FACULTY OF ENGINEERING
DEPARTMENT OF ELECTRICAL ENGINEERING

GRADUATION PROJECT 1

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Fault Detection in Transmission Lines Using Artificial Intelligence

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Abstract

The expanding dependence on renewable energy sources has highlighted the require for productive fault detection systems in electrical networks This study aims to plan a device based an AI- for detecting faults in power transmission lines.

Chapter one: Introduction

1.1 General Background

The reliability of power transmission lines is critical to ensuring a stable and continuous electricity supply, a cornerstone of modern infrastructure. However, these systems are frequently exposed to faults caused by environmental conditions, equipment failures, or operational anomalies. Prompt detection, classification, and localization of these faults is crucial to minimize downtime, reduce maintenance costs, and enhance overall system efficiency. Traditional techniques for fault detection, such as impedance-based methods and traveling wave fault location (TWFL), have been extensively used in transmission line monitoring. The limitations of these conventional approaches have been highlighted by the evolving complexity of power systems, particularly with the integration of renewable energy sources

1.2 Problem Statement

Fault detection in power transmission systems faces several challenges. Traditional methods often struggle with accuracy under dynamic network conditions, such as load variations and high grounding resistance. Also, the increasing use of renewable energy brings about variability and intermittent production, which complicates fault localization even further. While promising, AI-based approaches are often restricted to simulations and face challenges such as high computational demands and latency, which limit their real-world applicability.

1.3 Motivation for Using AI

Artificial intelligence (AI) has the potential to revolutionize fault detection in power systems. By processing vast amounts of data, recognizing intricate patterns, and adapting to changing conditions, AI provides solutions that address the shortcomings of conventional methods. Techniques like artificial neural networks (ANNs) and convolutional neural networks (CNNs) have shown remarkable precision in identifying and categorizing faults. Additionally, progress in edge computing and the development of lightweight AI models are paving the way for real-time fault detection and pinpointing in transmission lines.

1.4 Purpose of the Research

This study focuses on creating an affordable device that utilizes AI for fault detection and localization in power transmission lines. The main goals are:

- Developing a system that can detect and locate faults in real-time.
- Ensuring high levels of accuracy and scalability.
- Closing the gap between AI research in simulations and its practical application in real-world scenarios.

1.5 Report Structure

This report is organized as follows:

1. Introduction**:** Overview of the background, problem statement, and objectives.
2. Literature Review: Examination of existing fault detection techniques and their limitations.
3. Methodology: Description of the proposed device, components, and algorithms.
4. Results and Discussion: Presentation of findings and analysis of their implications.
5. Conclusion and Future Work: Summary of the research and suggestions for further development.

1.7 Scope and Limitations

The proposed device leverages AI-based techniques to tackle specific fault scenarios in transmission lines. However, it faces certain limitations, such as hardware constraints, challenges in managing high-voltage signals, and a focus limited to predefined fault conditions. Future work will involve field testing across various network configurations to validate its performance.

1.8 Methodology

The proposed device integrates traditional fault detection methods with AI-based models. Key components include:

- **Potential Transformers (PTs)** and **Current Transformers (CTs)**: For voltage and current signal measurements.
- **Analog-to-Digital Converters (ADCs)**: For converting analog signals to digital form.
- **Microcontroller**: A Raspberry Pi is chosen for its AI capabilities, ease of use, and availability. TensorFlow and PyTorch frameworks are used to develop and deploy AI models.

The methodology includes preprocessing input data, utilizing AI algorithms for fault detection, and determining fault locations through a straightforward reactance method. The device is engineered for real-time operation, with both hardware and software components optimized to ensure high performance while maintaining cost-effectiveness.

1.9 Significance of the Study

This study advances the field of power systems by offering a scalable, precise, and practical approach to fault detection in transmission lines. Its outcomes have the potential to minimize downtime, boost system reliability, and support the seamless integration of renewable energy sources into contemporary power grids.

Chapter two : literature Review

Power transmission lines must be reliable and stable to ensure a continuous electricity supply. Fault detection, classification, and localization are vital processes that ensure quick response to faults and minimal downtime. Both traditional and modern AI-based techniques have evolved over the years to address these challenges. The aim of this review is to consolidate previous studies and explore advancements in fault detection technologies, which highlight their achievements, limitations, and potential applications.

