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Line to Ground Fault Detector in 400 KV Transmission Line by Using Intelligent System

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Abstract: The design of electricity systems is all about ensuring the stable and effective operation of electrical grids, the capacity to discover and diagnose faults in power transmission lines is the most important component. to preserve the stability of the power system, save downtime, and avoid cascading failures. The process of precisely locating the issue and expediting the restoration of the power supply is known as problem localization, which also helps to minimize the disturbance to customers. The automatic fault localization and detection using adaptive neural fuzzy inference systems (ANFIS) method for transmission lines that is measurement-based is presented in this work. The development and application of ANFIS enables high-speed processing of real-time error localization and detection. Digital distance protection systems should have the ability to identify problems in addition to detecting them, according to ANFIS recommendations. After a transmission encounters a three-phase issue As a result, the recommended approach can identify the affected stages with accuracy. Numerous types of field data have been used to train and evaluate ANFIS. Using computer software based on Matlab, the field data are gathered by simulating faults in the Simulink Matlab model that illustrates the transmission line at various places between Misan – Kut station 400 Kv along 200 Km. Phase current and voltage data are provided at the busses and are used as ANFIS inputs. In terms of defect type and detection, the output will show fault and location identification using simulated processes with a very low error percentage; the results also show that the approach's selectivity and speed are fairly dependable and offer sufficient performance for applications involving distribution and transmission monitoring; as well as safety. The study highlights how crucial it is to identify power transmission line defects quickly and accurately to maintain the stability and security of the power system. The experimental results show that the two approaches improve the detection with an accuracy of 100% and the localization reached 99.9% for (35 Km) the result of the test program after comparing it with the ANFIS file is (35.00173 Km).

Keywords: ANFIS techniques, Fault Detection, Localization, protection, and Transmission Line Faults.

1. Introduction

The stability and dependability of power systems depend on the localization and identification of faults in power transmission lines. Roughly 90% of all power transmission line defects are line-to-ground (LG) faults, which are the most prevalent kind of fault.[1]. The application of intelligent systems for fault identification and localization in power transmission lines has increased recently. These systems include artificial neural networks (ANN), adaptive neural fuzzy inference systems (ANFIS), and other cutting-edge methodologies.
Intelligent systems offer some benefits over conventional techniques for fault localization and

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detection in power transmission lines. Intelligent systems, for instance, can manage massive volumes of data, gain experience, and adjust to shifting circumstances. Furthermore, sophisticated systems can detect and monitor faults in real time, minimizing downtime and repair expenses related to power outages[2]. Intelligent systems have been successfully applied for problem localization and detection in 400 kV transmission lines. For instance, a study that used artificial neural networks (ANN) for fault localization and detection in a 400 kV transmission line discovered that the system had a 98.5% success rate in correctly identifying and locating faults[3]. To sum up, there is a lot of promise when it comes to using intelligent systems for problem localization and detection in power transmission lines, especially when it comes to 400 kV transmission lines. These systems have some benefits over conventional techniques, such as high precision, adaptability, and real-time monitoring [4]. The usage of intelligent systems for problem detection and localization is expected to become more and more significant as the need for dependable and stable power systems grows. Further signal processing methods used for fault detection and location in transmission lines include discrete wavelet transform (DWT) and Hilbert transform (HT). One study that used DWT for fault detection and location in a 400 kV transmission line found that the method was able to accurately detect and locate faults with an accuracy of 100% for a range of fault resistances and at different fault locations[2]. Furthermore, the detection of high-impedance faults in transmission lines can also be accomplished by intelligent systems. According to a review of research, artificial intelligence methods for detecting high-impedance faults in transmission lines include decision trees, support vector machines (SVM), and artificial neural networks (ANN) [5]. In this paper, the technology employed in 400 kV transmission lines for line-to-ground fault detection using the adaptive neural fuzzy inference systems (ANFIS) technique ANFIS. By analyzing voltage and current signals, these methods can find and identify transmission line defects, enhancing the stability and safety of power networks.

2. Adaptive Neural Fuzzy Inference System (ANFIS)

An artificial neural network architecture that utilizes the Takagi-Sugeno fuzzy inference system integrates fuzzy logic concepts with neural networks Function Approximationhaving the ability to approximate nonlinear functions made up of five layers: output, defuzzification, rule, normalization, and fuzzification. An artificial intelligence system called the adaptive neural fuzzy inference system (ANFIS) combines the advantages of fuzzy logic systems and neural networks. Like a neural network, ANFIS may learn and make judgments based on data; but, it can also handle partial or inaccurate data, much like a fuzzy logic system. Because of this combination, ANFIS is perfect for applications where data is not always precise or is changing often [6]. ANFIS is an effective tool that can decrease the amount of time required and increase the accuracy of predictions provided by AI models.

