time (s)

APPENDIX E

Constants For (132&400)KV Overhead Lines

Items	Conductor Type	C.S Area (mm^2)	Code	R0 (Ω/Km)	R1 (Ω/Km)	X0 (Ω/Km)	X1 (Ω/Km)	B1 (Ω/Km)	XM0 (Ω/Km)	X00 (Ω/Km)	$\frac{X0}{X1}$ (Ω/Km)	$\frac{X00}{X1}$ (Ω/Km)	Thermal Power (MVA) Rated	Thermal Power (MVA) Max.	Current (Amp.) Rated	Current (Amp.) Max.
132KV Single Lines	Lark	248	L	0.378	0.147	1.231	0.428	2.66	---	X0	2.87	X0/X1	96	116	420	510
	Teal	377	T	0.3275	0.097	1.218	0.415	2.75	---	X0	2.93	X0/X1	120	151	525	660
	Oriole	210	O	0.406	0.174	1.236	0.433	2.63	---	X0	2.85	X0/X1	85	104	370	455
	Partridge	157	P	0.4495	0.219	1.246	0.444	2.57	---	X0	2.81	X0/X1	73	89	320	390
	Twin Lark	2×248	TL	0.3065	0.0735	1.109	0.3065	3.70	---	X0	3.62	X0/X1	192	232	840	1020
	Twin Teal	2×377	TT	0.2805	0.0485	1.113	0.301	3.78	---	X0	3.71	X0/X1	240	300	1050	1320
	Twin AAAC	2×551	TAA	0.300	0.034	0.976	0.315	---	---	X0	3.10	X0/X1	330	395	1440	1720
132KV Double Lines	Lark	248	L	0.378	0.147	1.287	0.400	2.87	0.801	2.088	3.21	5.22	96	116	420	510
	Teal	377	T	0.3275	0.097	1.274	0.387	2.97	0.801	2.075	3.30	5.36	120	151	525	660
	Oriole	210	O	0.406	0.174	1.292	0.405	2.83	0.801	2.093	3.20	5.16	85	104	370	455
	Partridge	157	P	0.4495	0.219	1.303	0.417	2.76	0.804	2.107	3.12	5.05	73	89	320	390
	Twin Lark	2×248	TL	0.3065	0.0735	1.165	0.278	4.13	0.801	1.966	4.20	7.07	192	232	840	1020
	Twin Teal	2×377	TT	0.2805	0.0485	1.159	0.2725	4.23	0.801	1.960	4.25	7.19	240	300	1050	1320
	Twin AAAC	2×551	TAA	0.300	0.034	0.734	0.285	3.76	0.801	1.535	2.57	5.38	330	395	1440	1720
400KV Single Lines	Twin AAAC	2×551	TAA	0.265	0.035	0.6843	0.3175	---	---	X0	2.15	X0/X1	1000	1177	1440	1700
	Twin ACSR	2×490/65	ACSR	0.15	0.0361	0.69	0.314	---	---	X0	2.19	X0/X1	970	1154.3	1400	1666

Remarks :-

- The value of earth resistivity(ρ)=100Ω.m is assumed in the calculations.
- X0: Reactance for one circuit.
- XM0: Mutual reactance between two circuits.
- X00 = (X0+XM0): Reactance for double line.

المهندس
حسن احمد ناكى

APPENDIX F

- The ANFIS's configuration for detecting contains the following design parameters :

[System]

'Name='anfis rule

'Type='sugeno

Version=2.0

NumInputs=6

NumOutputs=1

NumRules=729

'AndMethod='prod

'OrMethod='probor

'ImpMethod='prod

'AggMethod='sum

DefuzzMethod='wtaver'