2.1 Traditional Techniques

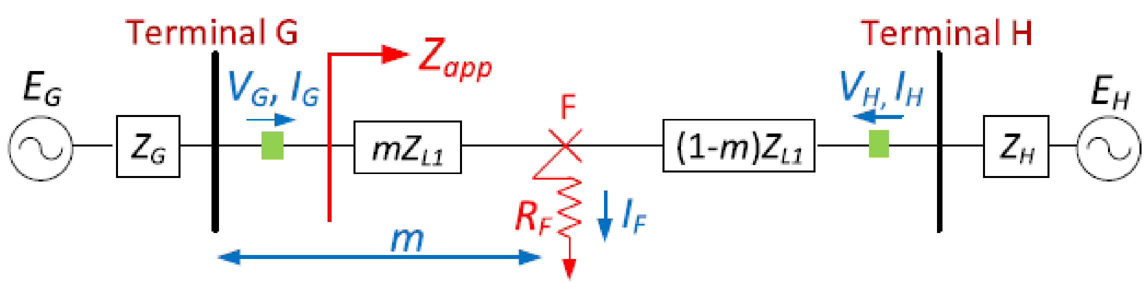
2.1.1 Impedance-Based Methods:

The fault location is determined by comparing the impedance between measurement points and the fault using these foundational algorithms. Their effectiveness is limited by challenges including load variations, high grounding resistance, and series capacitor banks, even though they are widely used.

In this method there are two categories:

A. ONE-ENDED IMPEDANCE-BASED FAULT LOCATION ALGORITHMS

The one-end impedance-based fault location algorithms estimate fault location using measurements (voltage and current waveforms) captured from one end of the transmission line, as shown in the figure.



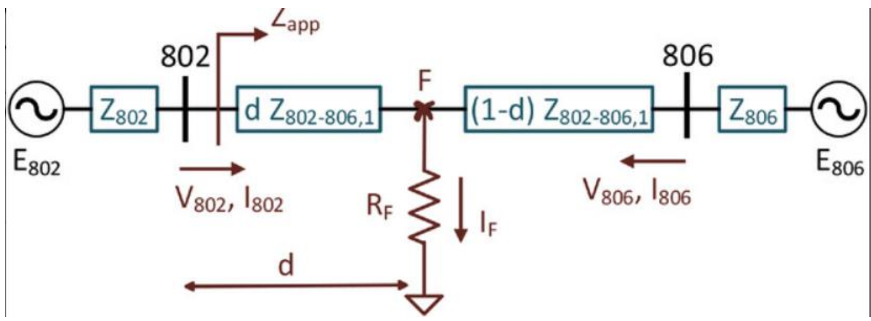
The value of the current that leaves terminals G and the voltage at the terminals of G determine the fault distance for this type. These values are used to calculate the resistance value, and the fault distance is determined as shown in the following equations.

$$V_G = mZ_{L1}I_G + R_F I_F$$

$$Z_{app} = \frac{V_G}{I_G} = mZ_{L1} + R_F\left(\frac{I_F}{I_G}\right)$$

B. TWO-ENDED IMPEDANCE-BASED FAULT LOCATION ALGORITHMS

The location of a fault is estimated using waveform data captured at both ends of a transmission line by two-ended impedance-based algorithms.



This type's fault distance calculation is based on the current value that exits from terminals G, the voltage at terminals G, and the current voltage at the terminals of H. The resistance value is calculated using these values, and the fault distance is determined according to the following equations

$$\text{Terminal G:} \quad V_{F2} = V_{G2} - mZ_{L2}I_{G2}$$

$$\text{Terminal H:} \quad V_{F2} = V_{H2} - (1-m)Z_{L2}I_{H2}$$

$$m = \frac{V_{G2} - V_{H2} + Z_{L2}I_{H2}}{(I_{G2} + I_{H2})\, Z_{L2}}$$

2.1.2 Traveling Wave Fault Location (TWFL):

TWFL methods employ fault-induced traveling waves to pinpoint faults with high precision. Although they are more precise, their use is complex in non-homogeneous networks with bi-directional power flows.

In this method, two ways are used which

A. Single-Ended Traveling-Wave Fault Locating

The single-ended traveling-wave method uses only one device to detect the initial traveling wave and its subsequent reflections. The result is a list of possible fault locations that are prioritized.

When device-to-device communication is unavailable or when the communication channel is disrupted, this approach is particularly effective.

B. Double-Ended Traveling-Wave Fault Locating

The double-ended traveling-wave method accurately determines fault locations by measuring the arrival times of the initial traveling waves at both ends of the line. The success of this process is dependent on precise time synchronization between the two devices.

