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ClasLoc : A Robust Fault Management Methodology for Transmission Lines Using RBFNN and ANFIS

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ABSTRACT

Transmission lines are crucial for efficient and reliable electricity delivery of electricity but can also be susceptible to faults due to various factors such as external interference, device failures, and ambient conditions. The reliability, accuracy, and efficiency of fault management on the power grid depend heavily on fault classification and fault location. This study integrates a fault detection and classification system for transmission lines and an automatic fault localisation system (ANFIS) for fault location to present a comprehensive approach to managing transmission line problems. The proposed methodology aims to address the technological challenges associated with fault management in power grids by leveraging existing research on radial basis function neural networks (RBFNN) and ANFIS. The integration and validation of the proposed methodology involve incorporating improved fault classification via RBFNN and robust fault locating through ANIS. Simulations and real-world testing will validate the integrated methodology, assessing its performance in various fault scenarios and system configurations. The WSCC 9-bus system is used to validate and test the proposed design, which includes power plants, transformers, transmission networks, and distribution networks. The ClasLoc system has a classification accuracy of 90% and a location accuracy of 89%, ensuring a safe working environment.

Keywords : Transmission Line Fault, RBFNN, ANFIS, Fault Management

I. INTRODUCTION

Transmission lines are crucial for efficient and reliable electricity delivery of electricity [1], but can also be susceptible to faults due to various factors such as external interference, device failures, and ambient conditions [2]. To maintain the integrity of transmission lines and save downtime, advanced problem classification processes are necessary. Radial basis function neural networks (RBFNN) are now recognised as a valuable tool for fault classification in transmission lines [3]. RBFNNs outperform traditional neural networks by replacing the sigmoidal transfer function with radial basis functions, providing superior generalisation capability [4,5].

Data collected from distant sensors and remote sensing methodologies is used to train the RBFNN and ANFIS algorithms [6]. The RBFNN-based fault classification system aims to efficiently and precisely identify transmission line transmission line faults by analysing parameters such as the the three-phase current and the the ground current [7]. The RBFNN-based fault detection system aims to minimise false alarms by precisely identifying various types of problems and differentiating them from transient disturbances.

Technological challenges have led to the investigation of alternative fault location approaches that can surpass the limitations of traditional methods [8]. An example of this technique is the use of the ANFIS, which integrates the functionalities of neural networks with fuzzy logic to offer a resilient and adaptable method for fault localisation [9]. ANFIS can efficiently address the uncertainty and imprecision in fault location data by combining numerical and verbal information [10,11].

The combination of RBFNN for fault classification and ANFIS for fault location exemplifies a comprehensive strategy for managing transmission line faults, incorporating both precise fault classification and accurate fault placement. Using the potential of these sophisticated computational intelligence tools, utilities and operators can improve the performance and dependability of transmission lines, thus advancing a more robust and environmentally friendly electrical infrastructure.

The ANFIS-based fault localisation system for transmission lines and a RBFNN-based detection and classification system aim to improve fault management on the power grid. The RBFNN system can quickly detect faults, reduce false alarms, and learn from past location data, ensuring reliable position forecasting under difficult conditions.

The work is divided into chapters, focussing on motivation, technical obstacles, and goals. It assesses the existing literature, outlines a methodology for identifying faults in transmission lines, and details the datasets used for training and testing. The output results of the suggested model are described, and the findings of the experimental study are presented.