الخلاصة

تكمن أهمية دراسة اكتشاف الأخطاء المتقدمة وتصنيفها وتوطينها في خطوط النقل في تعزيز دقة وكفاءة اكتشاف الأخطاء وتوطينها في أنظمة نقل الطاقة. تهدف الدراسة إلى الاستفادة من التقنيات المتقدمة مثل أنظمة الاستدلال العصبي الضبابي التكيفي (ANFIS) والشبكات العصبية والطرق الهجينة لتحسين اكتشاف الأخطاء وتوطينها في خطوط النقل، حيث تمت مقارنة العمل باستخدام نموذج يعتمد على الخلايا العصبية الاصطناعية الشبكات(ANN) ، وكان النظام المقترح هو المفضل. تؤكد الورقة على فوائد النظام مقارنة بالمناهج البديلة، مثل قدرته على إدارة حالات عدم اليقين والأنظمة غير الخطية وإمكانية تكامله مع استراتيجيات الهجرة الوقائية الأخرى لاستخدام شبكات الطاقة. في العالم الحقيقي. وتركز الدراسات اللاحقة على تحسين دقة وموثوقية النموذج المستخدم. توضح هذه الدراسة تطبيق تقنية ANFISللتعرف التلقائي على اضطرابات الأعطال في خطوط النقل وتوطينها باستخدام البيانات المقاسة من محطة خط نقل واحدة. الهدف من تصميم هذه التقنية وتنفيذها هو المعالجة عالية السرعة التي يمكن أن توفر اكتشاف الأخطاء وتوطينها في الوقت الفعلي. وقد تم اقتراح استخدام هذا الأسلوب لتحديد الأخطاء ومواقع أنظمة الحماية الرقمية عن بعد بالإضافة إلى الكشف عن جميع أخطاء التحويل. حيث تم استخدام خط نقل قدرة جهد 400 كيلو فولت، بمسافة 200 كيلومتر، يربط من محافظة ميسان إلى محافظة واسط. لقد تم تحديد الأشكال العشرة المختلفة لأخطاء التبديل التي قد تحدث في خط النقل بعناية من خلال المرحلة (المراحل) التي ينطوي عليها استخدام التقنية المقترحة. تم استخدام مجموعات بيانات ميدانية مختلفة لتدريب واختبار نظام التقنيات المستخدمة. باستخدام برامج الكمبيوتر المبنية على منصة . يتم استخراج البيانات الميدانية من عمليات محاكاة الأخطاء في مواقع مختلفة على طول خط النقل. تتناول هذه الدراسة مجموعة متنوعة من سيناريوهات الأخطاء، بما في ذلك أنواع الأخطاء ومواقع الأخطاء ومقاومة الأخطاء. يعد قياس تيار الطور والجهد المتوفر في موضع الترحيل بناءً على قيم RMS بمثابة مدخلات .ANFISs عندما يتعلق الأمر باكتشاف الخطأ ونوع الخطأ، تكون مخرجات التقنية المستخدمة إما 1 أو 0. وتظهر نتائج عملية المحاكاة أن سرعة وانتقائية النهج يمكن الاعتماد عليها للغاية بالنسبة لنظام ANFIS مقارنة بـ .ANN نتائج اكتشاف الأخطاء لخط نقل بطول 20 كم في ANFIS هي (19.99821) كم، بينما لخط نقل ANN بنفس الطول هي (19.0988) كم . وهذا يوضح بوضوح أن ANFIS أكثر دقة وأسرع من .ANN يُظهر اختبار ومقارنة نموذجين من التقنيات في تحديد العيوب وتوطينها أن ANFIS يتفوق على ANN من حيث دقة التنبؤ واتساق النتائج ومدة التدريب. ولكنها لا تزال توفر أداءً كافيًا للتطبيقات التي تتضمن مراقبة النقل والتوزيع والتحكم والحماية. الأداء للتطبيقات بما في ذلك حماية المراقبة.

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة ميسان
كلية الهندسة

اكتشاف العطل الثلاثي الطور المتماثل وتحديد مكانه: دراسة حالة :محطة ميسان- الكوت 400kV

رسالة مقدمة الى مجلس كلية الهندسة في جامعة ميسان كجزء من متطلبات الحصول على شهادة الماجستير في علوم الهندسة الكهربائية (قدرة)

اعداد

بتول عبد المطلب مسلط

بكالوريوس هندسة كهربائية

باشراف

الأستاذ المساعد الدكتور احمد ريسان حسين

اب 2024