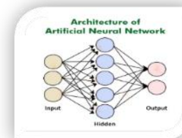
This method is suitable for lines with two terminals, including overhead lines, cable lines, and hybrid lines that combine overhead and cable sections. The accuracy of the double-ended traveling-wave method is superior to that of the single-ended approach for series-compensated lines.

2.2 AI-Based Techniques for Fault Detection

AI has revolutionized fault detection, offering robust and efficient solutions. Key methodologies include:

1. Artificial Neural Networks (ANNs):

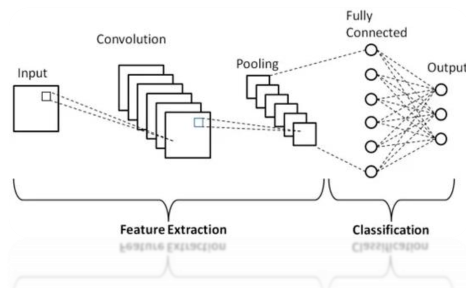
ANNs are commonly used for fault detection and classification, demonstrating their resilience in different conditions. A system that uses feedforward neural networks successfully identified faults in single-line-to-ground and double-line-to-ground, achieving high accuracy.



The challenges of hardware complexity and scalability are still present.

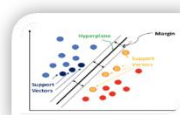
2. Convolutional Neural Networks (CNNs):

CNNs utilize transformed voltage waveform data to classify faults based on images. Up to 93.1% classification accuracy can be achieved by these models, which also incorporate noise reduction techniques like sinusoidal fitting to enhance precision.



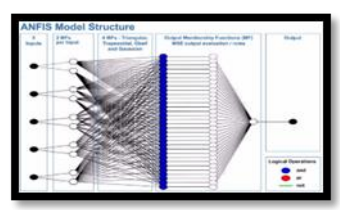
3. Support Vector Machines (SVMs):

SVMs have been utilized to classify fault conditions in various system states, particularly when combined with wavelet transforms. While this hybrid approach improves accuracy, it may encounter difficulties with large-scale datasets.



4. Adaptive Neuro-Fuzzy Inference Systems (ANFIS):

ANFIS combines the strengths of neural networks and fuzzy logic to make robust decisions in uncertain conditions. Their potential can be limited by boundary conditions (Study 1), even though they have potential

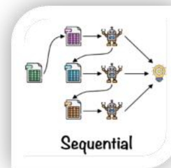


5. Ensemble Methods:

Techniques like Random Forest and Decision Trees, optimized through algorithms such as Wild Horse Optimization, have shown exceptional accuracy, up to 100% in simulations, and minimal fault localization error (Study 5). Although these methods are scalable and robust, real-time constraints pose a challenge.

6. Deep Learning Models:

Processing sequential data with Long Short-Term Memory (LSTM) networks can lead to real-time detection. The deployment of their high computational demands necessitates optimized hardware.



2.3 Challenges and Gaps

1. Real-World Applicability:

The validation of AI-based techniques is limited to simulations, which limits their real-world applicability.

2. The limitations of latency and hardware:

To meet real-time performance requirements while avoiding high computational costs, optimization is often necessary for neural network-based systems.

3. Integration of Renewable Energy:

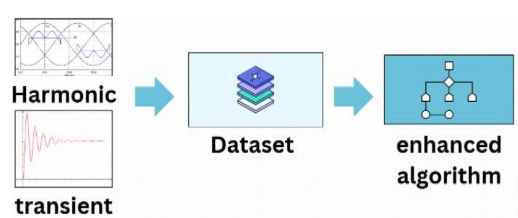
The increasing adoption of renewable energy sources complicates fault localization due to variability and intermittent generation.

4. Limited Fault Scenarios:

Some methods are restricted to specific fault types, such as asymmetric faults, which reduces their generalizability.

2.4 Future Directions

1. **Hybrid Approaches:**
   By integrating traditional methods with AI models, fault detection accuracy and adaptability in complex networks could be enhanced..
2. **Advanced Feature Engineering:**
   Harmonic and transient characteristics can be added to datasets to enhance algorithm performance and robustness.



3. **Edge Computing:**
   By distributing computation at sensor nodes, it is possible to reduce latency and enable real-time fault detection, addressing current hardware constraints.