II. LITERATURE REVIEW

Machine learning has been used in the power system in different aspects such as load forecasting [12], power generation prediction [13], fault classification and localisation [14]. Multiple research papers have investigated the application of sophisticated computational intelligence methods for fault classification and localisation in power systems. Adnan et al. demonstrate the efficacy of the fuzzy adaptive neural Takagi Sugeno-Kang (TSK) intelligence system in detecting high impedance faults (HIF) [15]. Jamil et al. focused on the use of artificial neural networks to identify and categorise flaws in electrical power transmission cables. The proposed approach uses the MATLAB platform and requires three-phase currents and voltages from one end as input [16]. However, they limit their work to line-to-ground problems. In the same way, Sundararaman et al. did tests to see how wavelet transform (WT) could find five different kinds of problem in a normal IEEE 5-bus system. It was demonstrated that WT was successful in identifying flaws, allowing utilities to quickly fix them, and offering recommendations for using algorithms based on artificial neural networks. Ray et al. [17] demonstrated exceptional precision in defect identification and classification using the discrete wavelet transform (DWT) and ANN, achieving a precision rate of 97%. The system can identify and detect eleven (11) different types of faults that can occur in a 735 KV, 50 Hz transmission line.

Multiple studies have widely acknowledged the effectiveness of RBFNNs in accurately categorising defects in transmission lines. The RBFNN has shown its ability to quickly and accurately detect defects while minimising false alarms by analysing factors such as three-phase current and ground current. The WOA algorithm for hybrid multistrategies, known as CASAWOA, demonstrates superior performance compared to existing state-of-the-art WOA algorithms in terms of both convergence speed and exploration ability [18]. In addition, the CASAWOA-RBFNN-based fault diagnosis model for electronic current transformers (ECT) is 97.77% accurate, which is 9.8% more accurate than WOA-RFB [18]. Furthermore, the use of RBFNN has improved the reliability, accuracy, and efficiency of fault management on the power grid.

Many people are interested in using the ANFIS to find faults because it can handle inaccurate and uncertain fault location data well [9]. ANFIS utilises a combination of neural networks and fuzzy logic to provide a resilient and flexible method for fault detection. Its main goal is to improve the precision and dependability of problem identification and localisation.

Due to the persistent technological difficulties in classifying and locating faults in transmission lines, sophisticated approaches are needed to address these problems. Advances in problem categorisation and fault localisation methods have the capacity to enhance the longevity and reliability of power distribution networks. This study integrates RBFNN for fault classification and ANFIS for fault location to present a comprehensive approach to managing transmission line problems. The objective is to improve the performance and reliability of electrical infrastructure.

III.PROPOSED ClasLoc ARCHITECTURE

A. ClasLoc Arthitechture

To make progress in the area of transmission line safety, it is crucial to create a detailed plan that incorporates modern computational intelligence techniques for fault identification and localisation. The proposed methodology aims to address the technological challenges associated with fault management in power grids by leveraging existing research on RBFNN and ANFIS. Presented below is a streamlined diagram illustrating the suggested ClasLoc model.

