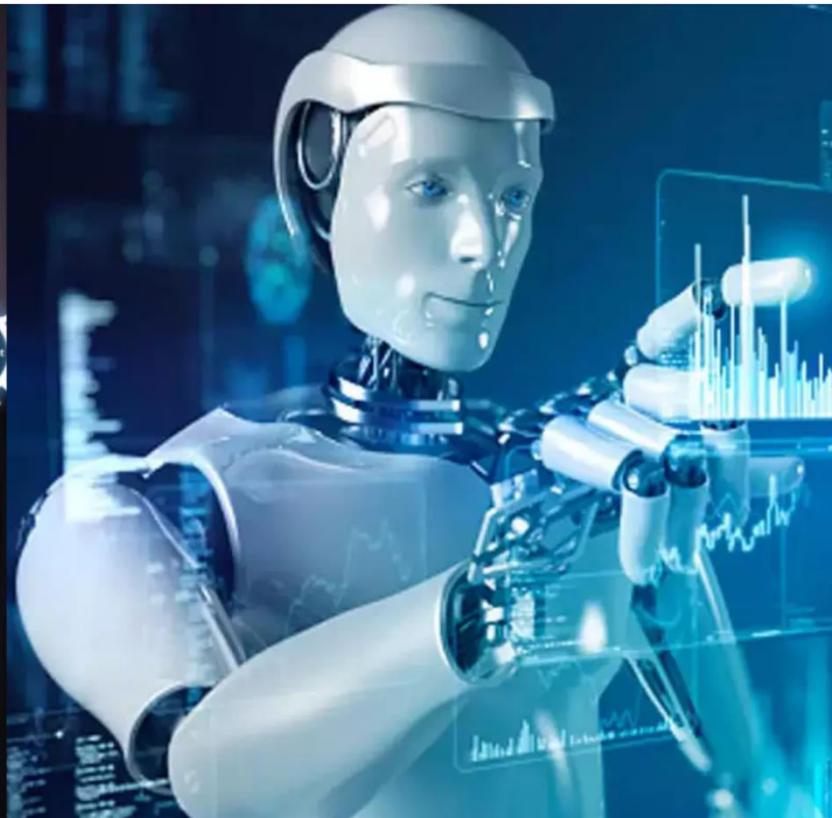




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Advanced Computational Approach for High Voltage Transmission Line Fault Identification and Classification

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ABSTRACT: Today, the ability to identify and classify faults in a high-voltage transmission line is crucial for maintaining power stability and a continuous supply. Common faults, such as single-line-to-ground faults, frequently occur in a high voltage transmission line. Developing an effective system to precisely identify and classify faults is vital. To achieve this, advanced computational techniques such as, the Fuzzy Inference System (FIS) and the Artificial Neural Network (ANN) are employed. This study presents the architecture of an advanced computational approach for fault identification and classification in a high voltage transmission line. These methods help in identifying and classifying various faults. A MATLAB Simulink model is used to analyse different fault scenarios, and the Mean Square Error (MSE) method evaluates the performance of the algorithm. The comparative analysis of these techniques has been done on the basis of learning capability, interpretability, data dependency, application and accuracy.

KEYWORDS: Fault identification, High-voltage transmission line, Fuzzy Inference System (FIS), Artificial Neural Network (ANN), Mean Square Error (MSE).

I. INTRODUCTION

Bulk electricity is transferred from producing stations to the load centres via the power transmission line, a crucial component of the utility grid. This aids in supplying our enormous need for electricity. As a result of this, transmission lines have rapidly expanded in length and quantity since 1945 [2]. Frequent faults on power transmission lines can cause damage to the customer's equipment and interruptions in the power supply [3]. Therefore, prompt fault identification aids in quick fault clearance, which eventually guarantees power supply restoration in the shortest amount of time. Numerous methods and schemes for transmission line fault identification and categorisation have been documented. Steady-state characteristics are the foundation of traditional fault identification and classification techniques. Low protection speed is a drawback of these approaches.

Numerous fault types affect high voltage transmission lines; some are electrical in nature, while others are caused by natural disasters like storms or fallen trees. Identifying a fault is essential to ensure a quick electrical network recovery. Despite this, several approaches that depend on quick identification processes and challenging environmental circumstances have been used for fault analysis and identification. This makes it necessary to create new methods that offer quick, precise, and trustworthy judgements on fault identification and classification.

Artificial intelligence (AI) methods have recently been used to classify and identify faults. Among the methods employed are genetic algorithms, artificial neural networks, and neurofuzzy. Protection relays can leverage historical data, learn from past errors, and forecast system behaviour by utilising artificial intelligence. The mathematical formulae won't need to be handled, but a model that incorporates the history of every fault type will be put into place. This model will be taught to quickly and accurately identify the type of fault.

The use of simulation tool such as MATLAB- Simulink facilitates the creation of transmission line-emulating models and aids researchers in creating the required fault history for artificial intelligence model training. The fuzzy inference

system is used in this study. Lotfi A. Zadeh created a fuzzy logic algorithm in 1965 after seeing that we needed a different kind of logic that could handle ambiguity and inaccuracy rather than the rigidly binary traditional logic. This reasoning was dubbed fuzzy logic by him.

More versatility than binary logic is provided by FL's many logic values, which enable the definition of intermediate states such as slightly high or almost low. Because FL simulates human thought processes, it is very appropriate for evaluating errors and uncertainty. Every element in fuzzy logic has a degree of membership in a specific collection. The task of mapping the degree of membership between input and output data is known as the membership function. The degree of input and output membership is the membership function's output.

Let x be an element of X and X be a space of objects. A collection of components $x \in X$, such that x may or may not be held by the set A , is referred to as a conventional set A , $A \subseteq X$. Alternatively, set A is represented by

$$A = \{x | x \in X\}, \quad (1)$$

where a fuzzy set A in X is determined by

$$A = \{(x, \mu_A(x)) | x \in X\}, \quad (2)$$

where the degree of the fuzzy set is mentioned by the membership function, denoted by $\mu_A(x)$. The fuzzy set specifies a linguistic phrase (label), denoted by A . Each element of X is mapped by the membership function to a membership grade between 0 and 1 ($\mu_A(x) \in [0, 1]$).

The membership degree is always restricted to a range of 0 to 1. In order to transfer non-fuzzy input values to fuzzy values and vice versa, membership functions are crucial to the fuzzification and defuzzification processes. In 1985, Japan implemented fuzzy systems for the first time, using them to regulate railway braking and acceleration.

An actual system that uses fuzzy logic to develop the mapping from a given input to an output is called a fuzzy logic controller, often referred to as a fuzzy inference system (FIS). After that, the mapping offers a guideline that may be used to identify trends or make judgements.

The fuzzification, rule base, inference engine, and defuzzification—the definition of a nonlinear matching between one or more input variables and one output variable—are the four primary components that typically make up the FIS architecture. Fuzzy logic systems have several benefits, including being extensively used for practical and commercial applications, being easily adaptable to improve or alter system performance, offering the effective answer to challenging issues, and having an easy-to-understand framework.