4. **Field Testing:**
   Assessing system performance under noise, hardware limitations, and varying network topologies requires extensive real-world validation.

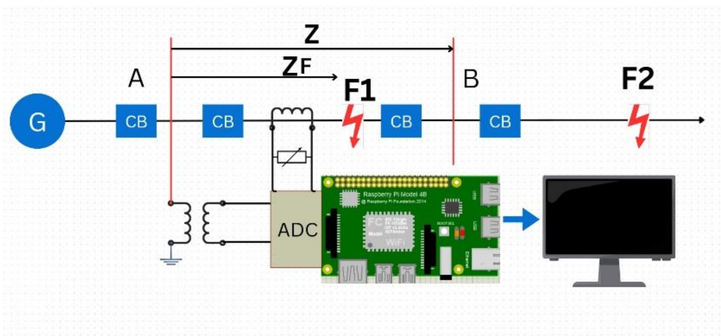
Traditional impedance-based techniques have been replaced by sophisticated AI-driven models in fault detection methods. Although AI methodologies such as ANNs, CNNs, and hybrid approaches have impressive accuracy and efficiency, their implementation in the real world is still limited. To address these gaps, this project proposes the development of a cost-effective device that utilizes artificial intelligence to locate faults in transmission lines. The goal of this device is to provide accurate and scalable fault localization solutions for modern power systems by bridging the gap between simulation and practical application

Chapter three: Project Design

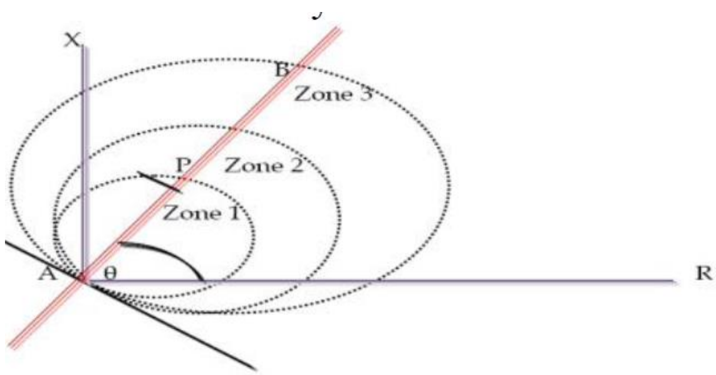
This chapter covers the description of the project design. Also it illustrates the methodology.

3.1 Methodology

Our project's working principle is that when a fault occurs, the current and voltage signals from the transformers are transmitted to the microcontroller via an ADC. The fault distance is calculated by the microcontroller and artificial intelligence algorithms are used to predict and enhance the results, which are then displayed.



Transmission line fault detection will be based on the resistance value, which will be used to determine the distance of the fault. Transmission lines will be divided into regions due to their length, and each region will have a specific range of resistance values. The first region will be associated with a resistance range of A to P, while the second region will be associated with a range of P to B, and so on. Dividing transmission lines into regions is crucial for ensuring selectivity in the power system, which thereby enhances its protection and reliability.



Our project consists of two parts.

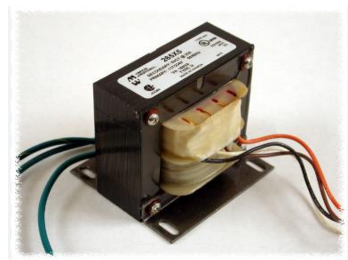
- Hardware
- Software

3.2 Design description

The hardware consists of the following components:

- **Potential Transformer, PT**
- **Current Transformer, CT**
- **Analog-to-Digital Converter (ADC)**
- **Microcontroller**
- **Breadboard/PCB**
- **Power Supply**

3.2.1- (Potential Transformer, PT):



The purpose of its use is to lower the voltage value to suit the value of the microcontroller. The voltage transformer can be connected in two ways: either by connecting the primary coil with the phases phase to phase, and thus the value of the primary voltage on its ends is equal to the value of the line voltage, or by connecting it with one of the phases to the ground, and thus the value of the voltage on the primary coil is equal to the value of the phase voltage.

When a fault occurs on the transmission lines, the voltage value will drop due to the increase in the value of the current, and thus the voltage transformer is more than sufficient to make the value suitable for entering the voltage into the microcontroller.