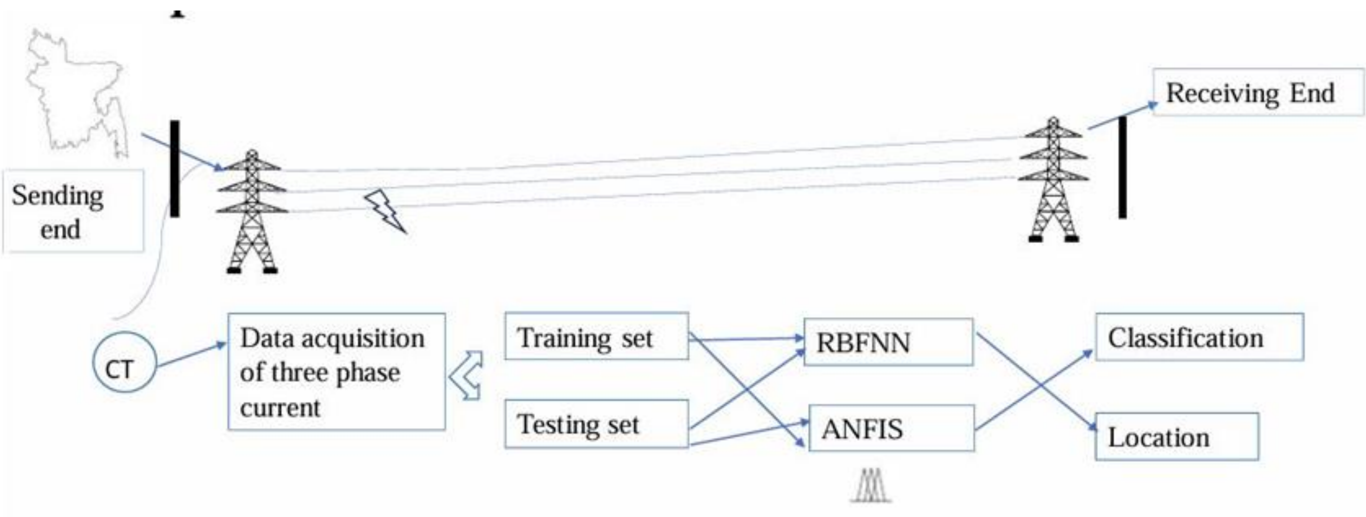

Figure 1 : Streamlined schematic representation of the proposed ClasLoc Model

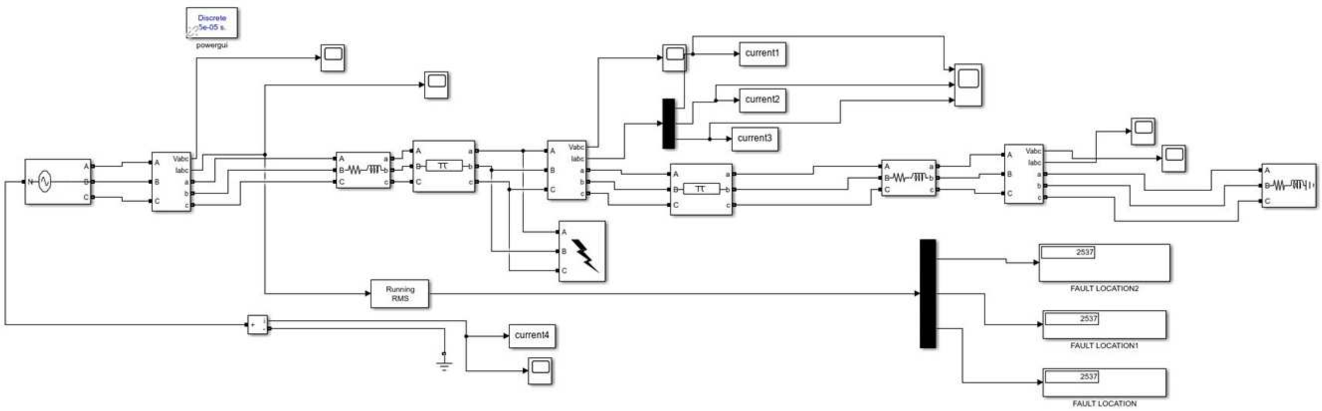

Figure 2 : MATLAB Implementation of the proposed ClasLoc model

The proposed methodology focusses on improving fault classification using RBFNN, which has demonstrated its effectiveness in detecting problems quickly and accurately. By analysing factors such as the three-phase current and ground current, the RBFNN can be improved to accurately categorise various errors with increased reliability, accuracy, and efficiency. ANFIS, an integrated approach that integrates neural networks with fuzzy logic, is used for precise fault location, ensuring accurate fault location even in demanding operational environments.

The integration and validation of the proposed methodology involve incorporating improved fault classification via RBFNN and robust fault locating through ANFIS. Simulations and real-world testing will validate the integrated methodology, assessing its performance in various fault scenarios and system configurations. The WSCC 9-bus system is used to validate and test the proposed design, which includes power plants, transformers, transmission networks, and distribution networks.

The proposed ClasLoc model is implemented using MATLAB Simulink, a graphical user interface tool that allows visualisation and analysis of the dynamic behaviour of power systems shown in Figure 2.

Three-phase faults are crucial for power system protection and stability analysis. Multiplexers and demodulators are used to combine input signals into a single virtual vector output, while workspaces store variables, arrays, matrices, and other data. Fuzzy logic controllers (FLC) are used to accurately represent and regulate intricate, nonlinear systems, incorporating uncertainty and imprecision in a system. Current measurement is the process of determining the magnitude of electric current flowing through a conductor, and three-phase RMS is a mathematical technique used to determine the effective value of a three-phase electrical signal.