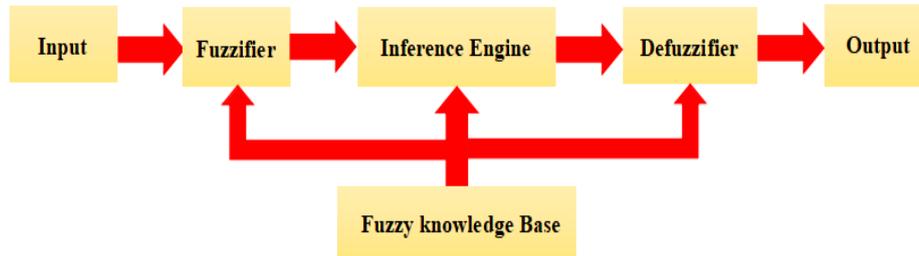
The fuzzy thinking (reasoning) used to generate conclusions and inferences from the fuzzy rules is known as the inference engine. It also aids in defining the extent to which the rules and fuzzy input match.

A knowledge base : Linguistic variables are applied to fuzzy rules in fuzzy competent systems. Several methods for designing and fine-tuning fuzzy controllers are offered by the recent developments in fuzzy theory.

The method of defuzzification involves using the output membership functions—exactly the inverse of the fuzzifier—to transform the fuzzy output of an inference engine into a defined output.

Only modeling systems, where the operator's interpretation of the variable features in the system essentially pre-agrees the structure of fuzzy rules, may use fuzzy inference systems. One way to conceptualize the structure of the FIS type is as a function that associates input space with input membership functions. As a result, it converts every membership function into an input for rules and rules into a collection of FIS output spaces.

The last step is a fuzzy system mapping output characteristics to membership functions as output and the membership function as output to an output-related decision. Fig.1 shows the common architecture of a Fuzzy Logic System as well as the block structure of these components.



.Fig.1. Typical block diagram of fuzzy logic architecture

There are many advantages of fuzzy logic systems which are their widespread usage in real-world and business applications, their ease of adaptation to enhance or modify system performance, their ability to provide the most efficient solution to difficult problems, and their simple framework.

Mamdani and Assilian were the ones who first used this technique in 1977. Sugeno introduced the Takagi-Sugeno Fuzzy Model, sometimes known as the TS technique, in 1985. This is the format for the rules.

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ Then } z = f(x,y) \tag{3}$$

In this case, $z = f(x,y)$ in the consequent is a crisp function, while AB is the fuzzy set in the ancestry. The TS method's fuzzy inference mechanism.

The Sugeno model's membership function is either continuous or linear, which is the primary distinction between it and the Mamdani fuzzy inference systems. The Sugeno rule has more adjustable parameters than the Mamdani rule, and the Sugeno model is more mathematical than the Mamdani model. Applications of the Mamdani type are common, especially in decision assistance. Several distinctions between Sugeno and Fuzzy Mamdani are shown in Table 1.

Table 1. Difference between Mamdani and Sugeno FIS

Mamdani Controller	Sugeno Controller
Membership function output.	No membership function output.
Human input works well with the Mamdani inference system.	The Sugeno inference method is ideally suited for analytical mathematics.
The system design of Mamdani FIS is less flexible.	Sugeno FIS has a more flexible system architecture.
Expressive power and interpretable rule consequent.	Here is loss of interpretability.
Through defuzzification of rules, a clear outcome or crisp result is obtained.	This isn't defuzzified. A crisp result is obtained by utilising the weighted average of the rules of consequence.
Application: Medical Diagnosis System.	Application: To remain track of the change in aircraft performance with altitude.

Reliance on human-defined rules is one of the primary disadvantages of fuzzy inference systems (FIS) in fault identification. For example, "if the voltage is low, then a fault might have occurred." These guidelines are developed using professional expertise and experience. Although this method is helpful in some circumstances, it loses effectiveness in complicated and uncertain fault conditions.

Because its rules are preset, FIS frequently finds it difficult to respond to unexpected circumstances, making it challenging to manage a variety of dynamic fault patterns without regular manual modifications.

Conversely, artificial neural networks (ANN) don't need rules that are created by humans. Rather, they acquire knowledge directly from data, which makes them extremely flexible and effective for jobs involving fault identification. Large datasets with a variety of fault situation instances are used to train ANN systems. As a result of this training, the network can detect faults without the need for explicit rule development since it automatically modifies its internal parameters to find patterns in the data.

Because of its capacity for self-learning, ANNs are particularly helpful in high-voltage transmission systems, where faults can vary widely and don't necessarily follow expected patterns.

An input layer, one or more hidden layers, and an output layer make up an ANN's structure. After data (voltage and current sensor readings) is received by the input layer, it is processed by the hidden layers, which use activation functions to find intricate patterns.

Without requiring manual rule updates, the ANN can reliably identify and classify faults in real time after it has been taught. ANNs are the perfect answer for fault identification and classification because of their capacity to automatically learn from data, which offers flexibility and dependability in handling power system faults.

II. PROPOSED TEST SYSTEM

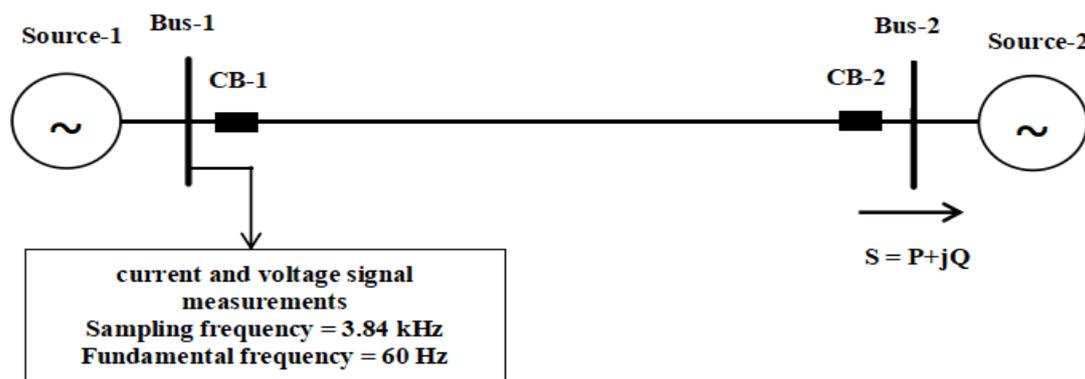


Fig.2. Proposed test system of transmission line

Fig.2 depicts the test system for the two terminal transmission lines employed in the proposed study. Between buses 1 and 2, the transmission line under consideration for the planned research is linked. Large utility grids are represented by sources 1 and 2. CB-1 and CB-2 are the circuit breakers.

Bus 2 is regarded as the receiving end of the transmission line, whereas bus 1 is regarded as the sending end. The base voltage (V_{rms} ph-ph) and base MVA for both buses, used for per-unit calculations, are 500 kV and 100 MVA, respectively.