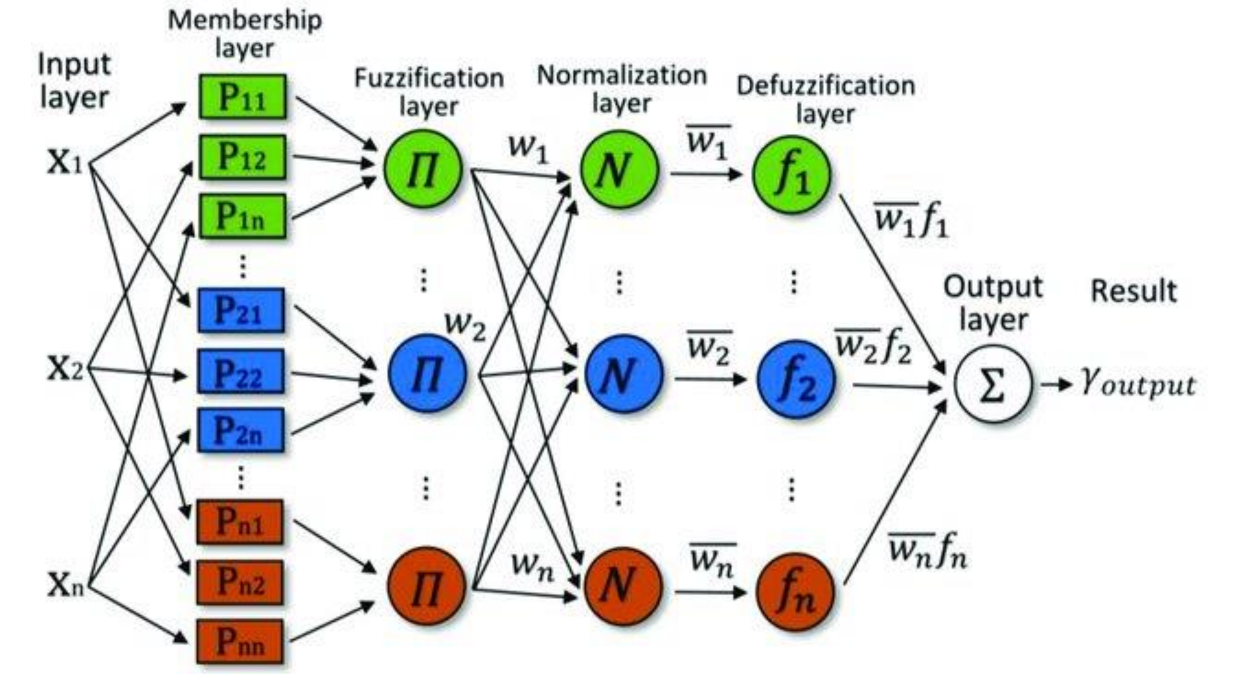

Figure. 1 The Structure of the Adaptive Neuro-Fuzzy Inference System (ANFIS) [7].

There are five layers in the ANFIS architecture, and each one has a distinct purpose. The input variables are transformed into fuzzy variables using membership functions in the first layer, known as the fuzzification layer. The fuzzy variables are multiplied in the second layer, known as the product layer, to determine the firing strength of each rule. The firing strengths are normalized in the third layer, known as the normalized layer so that their sum equals one. The normalized firing strengths are utilized in the defuzzification layer, which is the fourth layer, to determine each rule's output. The total output layer, which is the final layer, is where all of the rule outputs are merged to create the ultimate output. Each node in Layer 1 (the fuzzification layer) is adaptable[8]. Layer 1's outputs are the fuzzy membership grade of the provided inputs

The fuzziness layer creates fuzzy clusters based on input values by using membership functions.

This section may use a variety of membership functions, such as the generalized bell function (gbell) and the triangle function (trimf).

Antecedent parameters, such as {a, b, c}, are parameters that specify the form of the membership function in membership functions.

The membership degrees of each member function is determined by these parameters, which are given in Equations (1) and (2) [8].

The degrees of membership derived from this layer are shown using Convert input variables to ambiguous values. Create the membership grading system; this label features a flexible node. The layer's executed output is the fuzzy membership grade of the inputs, and it appears.

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

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

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

Determine the firing strengths for each rule or generate the firing strengths based on the inputs. We refer to this layer as the rule layer. Fuzzification layer membership data are used to create fir ing strengths (wi) for the rules [9]. wi values are found by multiplying the membership values as in equation (3).

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

Where i= 1, 2, …

Normalization layer: By normalizing the firing strengths, it makes sure that their total is equal to one. Furthermore, the nodes are stationary. The nodes with the N label show that the firing strengths from the previous layer have been averaged. The ratio of the ith rule's firing strength to the overall firing strength of all the rules is determined by this layer's node number.

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

A defuzzification layer calculates the weighted average of the effects related to each rule's firing strength. The term "defuzzification layer" refers to this layer. Each node in this layer calculates the weighted values of the rules according to (5). To determine this value, a first-order polynomial

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

where i = 1,2,3,…..

The normalization layer yields an output of ϵ, while the parameter set consists of pi, qi, and ri. The parameters in the end are these. There is one extra conclusion parameter for every rule then there are inputs. For instance, each rule in the ANFIS structure with four inputs has five conclusion parameters[9].
The output layer is sometimes known as the last layer.
The actual output of ANFIS is calculated by adding the outputs obtained for each rule in the defuzzification layer.

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

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

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

- **Optimize Parameter Tuning**: Use cutting-edge optimization strategies to efficiently adjust the ANFIS model's parameters, cutting down on the complexity and time needed to do so[22].
- **Boost Data Quality**: To ensure improved performance and robustness in real-world scenarios, increase the quantity and quality of data used to train ANFIS models.
- **Apply Ensemble Techniques**: By combining several ANFIS models using ensemble techniques, you can increase prediction accuracy, decrease overfitting, and boost system dependability.
- **Feature Engineering**: To improve the model's capacity to recognize intricate correlations and patterns, and perform comprehensive feature engineering to extract pertinent and instructive characteristics from the data[23].
- **Methods of Regularization**: Use regularization strategies to enhance and avoid overfitting**.**
- **Hybridization with Optimization Techniques**: To improve the model's capacity for learning and efficiency, hybridize ANFIS with sophisticated optimization techniques like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO).
- **Cross-validation**: Use cross-validation techniques to evaluate the ANFIS model's performance on hypothetical data to make sure it is robust and able to generalize to real-world

situations. Based on real-time data, continuously assess and update the ANFIS model to maintain optimal performance and adjust to changing circumstances.

- **Collaborative Research**: Encourage cooperation between researchers and domain professionals to address particular issues and modify the ANFIS model to successfully satisfy the needs of practical applications. These techniques can help overcome ANFIS's shortcomings in practical applications [23].