3.2.2-(Current Transformer, CT)

It aims to convert the current to another level for ease of handling and entering it into the microcontroller. The current transformer is placed on each line of the transmission lines and converts the value of the line current in the primary coil to a smaller value in the ends of the secondary coil according to the special ratio in the type used. A current transformer will be used in which the value of the secondary coil is equal to one ampere, which is a standard value.

3.2.3-Analog-to-Digital Converter (ADC)

The signal coming out of the voltage and current converter is an analog sinusoidal signal and the signals read by the microcontroller are digital signals. Therefore, the analog signal must be converted into a digital signal for the microcontroller to understand it. This is the function of the ADC.

Choosing the ADC depends on a number of factors and specifications. When choosing the appropriate ADC, it must be chosen to have good accuracy and be suitable for the application used, an appropriate sampling rate, and the number of channels, which refers to the number of signals that can be converted at the same time, in addition to the power consumption, the time it takes to implement the conversion, and the cost. All of these play an important role in choosing the ADC.

The required specifications for our device are that it should have an accuracy of 12 bits or more, a sampling rate of 10 kilobits per second, and a number of channels of 6, in addition to an SPI communication interface that provides a signal in the range of 0 to 3.3 volts.

Of the types that match the specifications ADC1115 , MCP3208 , any of them can be used.

3.3.4-Microcontroller

It is the part responsible for processing the incoming data and performing mathematical operations. There are many options but since we want to introduce artificial intelligence we need a Microcontroller with high speed and large memory.

There are several options available in the following table comparing a number of proposals.

Microcontroller	Performance	AI Support	Programming Ease	Connectivity	Recommended Use	Power Consumption
NVIDIA Jetson Nano	**High (GPU with 128 CUDA cores)**	**Supports heavy AI models**	**Moderate**	**Ethernet, USB**	**Complex fault detection using image data**	**High**
Raspberry Pi 4	**Medium to High**	**Supports AI with external accelerators**	**Easy**	**Wi-Fi, Ethernet**	**Sensor data processing, moderate AI tasks**	**Medium**
ESP32	**Medium**	**TensorFlow Lite Micro for lightweight AI**	**Easy**	**Wi-Fi, Bluetooth**	**Simple fault detection, wireless integration**	**Low**
STM32F7/H7	High	STM32Cube.AI library for real-time AI	Moderate	I2C, SPI, CAN	Real-time fault detection with low latency	Very Low
Arduino Portenta H7	Medium to High	TensorFlow Lite Micro for embedded AI	Easy	Wi-Fi, Bluetooth	Advanced embedded AI applications	Low
Google Coral Dev Board	Very High	TPU for fast AI model inference	Moderate	Wi-Fi, Bluetooth	Advanced AI applications with high accuracy	Low to Medium

As we can see in the previous table, there are many options, but we chose the Raspberry to be the device's microcontroller for several reasons. First, it is available in the market. Second, its performance is good. Third, it supports artificial intelligence. Fourth, it is easy to use.

3.3.5- Breadboard/PCB

For setting up initial connections.

3.3.6-Power Supply

The power supply ensures stable and regulated power delivery to all components of the system. It provides **5V, 3A** specifically for the Raspberry Pi, along with additional voltage levels as required for sensors and peripherals to operate efficiently.

3.3.7- Display (LCD/OLED)

To display the fault location data and any status updates.