B. Data Acquisition and Pre-processing

Data preprocessing is a sensitive and important step to handle data before they are usable by RBFNN and ANFIS. In this section, to apply this RBFNN for any power system network, it is required to determine the coefficients of all the phase currents and neutral currents by using a simulation of the power system model.

Data Splitting

Following completion of data pre-processing, it is necessary to partition our data set into separate training and testing sets. In this study, a training dataset comprising 70% of the entire data and a testing dataset comprising 30% of the total data were used to improve the accuracy of our model.

Tools and Implementation

In the implementation phase, MATLAB software is used to apply the RBFNN algorithm, to classify, and the ANFIS algorithm to locate with different training functions.

IV. DATASET DEVELOPMENT

A. Dataset Description

The ClasLoc is trained using data from fault conditions and fault conditions. The training data includes different types of faults, distances, and resistances. The output of different types of fault includes ABC, AB, AC, BC, BCG, CG, and BG faults. ABC faults occur when all three phases of the electrical system make direct contact, leading to high currents and potential damage. AB faults are critical events, while BC faults involve short circuits between two phases. BCG faults occur when two phase conductors simultaneously encounter the ground, causing insulation failure, equipment failure, or external influences. CG faults occur when one of the phase conductors contacts the ground, while BG faults occur when one of the phase conductors makes contact with the ground. These faults can be caused by insulation failure, device malfunction, or external influences.

B. Feature Selection

Data are necessary to determine the most significant characteristics to detect faults in transmission lines. We need to choose suitable characteristics. An excessive number of irrelevant or redundant characteristics can cause overfitting, whereas an excessive number of features might lead to insufficient detection. We utilise ANFIS to classify the three-phase fault current and ground current, as well as to determine the location of the three-phase current. It is not possible to utilise three-phase voltage, zero sequence voltage, and current. Increasing the amount of input data leads to an increase in the level of difficulty.