2.1 ANFIS-Based Proposed Fault Detection in Transmission Lines (Modeling of 400 Kv Transmission Line)

This section presents the modeling information for the two-terminal transmission line model. The transmission line model was made with MATLAB and the Simulink software version R2022a. Figure .2 shows the Proposed Algorithm of the work in this paper. The objective of developing the transmission line model was to create a model that could measure current and voltage at both buses on each side of the line. Transmission lines connecting two stations served as the foundation for the creation of the Simulink model used in this study. The two stations in the transmission line model, Kut and Misan station (The South West Networks), are connected by a 400 kV, three-phase, 200-kilometer transmission line as shown in Figure. 3 . The stations are depicted and each contains a 400 KV and 5000 KVA modeling block as a load. The transmission line topology, two equivalency mutual impedance blocks, and two voltage and current V-I measurement blocks (The buses on each side) show the total load in each city with load (1000 MW, 150 VAR).

In this work choosing a pi-section transmission line as shown in Figure 5 with impedance values, the value of real transmission lines between two stations is taken into account. The recommended model's fault parameters are shown in Table (1). The transmission line models used throughout this study will replicate the 200 km long, 50 Hz, 400 kV transmission line. In this specific piece, the line is broken into nine parts. The segment connecting two stations (the Pi model transmission line) is situated in the center of the block and is depicted in Fig. 4 with varying reactor and resistor values. The multiplicities of (L) and (1-L) are applied to each value of reactors and resistors in the transmission line at the start and end of the line, respectively.

L: Due to the uncertainty surrounding the fault's position, it is regarded as a variable. As a result, eleven segments, ranging in length from 0 to 90% of the transmission line, are separated. The line that applies single to the ground fault is where the fault detection and locating block is situated (Unsymmetrical fault). Table (2) shows that all of the constant data for the (132 and 400) KV overhead lines used in Simulink came from southwest networks in Misan. The researcher's task of locating the fault zone will be made simpler by this part.

Table 1. Shows the fault parameters of the proposed model.

System components	**Parameters /units**	**Value**
Short circuit level (S)	*MVA*	5000*106
Fault capacitance Cs	*F*	Infinite
Switching time (t)	*Seconds*	0.1
Ground resistance Rg	*Ohms*	0.01
Fault resistance Rf	*Ohms*	0.1
Frequency	*Herts*	50
Phase to phase voltages (RMS)	*Voltage*	400
Active Power (load)	*Watts*	$1000*10^6$
Inductive reactive power QL(Load)	*Var*	$150*10^6$

Table 2. Shows the 400 KV, 200 Km transmission line (overhead lines) constant.

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

2.1.2 Data Extraction

In this work gathering the data about transmission line defects, including fault distances (The distance at which the issue is located). This can be accomplished by taking data from nine different sections and multiplying the transmission line length value by (10 - 90) percent. The three-phase voltage readings and The data extraction in the Matlab Simulink model are displayed in Fig. 2 as a data features block that gathers the three-phase voltages and currents and a class data block as shown in Figure .4 that establishes the zone of the three-phase fault after applying the three-phase fault by the fault type and location block. Three-phase currents taken from the buses are shown in Fig. 2.

All feature data is collected into a 6 by 600 matrix with six inputs as shown in Fig. 4 the data collected in the features block and class block to save the location of fault compared with the values of three-phase currents and voltages measured in features. These dimensions are used to feed the data into ANFIS modeling techniques, which can be used for defect detection and localization. The Adaptive Neuro-Fuzzy Inference System, or ANFIS, is what will train these data and prepare the ANFIS file for later usage. To confirm the effectiveness of the Simulink model for defect localization and detection, Use testing data (Actual data) from a different network to test and validate it. Ensure that the model can accurately identify various fault locations and types in a variety of problem scenarios. Using the Matlab R2022a application figure 6 illustrates the training process of the data during preparing the ANFIS file, the efficacy of the ANFIS file extraction from the preceding stage was evaluated during the testing phase. By adjusting the output's duration and contrasting the real values with the measurements in the ANFIS file the training data shown in Fig. 6 in the ANFIS window program using the system as follows :

```
[System]
Name='FLOC'
Type='sugeno'
Version=2.0
NumInputs=6
NumOutputs=1
NumRules=729
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'
```

The findings were shown in different zones. The steps taken to identify and locate the flaws are depicted in Fig.2.