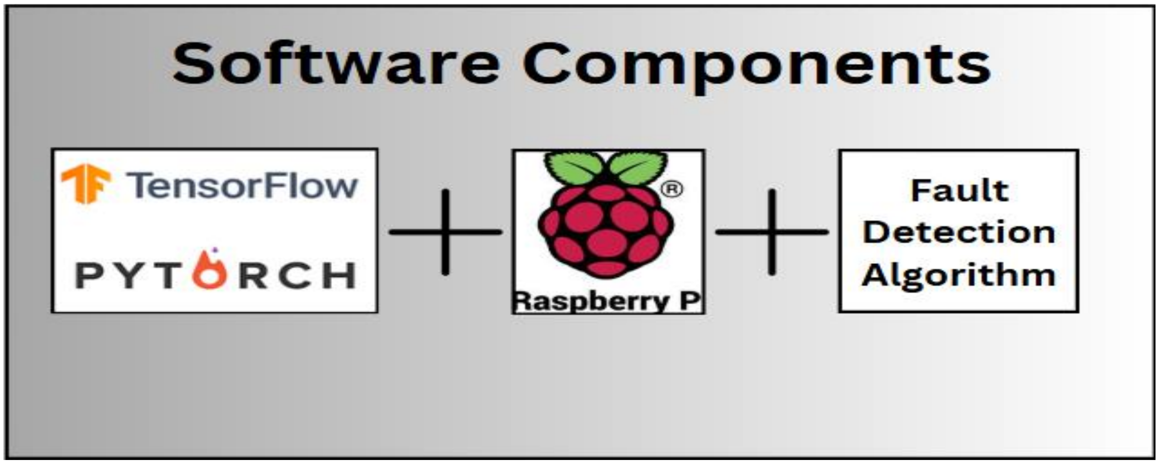
3.3.8- Additional Components

a. SD Card**:** Stores the operating system, data logs, and AI models. Specification Minimum 32GB, Class 10.
b. Protective Enclosure: Shields components from environmental factors such as dust, moisture, and physical damage.
c. Wi-Fi Dongle or Ethernet Cable (if required): Provides network connectivity for remote monitoring and data transfer.
d. Wires and Connectors: For making connections between components

e. Resistors to input the current value to the microcontroller. To carry its value, we will input it as a voltage signal by connecting a resistor in parallel with the secondary coil of the current transformer.

3.3 Software Components

To operate the device, software packages are required for programming and running the device.



a. Operating System:

- **Raspberry Pi OS**: Serves as the primary operating system for the Raspberry Pi, providing a platform for software development and execution.

b. AI Framework:

TensorFlow and PyTorch are frameworks used for developing and running AI models. They can be utilized to train machine learning models for fault detection using historical transmission line data and to perform real-time inference for anomaly detection.

c. **Fault Detection Algorithm:**

The implementation involves preprocessing input data by filtering noise and normalizing values, followed by applying machine learning models .

The method used to calculate the resistance value is the simple reactance method and is represented by the following equation:

$$m = \frac{\mathrm{imag}\left(\frac{V_G}{I_G}\right)}{\mathrm{imag}\left(Z_{L1}\right)}$$

Chapter Four : Artificial Intelligence

As mentioned in Chapter 2, there are many artificial intelligence models that can be utilized. The following table presents a comparison between different types of models.

Criterion	Artificial Neural Networks (ANNs)	Support Vector Machines (SVMs)	Fuzzy Logic Systems	ANFIS (Adaptive Neuro-Fuzzy)	CNN
Ease of Use	Moderate: Requires architecture design and tuning.	Moderate: Needs careful kernel selection.	High: Easy to set up with predefined rules.	Moderate: Balances fuzzy rules and ANN training.	. Moderate: Requires careful architecture design and parameter tuning.
Training Requirements	High: Needs large datasets for effective performance.	Moderate: Effective for small datasets.	Low: No training needed; rule-based.	Moderate: Requires data for fuzzy rules and ANN training.	High: Needs large datasets for effective performance.
Accuracy	High: Excels in complex fault detection scenarios.	High: Effective for binary/multi-class classification.	Moderate: Depends on rule precision.	High: Combines fuzzy logic robustness and ANN learning.	High: Excels in detecting complex faults and analyzing patterns or images.
Computational Complexity	High: Computationally demanding for large-scale systems.	Moderate: Kernel-based computations can be demanding.	Low: Lightweight and resource-friendly.	Moderate: Combines fuzzy logic and ANN but is less intensive than deep ANNs.	High: Demands significant computational resources, especially for large systems or frequent training.
Scalability	High: Scales well with increasing data and complexity.	Moderate: Handles moderate dataset sizes.	Low: Not scalable for complex systems.	Moderate: Scales better than standalone fuzzy systems.	High: Handles increasing data and complexity effectively.
Robustness to Noise	Moderate: Sensitive without preprocessing.	High: Handles noise with kernel functions.	High: Naturally handles uncertainty.	High: Deals well with noise and uncertainty.	High: Performs well with noise when pre-processing techniques are applied.
Interpretability	Low: Acts as a "black box."	Low: Kernel functions are not intuitive.	High: Rule-based and interpretable.	Moderate: Fuzzy rules are interpretable; ANN component is not.	Low: Functions as a "black box," making it difficult to interpret directly.
Adaptability	High: Learns complex and changing fault patterns.	Moderate: Adapts well with proper tuning.	Low: Rule-based, limited adaptability.	High: Adapts to new data and uncertainties effectively.	High: Learns complex and changing fault patterns effectively.
Best Use Case	Complex systems, fault detection and classification.	Multi-class fault classification, ground fault detection.	Detection of faults in uncertain conditions.	High-impedance fault detection, transient analysis.	Complex image analysis, pattern detection, and multi-class classifications.