The suggested technique is evaluated under reverse power flow conditions as well, though, because the transmission line is bidirectional. The study's system parameters are listed in Table 2 [7]. A load of 50 MW and 10 MVAR (inductive) is utilised for testing the algorithm under the line loading scenario.

Table 2. System parameters

S.No.	Parameter	Magnitude of Parameter
1	Line length	150 km
2	Source-1 voltage	500∠20 ° kV
3	Source-2 voltage	500∠0 ° kV
4	Equivalent impedance of source-1	17.177+j45.529 Ω
5	Equivalent impedance of source-2	15.31+j45.925 Ω
6	Line Positive sequence impedance	4.983+j117.83 Ω
7	Line zero sequence impedance	12.682+j364.196 Ω
8	Line positive sequence admittance	j1.468 mΩ
9	Zero sequence admittance of transmission line	j1.099 mΩ
10	Line power transfer capacity	433.63+j294.52 MVA

Phase-A to ground (AG), phase-A to phase-B (AB), phase-A, phase-B, and ground (ABG) and three-phase and ground (ABCG) fault events are among the fault occurrences that are being examined and this section elaborates on the specific findings about the identification of the faults that were evaluated. Fig.3 shows the voltages and currents during the various fault conditions.

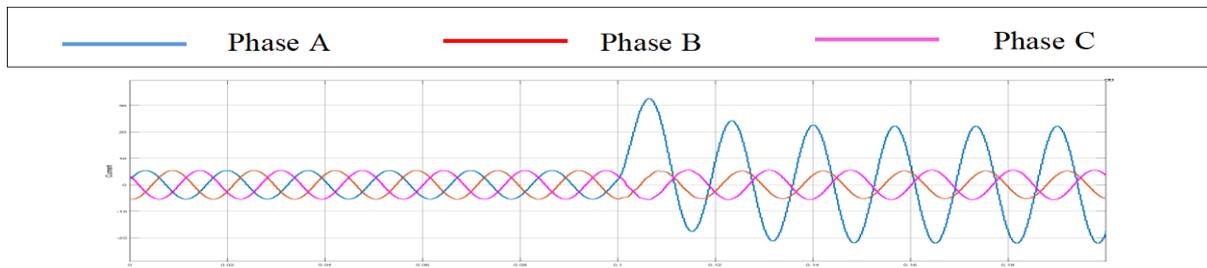


Fig.3(a). Current waveform of L-G (A-G) fault

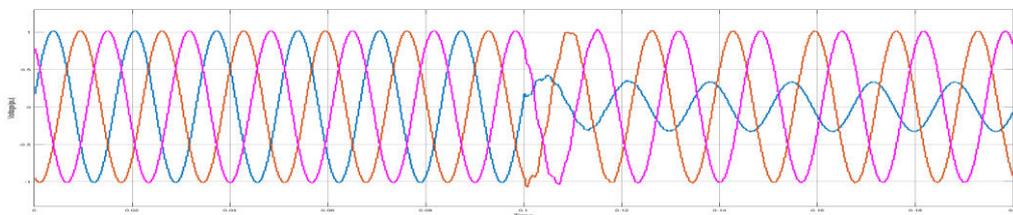


Fig.3(b). Voltage waveform of L-G (A-G) fault



Fig.3(c). Current waveform of L-L (A-B) fault



Fig.3(d). Voltage waveform of L-L (A-B) fault

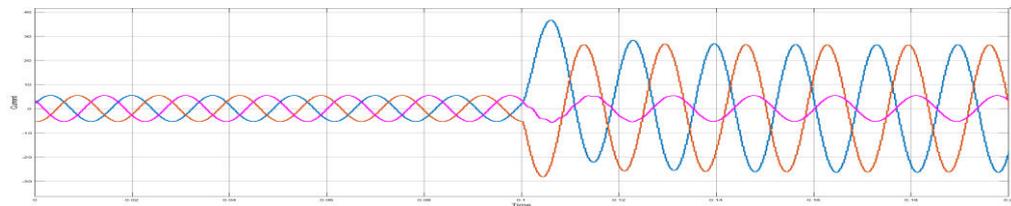


Fig.3(e). Current waveform of L-L-G (A-B-G) fault

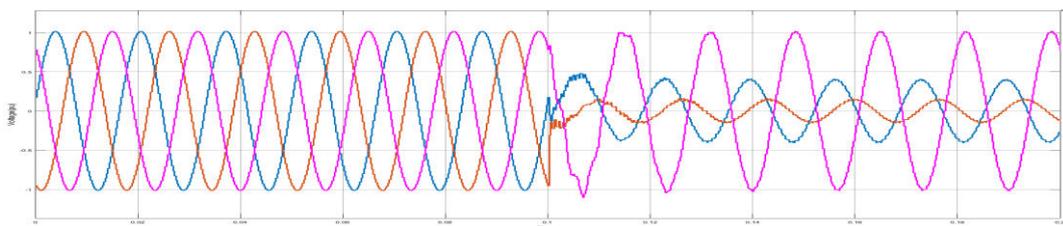


Fig.3(f). Voltage waveform of L-L-G (A-B-G) fault

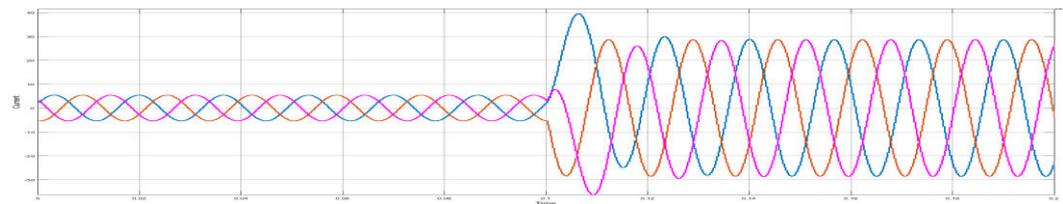


Fig.3(g). Current waveform of L-L-L-G (A-B-C-G) fault

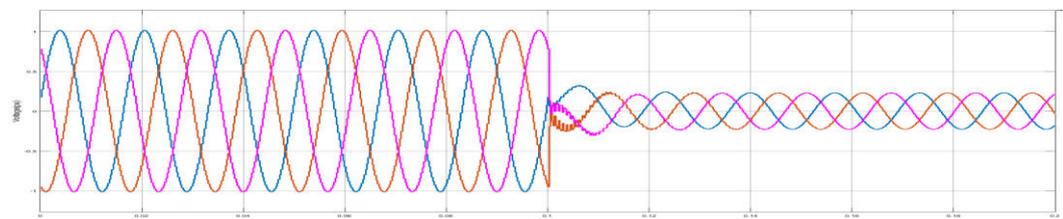


Fig.3(h). Voltage waveform of L-L-L-G (A-B-C-G) fault

III. ADVANCED COMPUTATIONAL APPROACH

III.1 The Fuzzy Inference System (FIS)

Four fault types—L-G (Line-to-Ground), L-L (Line-to-Line), L-L-G (Line-to-Line-to-Ground) and L-L-L-G (Line-to-Line-to-Line-to-Ground)—are classified into ten specific fault types: A-G, B-G, C-G, A-B, B-C, C-A, A-B-G, B-C-G,

C-A-G, and A-B-C-G. These fault types were simulated using the model shown in Fig.2. Cases per 10 km for different fault types, along with the no-fault condition, were analyzed. The inception angle varies in between 0° , 30° , 60° , 90° , 120° , 150° and 180° in each case, while the fault resistance varies in between 0Ω , 2Ω , 4Ω , 6Ω , 8Ω , 10Ω and 50Ω . In this way, the entire dataset has been generated.