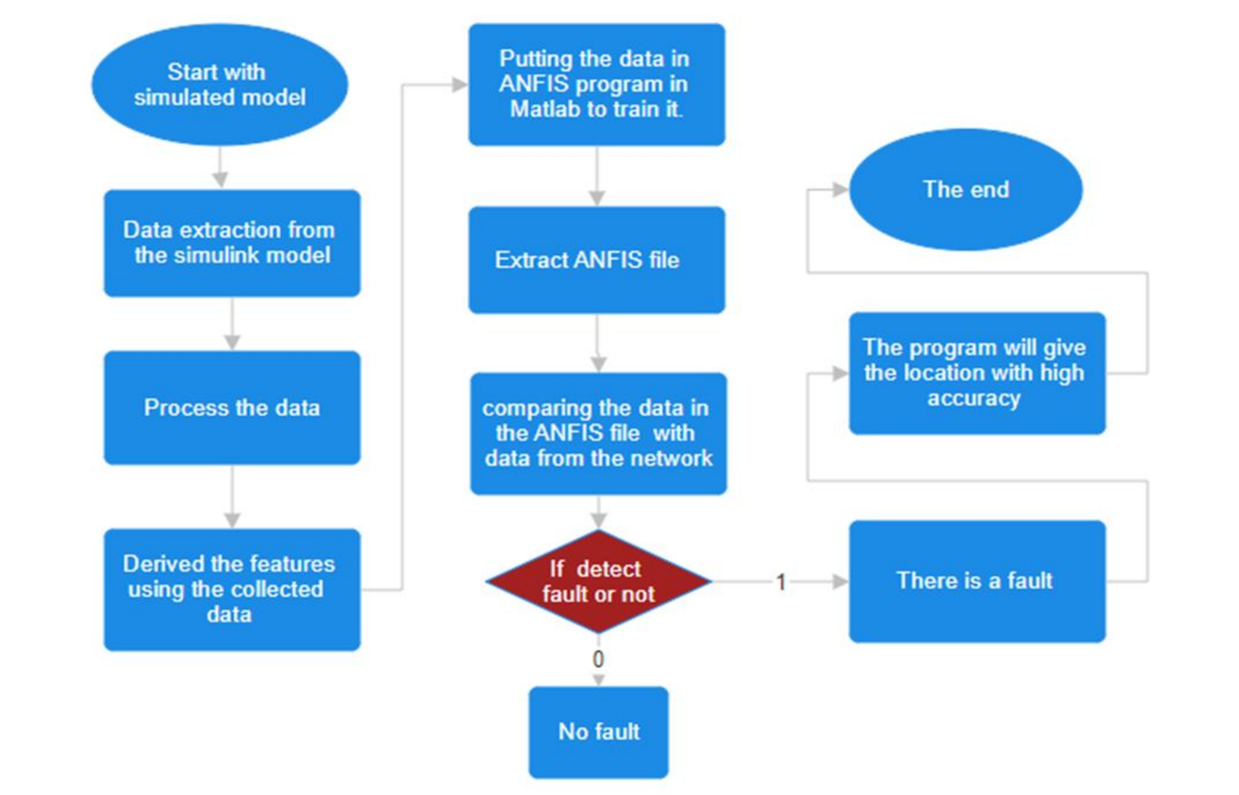

Fig.2 Flow chart for the proposed algorithm.