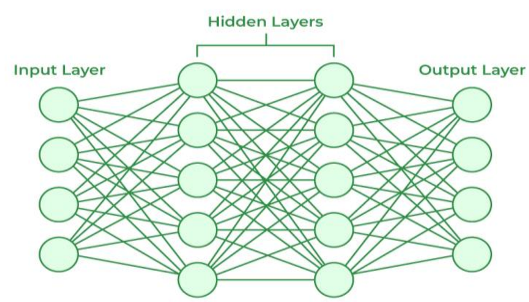
we will use ANN because it is not difficult to work with, offers excellent accuracy, has available frameworks for training, and is one of the most popular types of AI.

4.1 Artificial Neural Networks (ANNs) and How They Work

Artificial Neural Networks (ANNs) are computational frameworks modeled after the structure and functionality of biological neural networks found in the human brain. As a subset of machine learning, they are integral to the broader field of artificial intelligence (AI). ANNs are applied across diverse domains, including image recognition, natural language processing, medical diagnostics, and fault detection in power systems.

4.1.1. Structure of Artificial Neural Networks

An ANN typically consists of three main layers:



1. **Input Layer**: This layer receives the input data in a structured format. Each neuron in this layer corresponds to an individual feature of the input data.

The inputs to find distance fault are mainly the voltages and currents, thus three phase voltage and current signals fundamental components have been used as input to ANN.

The magnitudes of the fundamental components (50 Hz) of three consecutive post fault samples of each phase voltage and current measured V_a, V_b, V_c and i_a, i_b, and i_c has been selected as input to neural network. Thus the total nunmber of inputs for the neural network are 6.

2. **Hidden Layers**: The hidden layers are where the core computations occur. A network can contain one or more hidden layers, depending on its complexity. Each neuron within these layers connects to every neuron in the previous layer and processes the weighted sum of its inputs using a mathematical function.

3. **Output Layer**: This layer produces the final result of the network, such as a classification label or a prediction.
The purpose of the device is to find the fault distance, so the output number is only one, which is the fault distance.

Each neuron, or node, is associated with a **weight** and a **bias**, which determine the influence of the input on the neuron's output. These parameters are adjusted during the training process to improve the network's performance.

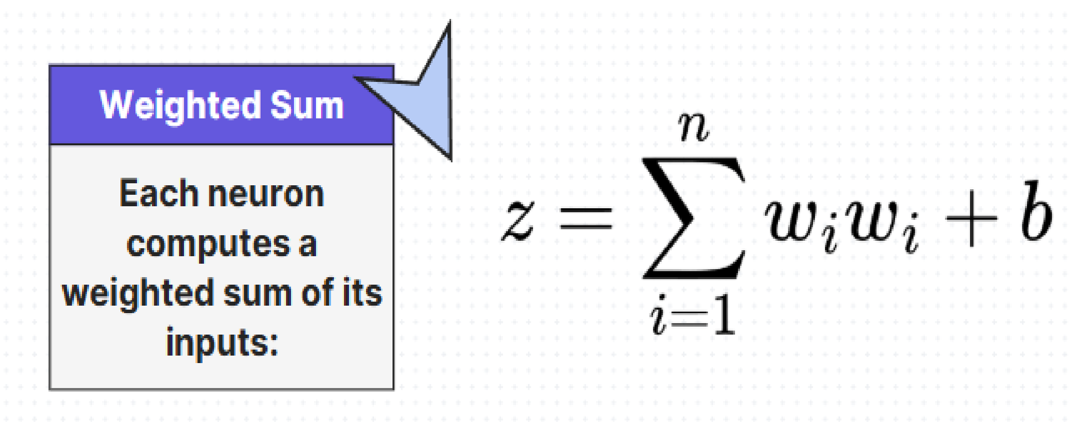
4.1.2. How Artificial Neural Networks Work

The operation of an ANN can be broken down into two main processes: forward propagation and back propagation.

1. Forward Propagation

Forward propagation is the process through which input data is passed through the network to generate an output. This involves the following steps:

- **Weighted Sum**: Each neuron computes a weighted sum of its inputs:



where Xi_are the inputs, Wi are the weights, b is the bias, and z is the result.