III.I.I Data Processing

A very effective numerical method for calculating a signal's Discrete Fourier Transform (DFT) is the Fast Fourier Transform (FFT). It is essential for analysing power system disruptions, especially when it comes to identify and categorise faults. The fundamental frequency components of recorded electrical signals, such as three-phase voltages and currents, are extracted using FFT in fault analysis applications. These essential elements are necessary to comprehend how the power system behaves both in normal and faulty condition.

The Discrete Fourier Transform (DFT) of a discrete-time signal $x[n]$, used for analyzing the frequency components of the signals, is defined as

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j\frac{2\pi kn}{N}} \quad (4)$$

For $k = 0, 1, 2, \dots, N-1$

Where:

- $x[n]$ = time-domain discrete signal
- N = total number of samples
- $X[k]$ = complex frequency-domain output at frequency bin k
- j = imaginary unit ($j^2 = -1$)

This technique applies the FFT across two full cycles to get the fundamental frequency values of three-phase voltage and current waveforms. This makes it possible to estimate signal properties accurately both before and after a fault occurs. These frequency-domain properties may then be sent into the micro-fuzzy system or other intelligent systems to carry out activities like monitoring identification and classification. FFT efficiently eliminates noise and harmonics by concentrating on the fundamental frequency. This increases the analysis's robustness and significance. This is especially helpful for real-time fault identification.

By breaking down a time-domain signal into its sinusoidal components, FFT produces a frequency spectrum that illustrates the relative contributions of the various frequency components to the total signal. This modification makes the complicated waveforms in power system fault investigations easier to understand and analyse. Engineers can use this method to separate higher-order harmonics and transients from the basic waveform behaviour. Assessing system stability, identifying fault and providing precise input data to decision-making models. FFT is the favoured technique for digital signal analysis in contemporary power systems because of its computing efficiency, which makes it popular in embedded systems and real-time monitoring tools. Fig.4 shows the fundamental frequency component of V_a before fault.

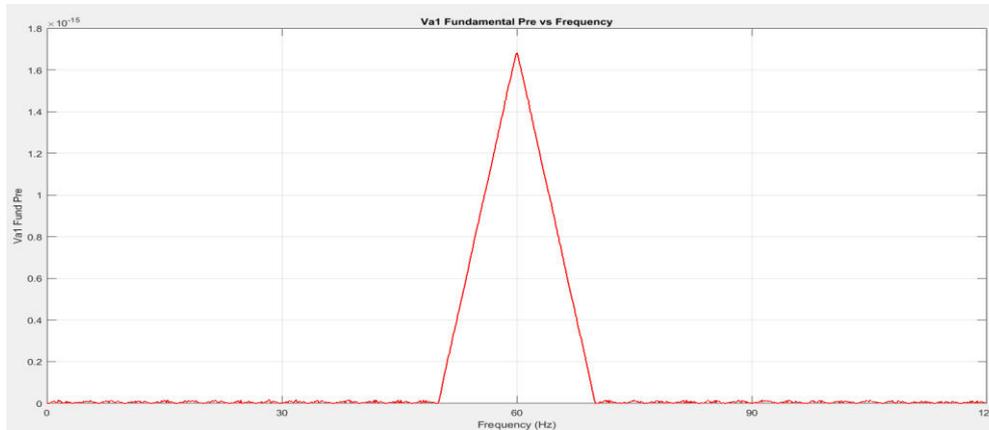


Fig.4. Pre-fault fundamental frequency component of Va

Following data processing, the normalized ratios of the fundamental frequency components of each output before and after the fault (I_{a2}/I_{a1} , I_{b2}/I_{b1} , I_{c2}/I_{c1} , V_{af2}/V_{af1} , V_{bf2}/V_{bf1} , and V_{cf2}/V_{cf1}) are used as inputs to the FIS.

III.I.II FIS structure, Input Membership Functions and Output Membership Functions

Fig.5 shows an exploited fuzzy inference system (the fuzzy controller), with six inputs standing for I_{a_norm} , I_{b_norm} , I_{c_norm} , V_{a_norm} , V_{b_norm} , and V_{c_norm} . As seen in Fig.6(a), tripartite membership functions are used to map the inputs in addition to low or high. As seen in Fig.6(b), Eleven tripartite membership functions are used as the output membership functions to depict various fault types, including the no fault condition. A Mamdani - type controller, which performs better in classifications, is employed.

III.I.III Fuzzy Rules

To setup the fuzzy controller and specify its thought process, fuzzy rules are required. The following fuzzy rules in Table 3 are derived from the three-phase voltage and current values that were often taken from the Simulink model. Each form of fault has its own membership function, as shown in Table 3, with the no-fault condition having the last membership function, MF11.

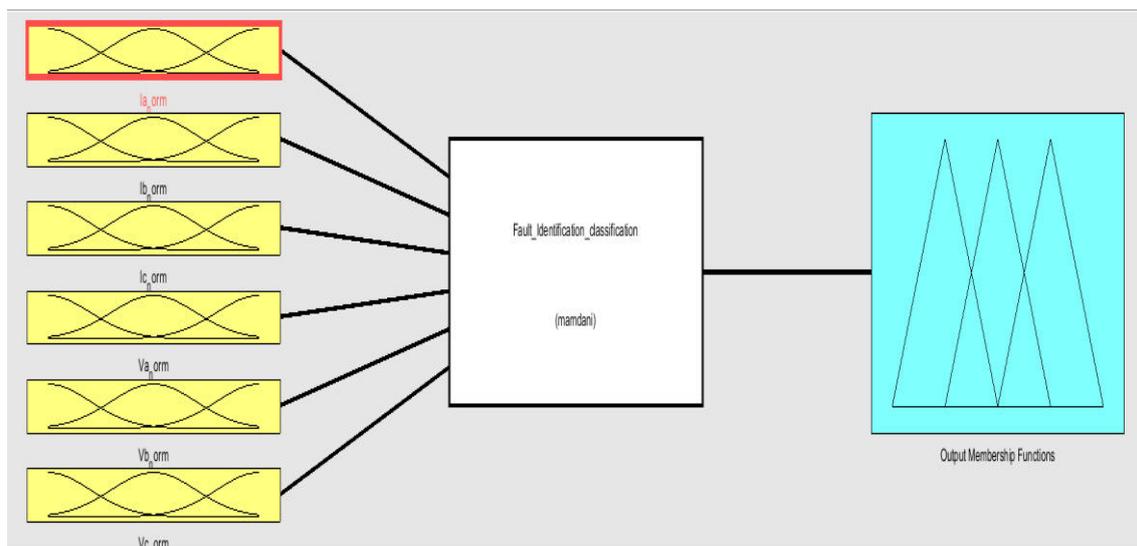


Fig.5. Fuzzy Controller System (FIS)