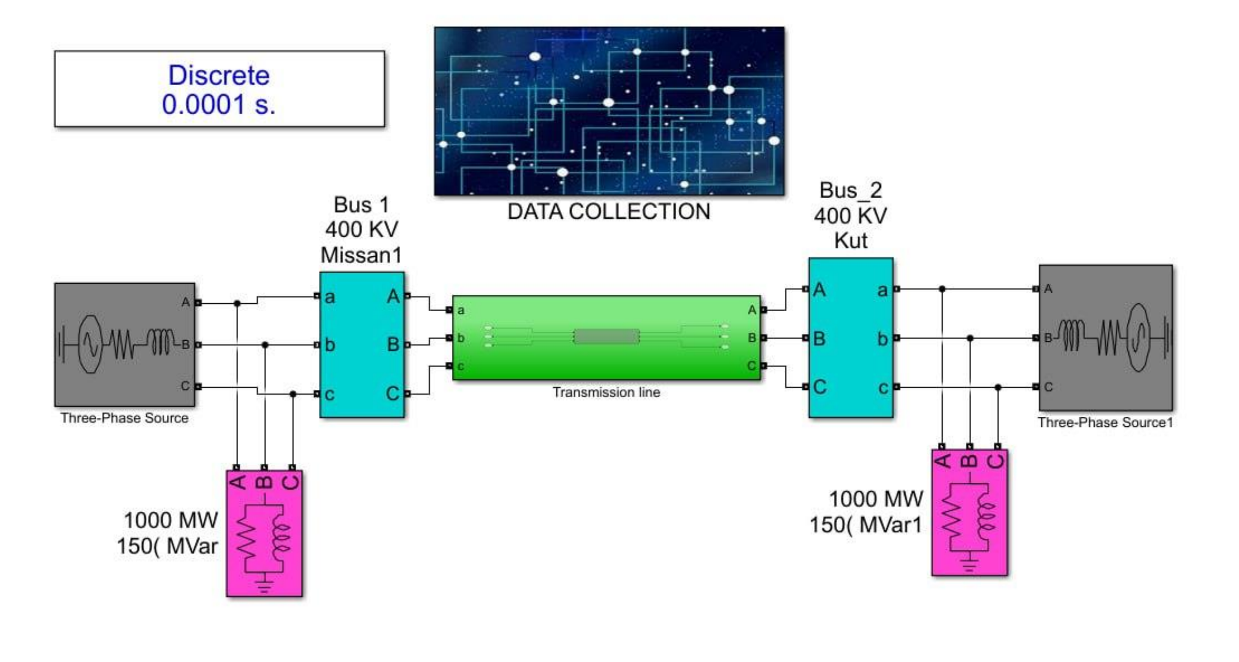

Fig.3 200 kilometers of 3. phase, 400 KV transmission Simulink model

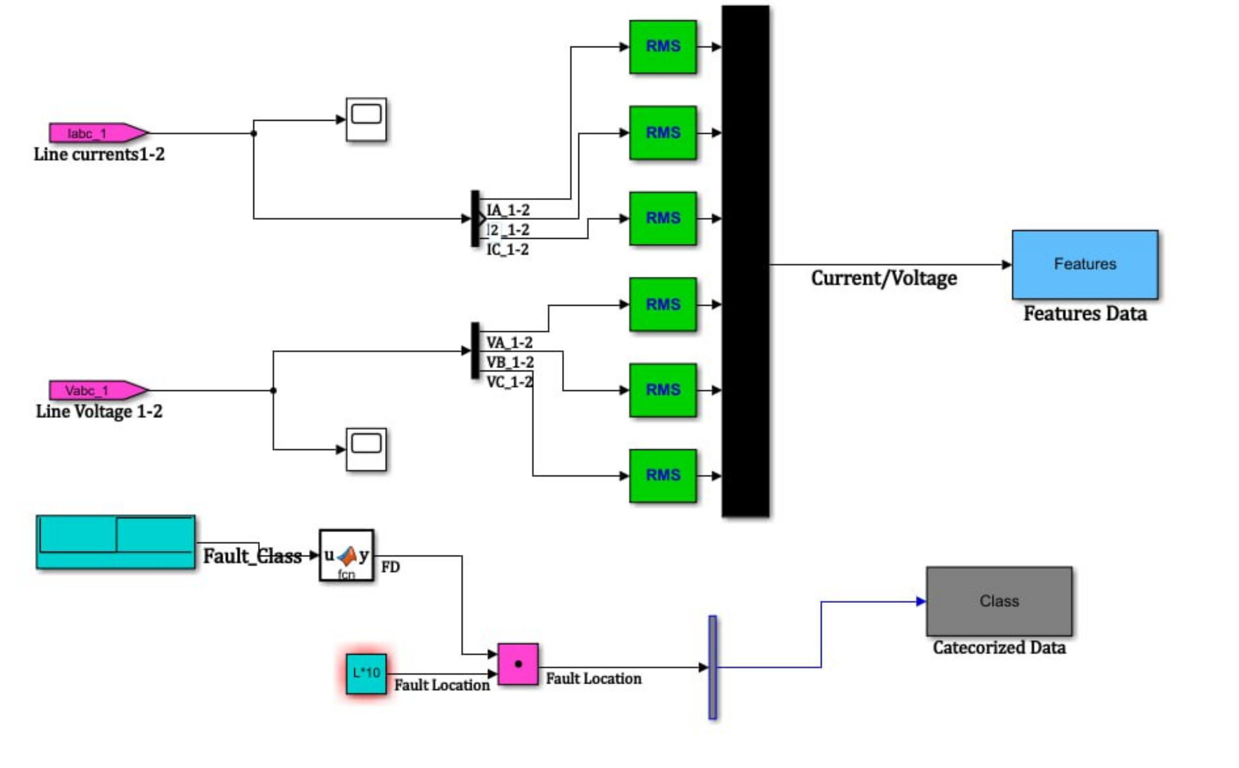

Fig. 4 The 200 km, 400 kV Simulink model of the Misan-Wasit stations.

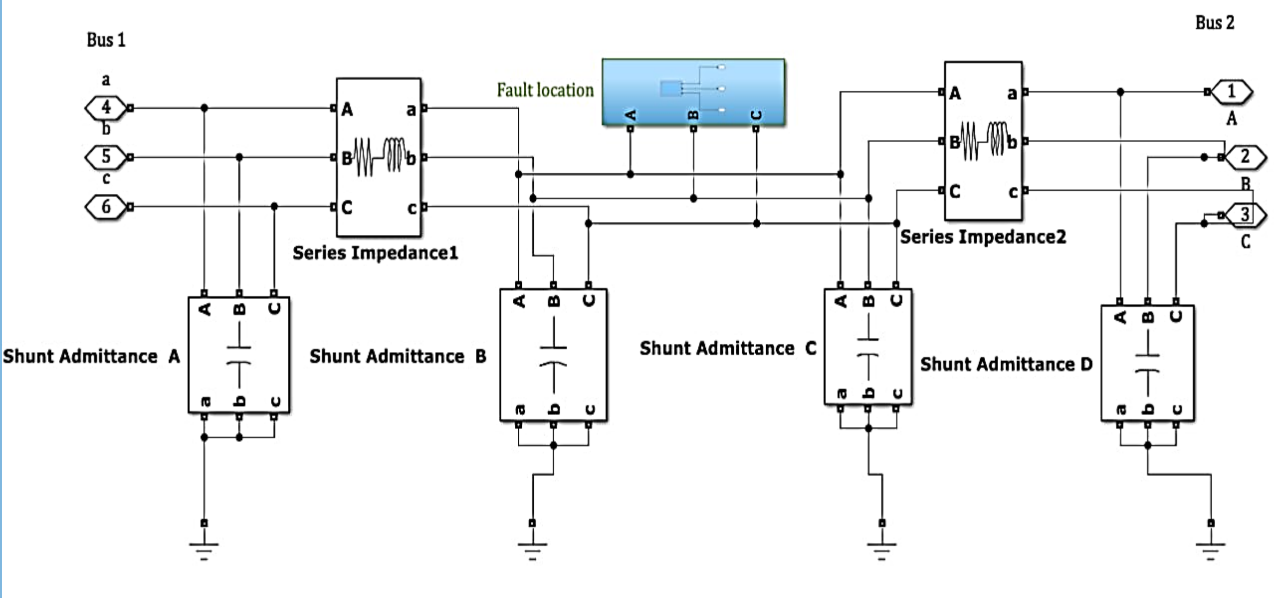

Fig.5 Transmission line Simulink model (pi- model)