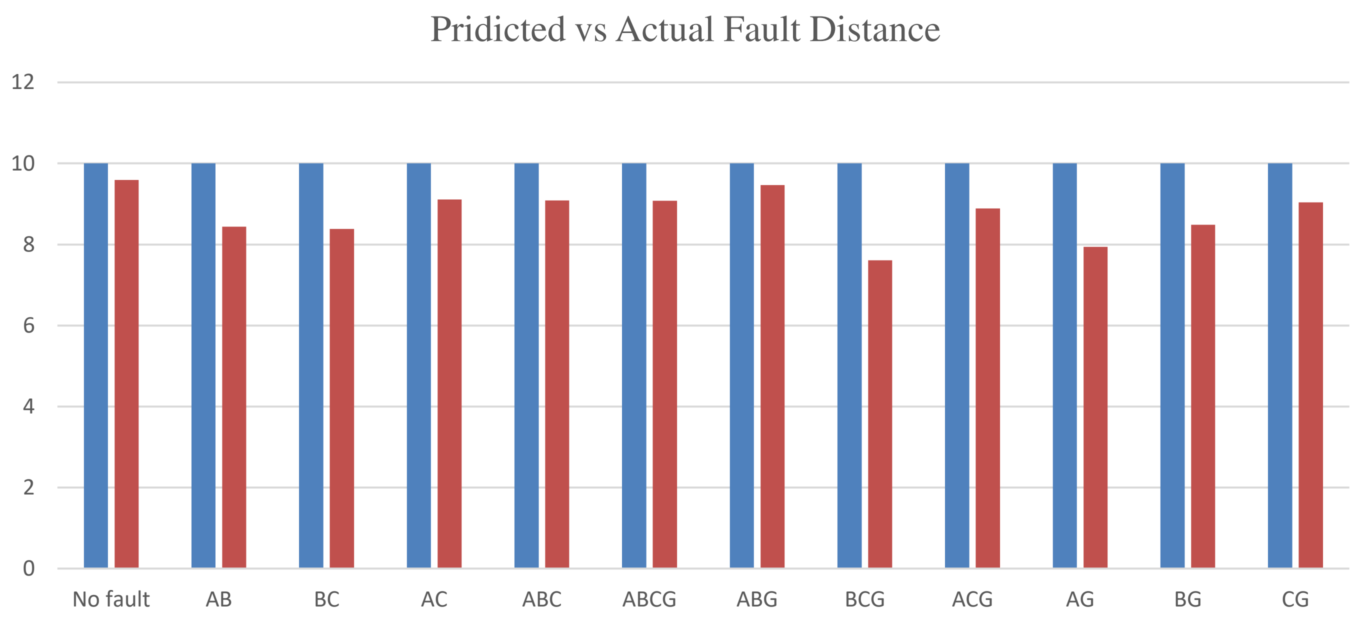

Figure 3 : Comparison between Predicted and Actual distance determination for different transmission faults condition

V. RESULTS AND DISCUSSION

A. Fault Location Accuracy

Table 1 shows the demo result of the actual fault location and the expected fault location for different types of faults. 70 and 30 samples have been chosen for the training and testing process, respectively. Between 100 cases, 83 of location output is very close to the expected location value, and 17 cases is a little far away from the expected location.so the efficiency is 83%.

$$\eta = \frac{Number\ of\ correct\ fault\ classsified}{number\ of\ test\ cases} \times 100\%$$

Table 1: Fault Location from the Reference Tower with ClasLoc

Type of Fault	Predicted Fault Distance(in km)	Actual Fault Distance (in km)
No fault	10	9.59159
BC	10	8.385198

The following chart shows the value of the expected transmission line fault location distance vs. the actual distance for different types of faults.

B. Accuracy of fault classification

In order to maintain a 70-30% train-test ratio, we select 100 examples for prediction. The classifier made 84 predictions of "yes" and 16 predictions of "no". Of the total number of cases in the data, 86 cases are attributed to a transmission line failure, while 14 cases have no fault. To evaluate our model, we compute its accuracy, precision, recall, and F1 score.

Table 2:Fault detection and classification performance matrices

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
ClasLoc	90	95.23	93	94.1
SVM	85	86.45	87.8	87.3

C. Comparison with Other Techniques

Our work demonstrates that the classification classification accuracy is significantly superior when wavelet techniques are used are used compared to other methods. Within the wavelet framework, a single threshold value can be employed to identify many types of defects. However, the effectiveness of this threshold value may not extend to additional fault detection scenarios.

A radial basis neural network utilising machine learning accurately predicts the classification of faults in transmission lines. Various writers have suggested fault categorisation algorithms based on Artificial Neural Networks (ANN) and other artificial intelligence approaches. The primary drawback of these approaches is their reliance on a substantial quantity of training data, but in the study outlined in this paper, the time required for training is reduced.
The SVM algorithm achieves an accuracy of 85%, whereas the ClasLoc approach achieves an accuracy of 90%.

VI. CONCLUSION

A novel computer programme has been proposed to simulate the transmission line and calculate currents for various types of faults, which can be used to train and test ANFIS. The ANFIS technique requires more computational resources, but it offers superior accuracy in detecting and classifying all shunt problems. The proposed ANFIS models can be utilised to detect and analyse many forms of shunt faults, including high-impedance and low-impedance faults. The simulations conducted by ANFIS demonstrate that the actual values produced by the suggested method accurately correspond to the desired values. The suggested approach to generate output using ANFIS can be used to protect the transmission line protective system.

Accurate fault detection is crucial for early identification of problems, improved system reliability, enhanced safety, optimised performance, increased productivity, data-driven decision making, and customer satisfaction. It allows timely corrective actions, increased productivity, and better decision making in system improvements, maintenance schedules, and resource allocation. The proposed ClasLoc system has a classification accuracy of 90% and a location accuracy of 89%, ensuring a safe working environment. Future directions include implementing hardware-based systems for location.

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