- **Activation Function**: The weighted sum is passed through an **activation function** to introduce non-linearity, which allows the network to solve complex problems. Common activation functions include:

Activation Function

The weighted sum is passed through an activation function to introduce non-linearity

Sigmoid :

$$f(z) = \frac{1}{1 + e^{-z}}$$

RelU (Rectified linear Unit):

$$f(z) = max(0,z)$$

Tanh:

$$f(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

The result of the activation function becomes the input for the next layer.

2. Back propagation

Back propagation is the learning process where the ANN adjusts its weights and biases to minimize the error in its predictions. This involves:

- **Error Calculation**: The error, or loss, is calculated by comparing the network's output to the true target value using a loss function, such as mean squared error (MSE) or cross-entropy.
- **Gradient Computation**: The gradient of the loss with respect to each weight is computed using the **chain rule** of calculus. This gradient tells the network how to adjust each weight to reduce the error.
- **Weight Update**: Using an optimization algorithm like **gradient descent**, the weights and biases are updated:

$$w_{new} = w_{old - \eta} \cdot \frac{\delta L}{\delta W}$$

where L is the loss function, ∂L/∂w is the gradient, and η is the learning rate.

Backpropagation is repeated for multiple iterations, often called epochs, until the network's performance reaches an acceptable level.

4.2 Advantages of ANNs

- **Adaptability**: ANNs can model complex relationships between inputs and outputs.
- **Generalization**: Once trained, they can generalize well to unseen data.
- **Versatility**: ANNs are suitable for a wide range of applications, including regression, classification, and sequence prediction.

4.3 Applications

ANNs are extensively used in fields such as:

- **Image Processing**: Facial recognition and object detection.
- **Speech and Language Processing**: Machine translation and voice assistants.
- **Power Systems**: Fault detection and classification in transmission lines.
- **Healthcare**: Disease prediction and drug discovery.

In summary, ANNs are powerful tools for solving complex problems, thanks to their ability to learn from data and adapt their internal parameters. Their working mechanism, involving forward propagation and backpropagation, enables them to model non-linear and intricate relationships in various domains.

Chapter five : Conclusion

5.1 Summary of Findings

This study focused on leveraging artificial intelligence (AI) to detect and foresee faults in electrical transmission lines. A comprehensive literature review highlighted the confinements of conventional strategies and illustrated the potential of AI-based approaches, counting Counterfeit Neural Systems (ANNs), Convolutional Neural Systems (CNNs), and half breed frameworks. By understanding their qualities and limitations, we effectively created a gadget able of distinguishing blame areas by analyzing voltage and current signals. This gadget utilizes AI highlights to improve blame localization and progress framework unwavering quality

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5.2 Key Contributions

1. **Device Design and Implementation**:
    - We constructed a device integrating potential transformers, current transformers, an ADC, and a microcontroller (Raspberry Pi) to process data in real-time.
    - Artificial intelligence algorithms, particularly ANNs, were employed to predict fault locations accurately.
    - Components such as protective enclosures and network connectivity ensure the device's reliability in practical scenarios.
2. **Integration of AI in Fault Detection**:
    - AI models were trained to handle various fault scenarios, offering superior accuracy and scalability compared to traditional methods.
    - The implementation of real-time data processing algorithms ensures prompt fault detection, reducing system downtime.
3. **Division of Transmission Lines**:
    - By dividing transmission lines into distinct regions based on resistance values, the device achieves selective fault localization, enhancing the protection system's effectiveness.

5.3 Expected Outcomes

1. **Improved Reliability**:
   The device is anticipated to significantly enhance the reliability of power transmission systems by quickly identifying and addressing faults.

2. **Scalability**:
   With modular components and adaptable software, the system is designed for seamless integration into various grid configurations.

3. **Real-World Applicability**:
   Through the adoption of cost-effective and readily available components, the device bridges the gap between theoretical advancements and practical deployment in fault detection technologies.

5.4 Future Work

The next step is to create a prototype of the device that will serve as a basic model to mimic real-world conditions. This decision is made because building a fully operational model would entail higher costs and greater complexity, leading to several challenges

5.5 Final Remarks

In conclusion, this study highlights the effectiveness of AI-based fault detection systems within electrical transmission networks. The device developed in this study illustrates how integrating advanced AI techniques with practical engineering solutions can tackle current challenges, leading to more reliable and efficient power systems. This work not only enriches the academic discussion surrounding AI applications in power systems but also sets the stage for future advancements in grid reliability and fault management.

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