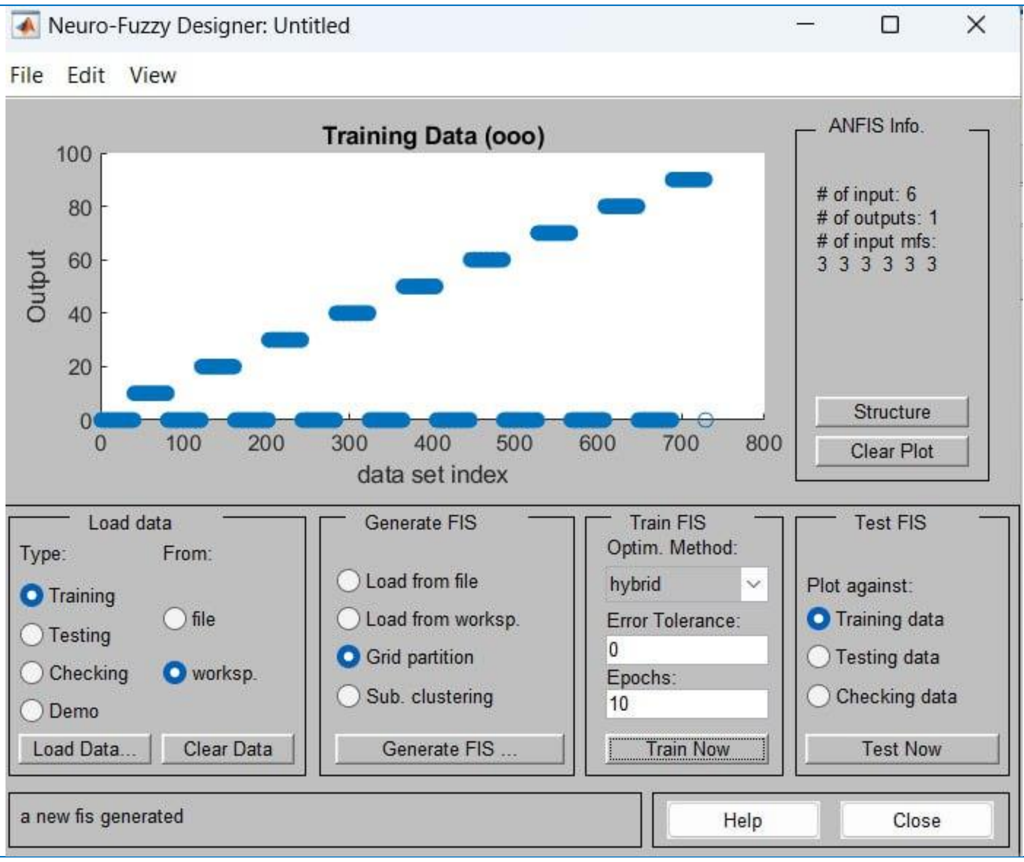

Fig. 6 Training Data Window in ANFIS.

2.2.2 Fault localization results

Applying a single phase fault on a network with a specific location as shown in table (3) and through a ANFIS program in R2022a MATLAB the output shows the location of the fault with high accuracy as it can be seen in a location with length (1km). The output shows (10.0059) as shown in table (3) and so on for the rest transmission line lengths with a very small error percentage. This test program confirms the importance of using the ANFIS program as a tool to detect and locate the faults in the transmission lines due to the high availability and high reliability of detecting the faults.

4. Result and Discussion

In the following application, this work contains a three-phase, symmetrical flaw. These buses are measuring units that read the voltages and currents of the three phases at each bus bar in the Simulink model (bus 1, bus 2). Each fault (single line to ground fault) will take 0.05 seconds to occur. We gathered the data from Misan station and Kut station, for two locations on the network since the buses will be gathering it right now. The information was gathered in the form of a feature data matrix. When the values of the feature data are compared using a Matlab function condition, then the data will be entered into the ANFIS program to prepare an ANFIS file that will be used later to detect and locate faults in another network. Using a different Simulink network of unknown length, a Matlab program is designed to test the accuracy of the ANFIS file before using it in networks. The output of this program displays a very low error percentage, which shows various transmission line length values. The results in Table 3 display the output value of the fault detection and the location of the fault. The accuracy of the results detecting the distance of fault spots with varying values of length. As indicated in the table, Using a different Simulink network of unknown length (L), a Matlab program is designed to test the accuracy of the ANFIS file before using it in networks. The output of this program, which displays a very low error percentage, the outcome of fault detection will yield logic one or zero for the detection of a fault or not so the detection of fault reached 100% with no error probably. From a column of the location in Table 3 the percentage of error in location is very low reaching 99.9% for example by giving (45 Km) to the test program in Matlab to evaluate the work of the ANFIS file the output is (45.0086 Km). The final five results display the output values when no faults are discovered. Figure 7 shows The three-phase currents in Single to Ground fault through nine cases along 200 Km between (Misan-Kut) station. Finally, ANFIS offers various advantages for fault, location, and detection in power systems. It can handle imprecise and unclear data, adapt to changing system conditions, and provide real-time analysis. However, ANFIS may find it challenging to manage complex, large-scale systems with lots of rules and variables. To enhance the training process, a substantial amount of labeled data is necessary. To sum up, ANFIS is a useful method for identifying and locating power system issues. Because of its ability to learn from data and approximate complex processes, it is a vital tool for maintaining the stability and dependability of the electrical grid. By using ANFIS, power system operators can enhance their fault management strategies, decrease downtime, and ensure a consistent supply of electricity. Finding and identifying mistakes. In Fig. 7 the waveforms show the increase of the currents in phase (a) after applying a single phase to ground fault in different locations along 200 Km between Misan -Kut stations and the current gradually decreases when the distance increases from the station and the voltage increases.