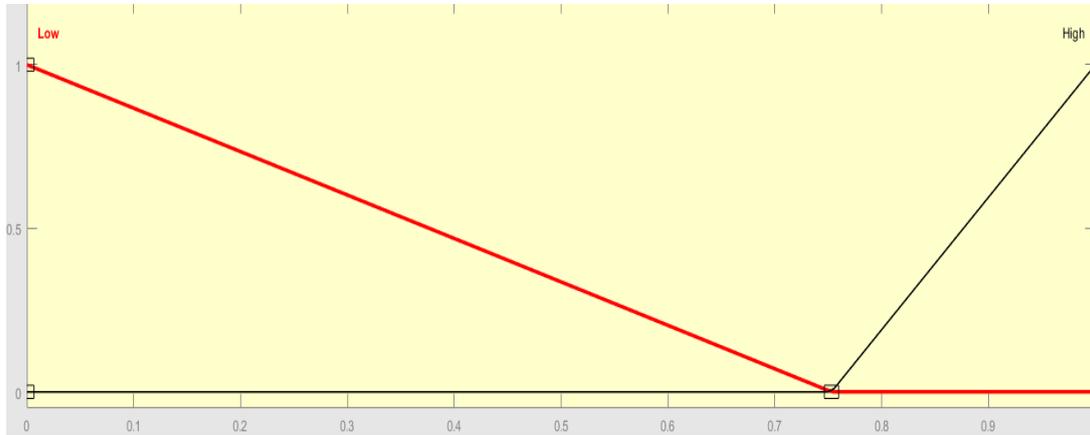


Fig.6(a). Input membership functions

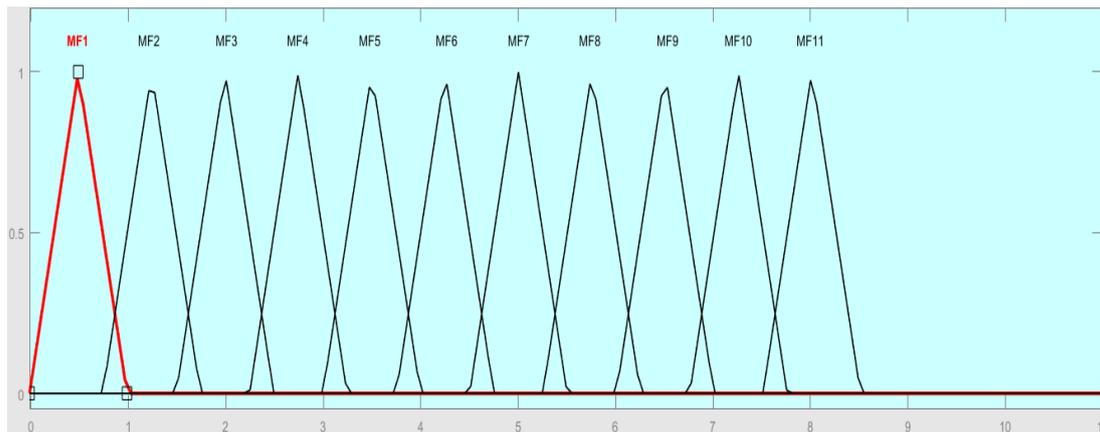


Fig.6(b). Output membership functions

Table 3. The fuzzy rules for controller

Ia	Ib	Ic	Va	Vb	Vc	Output
High	Low	Low	Low	Low	Low	MF1
Low	High	Low	Low	Low	Low	MF2
Low	Low	High	Low	Low	Low	MF3
High	High	Low	Low	Low	Low	MF4
Low	High	High	Low	Low	Low	MF5
High	Low	High	Low	Low	Low	MF6
High	High	Low	Low	Low	High	MF7
Low	High	High	High	Low	Low	MF8

High	Low	High	Low	High	Low	MF9
High	High	High	Low	Low	Low	MF10
Low	Low	Low	Low	Low	Low	MF11

Fig.7 shows the Simulink model where the FIS is implemented for simulation and defuzzification purposes.

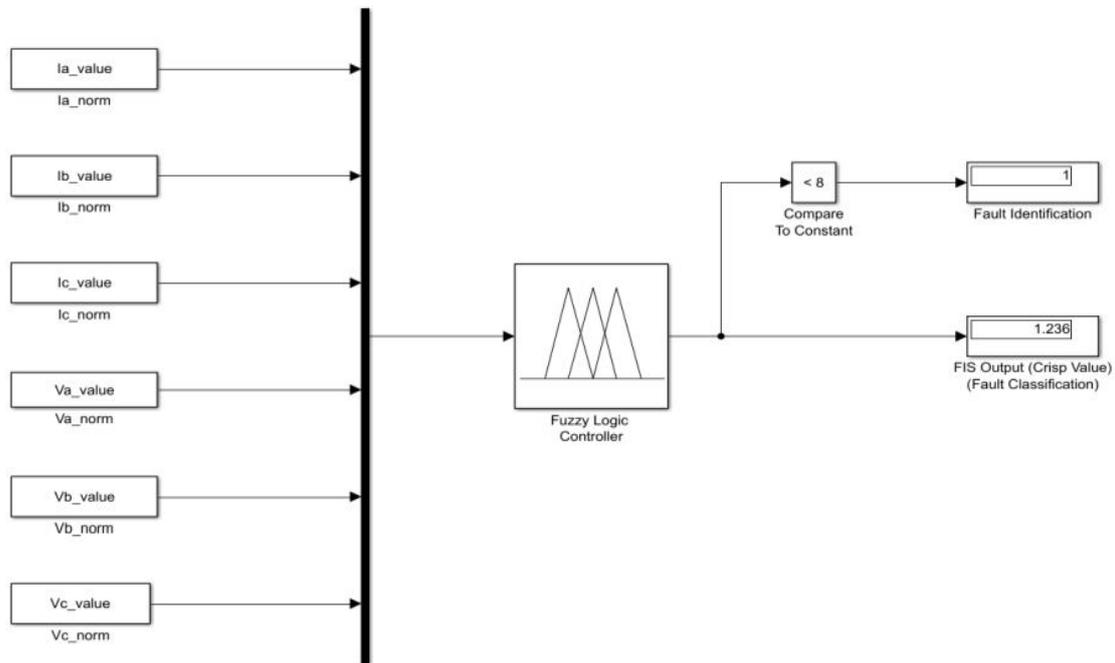


Fig.7. FIS model setup

III.II The Artificial Neural Network (ANN)

One of the advanced computational approaches employed was the Artificial Neural Network (ANN) which is frequently used for function approximation problems, such as fault identification and classification in power systems.