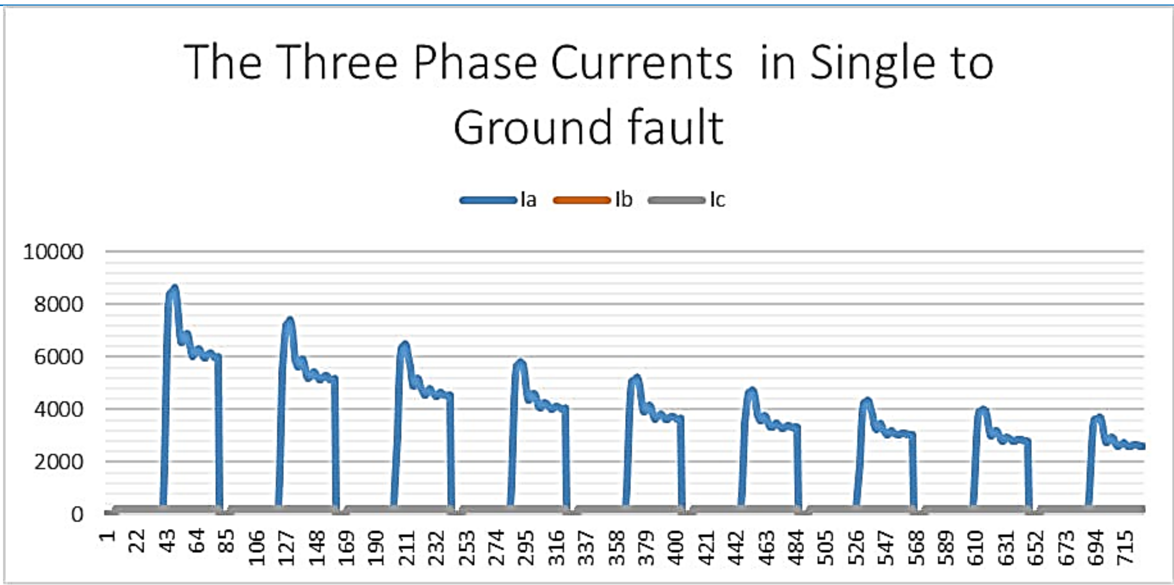

Fig.7 The Three Phase Currents in Single to Ground fault through nine cases along 200 Km between (Misan-Kut) station. (The x-axis indicates the NO. of data taken during the fault along 200 Km, y-axis indicates the values of the three-phase currents during the fault in different locations)

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

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

5. A Comparison with other techniques

An analysis of alternative methods for fault identification and localization in transmission lines, such as ANN (Artificial Neural Networks) and SVR (Support Vector Regression), in comparison with ANFIS (Adaptive Neuro-Fuzzy Inference System) Precision
It has been demonstrated that ANFIS and ANN algorithms perform better for defect local ization than other approaches in terms of accuracy. Fast fault localization execution times have been shown by ANFIS models. For defect localization, Compared to traditional me thods, the robustness of ANFIS and ANN models is more resilient to changes in operatin g conditions and system parameters. These methods are appropriate for transmission line fault diagnostics since they can manage complex and nonlinear interactions in the data. i nside a hybrid design, outcomes have been observed in defect detection, classification, an d localization when ANFIS is combined with other techniques including decision trees an d random forest algorithms. Performance can be further improved by hybrid approaches t hat combine the advantages of ANFIS with additional machine learning or signal processi ng techniques. Adaptability by modifying their parameters, ANFIS models can be made t

o account for newly available data or changing system conditions.
Because of its flexibility, ANFIS may be used in real-time applications and provides quic k defect localization and detection Table (4) shows the preference of ANFIS.
In conclusion, for fault identification and localization in transmission lines, ANFIS and A NN algorithms perform better in terms of accuracy, speed, robustness, and flexibility than other approaches like SVR. Hybrid strategies that combine ANFIS with additional metho ds can enhance performance even more. These cutting-edge techniques are essential for i mproving the dependability and durability of power transfer networks.

Table 4. Comparison between ANFIS and other Technologies.

Aspect	ANFIS	Other Technologies (e.g., ANN, SVR)
Training Time[15]	Trained quickly with consistent re sults	Longer training time, varying results
Performance[13]	Better performance in certain app lications	Varies depending on the technology
Accuracy	Accurate predictions in specific s cenarios	May provide more accurate predictions
Interpretability[16]	Transparent and interpretable	Interpretability may vary
Flexibility	Offers flexibility in system design	Varies based on the technology used
Application Suitabili ty	Suitable for forecasting and certai n tasks	Applicable in different scenarios
Memorization Error s[17]	Causes fewer memorization errors	May have higher memorization errors
Output Representati on	Output representation varies	Output representation differs
Ease of Use	User-friendly and easy to implem ent	Ease of use may vary
Prediction Errors	Predictions may have lower error s	Prediction errors may vary

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

In the following there are some advantages related to using ANFIS (Adaptive Neuro-Fuzzy Inference System) for defect localization and detection:
-Utilizes Illustrations Nonlinearity: Because ANFIS can capture a process's nonlinearity efficiently, it is a good fit for complicated systems where traditional approaches can have trouble[17].

-Automatic Adaptation Capability: ANFIS can automatically adjust to data changes, guaranteeing that the system continues to function properly even in dynamic situations.
-Rapid Learning Capacity: ANFIS can learn well and swiftly, which is critical in situations when quick learning is required[17].
-Excellent Generalization Capability: ANFIS can perform effectively on data that hasn't been seen because of its great generalization capability[18].
-High Flexibility: ANFIS's system design is very flexible, enabling a multitude of variations and making it appropriate for a broad range of applications.
-Interpretability: ANFIS is a useful tool for situations where it's critical to comprehend the decision-making process since it strikes a compromise between interpretability and accuracy[19].
-Fault Detection and Localization: The efficacy of ANFIS in locating and identifying faults has been demonstrated by its successful application in fault detection and localization along power transmission lines[20].
-Real-World Applications: The usefulness and efficacy of ANFIS have been demonstrated by its application in real-world settings, such as fault detection and localization in power transmission lines[21].
To sum up, ANFIS is an effective tool for defect identification and localization because of its many benefits, which include its capacity to capture nonlinearity, adjust to changing data, pick things up fast, and have a high degree of generalization ability.