The main processes that an Artificial Neural Network (ANN) takes to function are broken down below.

III.II.I Import the Input and the Target Data

Importing the input data that were directly taken from simulink model given in Fig.2 and target data into MATLAB was the first step. This stage makes that the data is loaded accurately and available for further processing, including neural network training. Importing data correctly is essential for precise model performance.

III.II.II Network Architecture Design

The input layer, one or more hidden layers, and the output layer are the three layers that make up the ANN architecture, which is defined in this stage. The output layer contains four neurons that represents the fault categorisation, whereas the input layer reflects the quantity of information in the dataset. Neurons in the hidden layers aid in the network's learning of intricate correlations and patterns between inputs and outputs. The hidden and output layers employ activation functions like ReLU or Sigmoid to add non-linearity, which helps the network recognise complex patterns. Determining the model's capacity to learn and generalise from the input data depends heavily on the architecture design.

The input layer, hidden layers, and output layer are all included in the architecture design depicted in Fig.8 , which shows how each element aids in the fault classification procedure.

III.II.III Data Division and Training Setup

The input and output data are splitted into three categories in this step: training, validation and for testing. This guarantees that the model gets assessed on the testing set, refines using the validation set, and learns patterns from the training set. Here the input and the target data were splitted as 30% for training , 35% for testing and remaining 35% for validation.

III.II.IV Network Training

The network training process starts after the data is split up and the training parameters are set up. In order to reduce the discrepancy between the expected and actual outputs, the ANN iteratively modifies its internal weights and biases during this process. Because of its quick convergence, the Levenberg–Marquardt algorithm was chosen for function fitting application. The network learned the input-output relationship over a predetermined number of training epochs. The validation set is used to continuously assess the network's performance throughout this phase to make sure it does not overfit to the training data and that it generalises well.

III.II.V Testing and Performance Evaluation

The testing dataset, which includes data not utilised during training or validation, was used to assess the network following the conclusion of the training phase. This step evaluates the network's generalisation ability, or how effectively it works with data that hasn't been seen yet. Important performance indicators were examined, including regression (R) values, error histograms, and mean squared error (MSE). The neural network's strong accuracy and dependability are indicated by a low MSE and a R value near 1. The trained ANN's ability to anticipate outputs and suitability for use in fault detection or classification applications are both confirmed by these measures.

III.II.VI Simulink Prediction and Deployment

A Neural Network block was used to include the trained ANN for fault identification and classification. The network processed the incoming data and forecasted the output when it was fed into the Simulink system. This makes it possible to use the ANN in real time within the simulation environment for tasks like fault diagnosis and classification.

The regression plot, which displays the relationship between the expected and actual outputs, is shown in Fig.9. The distribution of mistakes throughout the dataset is shown by the error histogram in Fig.10. The performance plot, which monitors the training and validation error over epochs to evaluate convergence and possible overfitting, is shown in Fig. 11. Simulink model where the trained ANN is implemented for simulation and prediction purposes as shown in Fig.12.

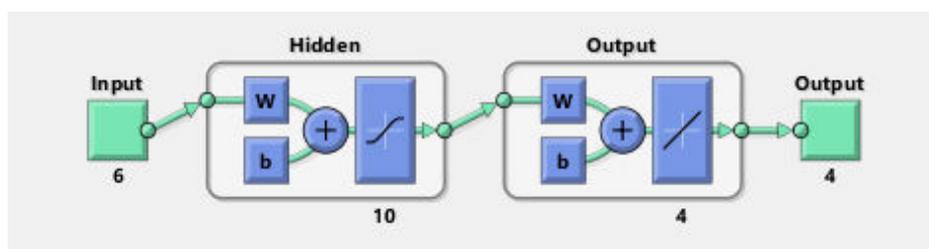


Fig.8. Network Architecture Design

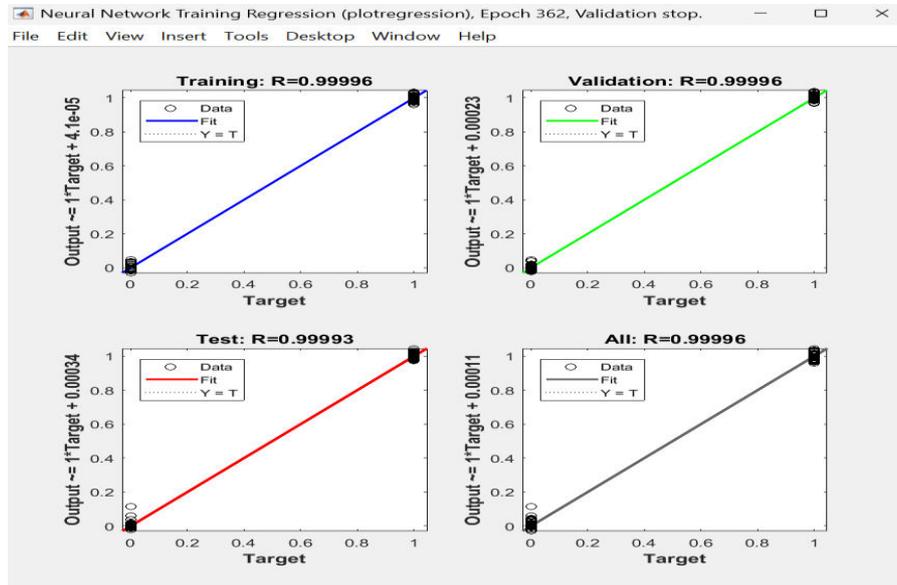


Fig.9. The regression plot

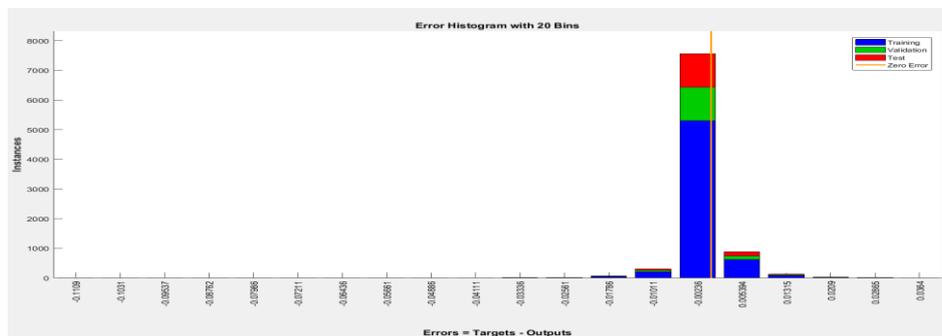


Fig.10. The error histogram

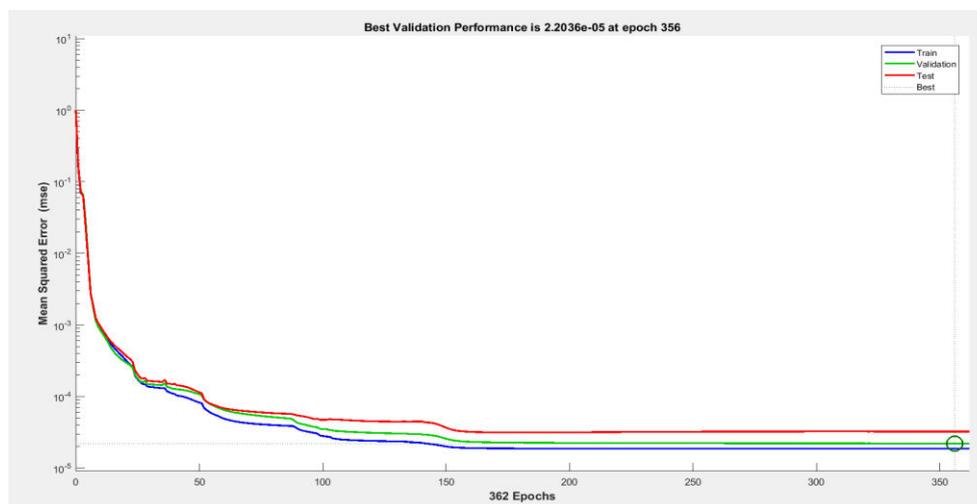


Fig.11. The performance plot

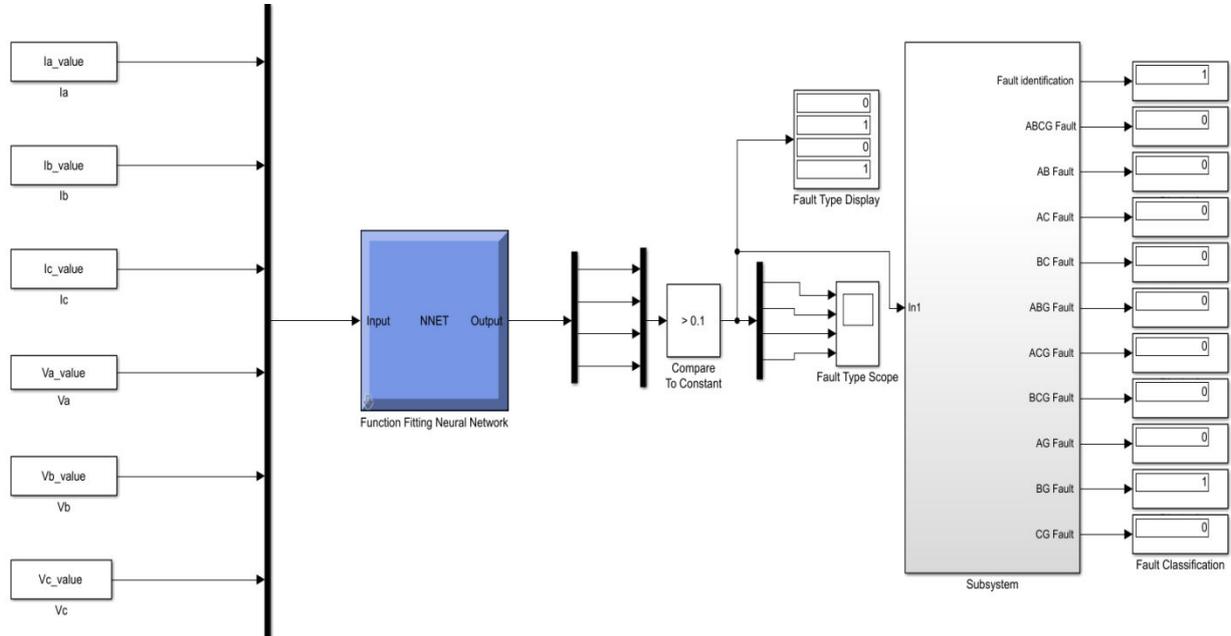


Fig.12. ANN model setup

IV. RESULTS AND DISCUSSION

IV.1 The Fuzzy Inference System (FIS) Results

After the setup, the fuzzy controller's performance was assessed using real-time data, as shown in Fig. 7. Table 4 lists the fault types and their output values predicted by the Fuzzy Inference System (FIS) shows the classification of high voltage transmission line faults . The output for fault identification is 1 and 0 for no fault.

After processing the input, the controller produces a numerical value as the output. As illustrated in Fig.13, this output is then mapped to the appropriate membership function. Based on the stated rules in Table 3, this mapping enables the fault type to be classified with Root Mean Squared Error (RMSE) of 0.001176. The fault type is to be precisely determined by examining the output values and the membership functions that correspond to them. This guarantees that the controller can distinguish between different fault scenarios.

Table 4. The output of the Fuzzy Inference System (FIS)

Fault Type		Output value of FIS	Membership function
L-G Fault	A-G	0.4854	MF1
L-L Fault	A-B	2.743	MF4
L-L-G Fault	A-B-G	5.003	MF7
L-L-L-G Fault	A-B-C-G	7.261	MF10

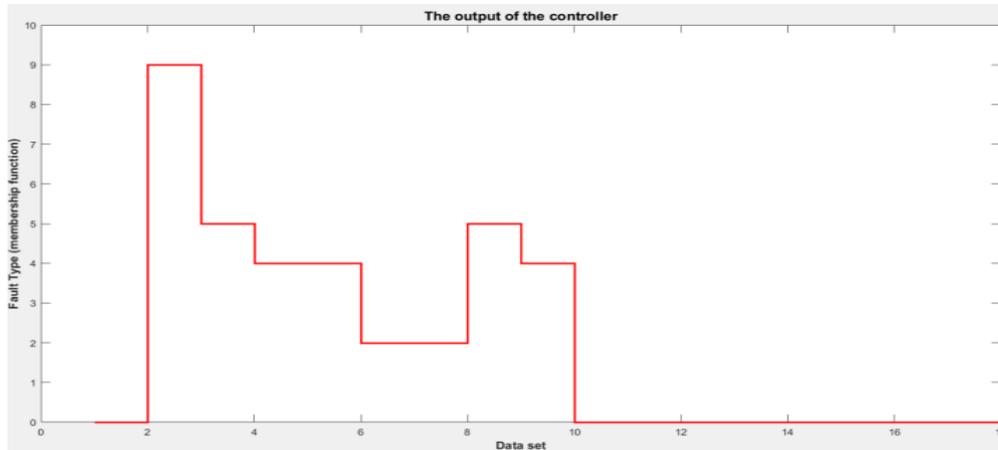


Fig.13. The Output of the controller

IV.II The Artificial Neural Network (ANN) Results

New input data was used to test the trained ANN model, as illustrated in Fig.12. The accuracy of predictions was evaluated by the confusion matrix as shown in Fig.14. Excellent learning and generalisation were demonstrated by the model's extremely low validation performance mean square error (MSE) 2.7318e-05 and test performance mean square error (MSE) 2.7785e-05. This outcome demonstrates how well the ANN recognised fault patterns and operated consistently on comparable unseen data.

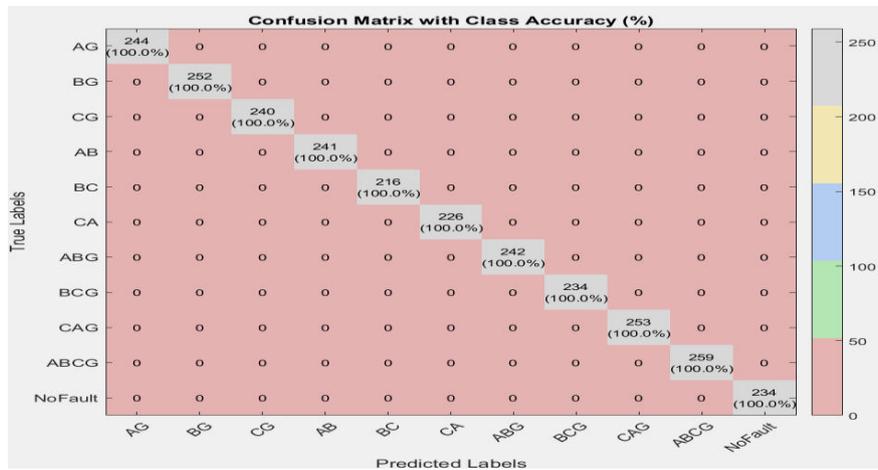


Fig. 14. The confusion matrix

The classification performance of a fault identification and classification model over 11 different classes, including different fault types (AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABCG) and a "NoFault" condition, is graphically represented by the confusion matrix in Fig. 14. The anticipated class is represented by each column, and the actual class is represented by each row. With 100% of data for each class correctly classified and no misclassifications (i.e., all values outside the diagonal are zero), the model reaches perfect classification accuracy. The class-wise accuracies displayed on the matrix diagonal demonstrate how well and accurately the model can differentiate between all fault kinds and the no-fault situation.

The values of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN) for each class are listed in Table 5, together with the derived metrics of Precision, Recall, and F1-Score, which further quantify the classification performance. Remarkably, the data demonstrates that the model produced zero false positives and false negatives for each of the 11 classes, yielding flawless scores (1.00) for precision, recall, and F1-score overall. This

supports the confusion matrix's results and shows that the classifier not only accurately detects every mistake but also does so without missing any, showing a very strong and dependable model performance.

Table 5. TP, FP, FN, TN, Precision, Recall, F1-Score

Class	True Positives(TP)	False Positives (FP)	False Negatives (FN)	True Negatives (TN)	Precision	Recall	F1-Score
AG	244	0	0	2397	1.00	1.00	1.00
BG	252	0	0	2389	1.00	1.00	1.00
CG	240	0	0	2401	1.00	1.00	1.00
AB	241	0	0	2400	1.00	1.00	1.00
BC	216	0	0	2425	1.00	1.00	1.00
CA	226	0	0	2415	1.00	1.00	1.00
ABG	242	0	0	2399	1.00	1.00	1.00
BCG	234	0	0	2407	1.00	1.00	1.00
CAG	253	0	0	2388	1.00	1.00	1.00
ABCG	259	0	0	2382	1.00	1.00	1.00
NoFault	234	0	0	2407	1.00	1.00	1.00

Table 6. The comparison of FIS and ANN

Features	FIS (The Fuzzy Inference System)	ANN (The Artificial Neural Network)
1. Learning Capability	No learning; relies on rules	Learns from data
2. Interpretability	Clear and transparent rules	Black-box model
4. Data Dependency	Low data requirement	Requires overall large data
5. Best Application	Ideal for rule-based control systems	Best for pattern recognition and forecasting
6. Accuracy	Moderate to high, based on rules	High, depends on training data
7. Input Data	Processed data (FFT-based features)	Raw time-domain data

V. CONCLUSION

In order to identify and categorise shunt faults in high-voltage transmission lines, this study evaluates two fault classification methods : the Fuzzy Inference System (FIS) and the Artificial Neural Network (ANN). According to MATLAB/Simulink simulations, ANN performs better than FIS, with overall 100% accuracy. ANN is superior in pattern identification. Even with 99.96%accuracy, FIS is still a straightforward, computationally effective solution that works well for resource-constrained real-time applications. More appropriate technique for high-accuracy fault

identification and classification is ANN. Because of its better accuracy, versatility, and performance in real-time fault identification and classification in dynamic power systems, ANN is typically chosen over FIS for creating effective protective relays.

REFERENCES

- [1]. Elnozahy A., Mohamed M., Sayed K., Bahyeldin M., & Mohamed S. A., “Fault identification and classification algorithm for high voltage transmission lines based on a fuzzy-neuro-fuzzy approach” International Journal of Modelling and Simulation, pp.1-12 ,October 2023.
doi :10.1080/02286203.2023.2274062.
- [2]. Fathabadi H., “Novel filter based ann approach for short-circuit faults detection, classification and location in power transmission lines”, International Journal of Electrical Power & Energy Systems, vol. 74, pp. 374–383 , January 2016. doi: 10.1016/j.ijepes.2015.08.005.
- [3]. Fei C., Qi G., Li C., “Fault location on high voltage transmission line by applying support vector regression with fault signal amplitudes”, Electric Power Systems Research , vol. 160, pp. 173–179 , July 2018.
doi: 10.1016/j.epsr.2018.02.005.
- [4]. Kumar A., Sharma H., Mahia R. N., Mahela O.P. , Khan B., “Design and Implementation of Hybrid Transmission Line Protection Scheme Using Signal Processing Techniques”, Hindawi International Transactions on Electrical Energy Systems, vol 2022, pp. 1-20, May 2022. doi :10.1155/2022/7209553.
- [5]. Tang L., Mahela O. P., Khan B., Miro Y., “Current- and Voltage- Actuated Transmission Line Protection Scheme Using a Hybrid Combination of Signal Processing Techniques”, Sustainability 2023, vol. 15, pp. 1-26, March 2023. doi: 10.3390/su15075715.
- [6]. Ola S. R., Saraswat A. , Goyal S. K., Jhajharia S.K., Rathore B., Mahela O. P., “Wigner distribution function and alienation coefficient-based transmission line protection scheme”, IET Generation, Transmission & Distribution, vol. 14, pp. 1842-1853, March 2020. doi: 10.1049/iet-gtd.2019.1414.
- [7]. Rathore B., Shaik A.G., “Wavelet-alienation based transmission line protection scheme”, IET Generation, Transmission & Distribution Vol. 11, pp. 995–1003, March 2017. doi: 10.1049/iet-gtd.2016.1022.
- [8]. Phy Thwe E, Min Min O., “ Fault detection and classification for transmission line protection system using artificial neural network” Journal Electrical and Electronic Engineering. vol. 4, pp.89–96, October 2016.
doi: 10.11648/j.jeee.20160405.11.



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