6. Conclusions

In this study, a transmission line protection method fault localization and detection application ba sed on ANFIS is presented. The suggested method consists of three steps: data extraction, data te sting, and location accuracy checking with the table. 3. The transmission line faults are found an d detected in this study using the recorded RMS currents and voltages. The main conclusions of t his study that can be drawn from the above results are as follows: A novel computer program th at mimics a transmission line and calculates voltage and current for three-phase faults used in A NFIS testing and training has been developed. The ANFIS approach provides better localizatio n and defect detection accuracy, although requiring more computation. several tests carrie d out in a variety of Transmission line fault circumstances demonstrate the accuracy and less than 0.01% error rate of this technique. The data gathered show that the recommend ed approach yields precise estimations. The real values generated by the proposed techniq ue match the expected data, as shown by ANFIS simulations.
The output methodology based on ANFIS can be employed by the transmission line prot ection mechanism. Adaptive neural fuzzy inference (ANFIS) has been investigated in this work as a transmission line fault localization and detection technique. Finding the mean absolute value of the incorrect voltage and current signals from the 50 Hz three-phase tra nsmission line was the goal of a 400 kV, 200 km Matlab/Simulink model. 600 data sam ples of faulty voltage and current were gathered from various places along the transmissi on line to locate faults utilizing the module and apply ANFIS to identify problems. There are nine places along the route where the faults are dispersed (10%-90%). The subject was brought up, particularly the three-phase. Table 3 displays the data's training in terms of speed, reliability, and sensitivity. The accuracy rate for identifying defects was 100%, and the accuracy rate for localizing problems at many locations was 99.9%. Because fau lt identification time is a crucial component of fault protection, this work has concentrate d on speed of execution to enable rapid fault detection. Generally speaking, the ANFIS a pplication for fault detection and localization in power systems may assist in enhancing f ault management strategies and ensuring the stability and dependability of power systems. transmission lines. It is a trustworthy, precise, practical response.

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References

[1] P. S. P. Eboule, J. H. C. Pretorius, N. Mbuli, and C. Leke, "Fault detection and location in power transmission line using concurrent neuro-fuzzy technique," in *2018 IEEE Electrical Power and Energy Conference (EPEC)*, IEEE, 2018, pp. 1–6.
[2] F. Wang *et al.*, "Artificial intelligence techniques for ground fault line selection in power systems: State-of-the-art and research challenges," *Math. Biosci. Eng.*, vol. 20, no. 8, pp. 14518–14549, 2023.
[3] S. Singh, K. R. Mamatha, and S. Thejaswini, "Intelligent fault identification system for transmission lines using artificial neural network," *IOSR J. Comput. Eng.*, vol. 16, no. 1, pp. 23–31, 2014.
[4] M. K. Singla, J. Gupta, P. Nijhawan, and A. S. Oberoi, "Electrical load forecasting using machine learning," *Int. J.*, vol. 8, no. 3, 2019.
[5] R. Varghese P, M. S. P. Subathra, S. T. George, N. M. Kumar, E. S. Suviseshamuthu, and S. Deb, "Application of signal processing techniques and intelligent classifiers for high-impedance fault detection in ensuring the reliable operation of power distribution systems," *Front. Energy Res.*, vol. 11, p. 1114230, 2023.
[6] K. K. Mohammed, S. Buyamin, I. Shams, and S. Mekhilef, "Maximum power point tracking based on adaptive neuro-fuzzy inference systems for a photovoltaic system with fast varying load conditions," *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 6, p. e12904, 2021.
[7] S. F. Stefenon *et al.*, "Electrical insulator fault forecasting based on a wavelet neuro-fuzzy system. Energies 2020, 13, 484."
[8] O. Obanijesu and O. J. Emuoyibofarhe, "Development of Neuro-fuzzy System for Early Prediction of Heart Attack," *IJ Inf. Technol. Comput. Sci.*, vol. 9, pp. 22–28, 2012.
[9] D. Karaboga and E. Kaya, "An adaptive and hybrid artificial bee colony algorithm (ABC) for ANFIS training," *Appl. Soft Comput.*, vol. 49, pp. 423–436, 2016.
[10] A. Saxena, R. Bhatnagar, and D. K. Srivastava, "Software Fault Localization: Techniques, Issues and Remedies.," *IAENG Int. J. Comput. Sci.*, vol. 49, no. 2, 2022.
[11] S. Pearson *et al.*, "Evaluating & improving fault localization techniques," *Univ. Washingt. Dep. Comput. Sci. Eng. Seattle, WA, USA, Tech. Rep. UW-CSE-16-08-03*, p. 27, 2016.
[12] Q. I. Sarhan and Á. Beszédes, "A survey of challenges in spectrum-based software fault localization," *IEEE Access*, vol. 10, pp. 10618–10639, 2022.
[13] D. M. Habashy and H. I. Lebda, "Comparison between artificial neural network and adaptive neuro-fuzzy inference system for the baryon-to-meson ratios in proton-proton collisions," *arXiv Prepr. arXiv2209.12709*, 2022.
[14] M. S. Zaghloul, R. A. Hamza, O. T. Iorhemen, and J. H. Tay, "Comparison of adaptive neuro-fuzzy inference systems (ANFIS) and support vector regression (SVR) for data-driven modeling of aerobic granular sludge reactors," *J. Environ. Chem. Eng.*, vol. 8, no. 3, p. 103742, 2020.
[15] E. Y. A. Rodríguez, A. A. R. Gamboa, E. C. A. Rodríguez, A. F. da Silva, P. M. S. R. Rizol, and F. A. S. Marins, "Comparison of adaptive neuro-fuzzy inference system (ANFIS) and machine learning algorithms for electricity production forecasting," *IEEE Lat. Am. Trans.*, vol. 20, no. 10, pp. 2288–2294, 2022.
[16] M. Şahin and R. Erol, "A comparative study of neural networks and ANFIS for forecasting attendance rate of soccer games," *Math. Comput. Appl.*, vol. 22, no. 4, p. 43, 2017.
[17] S. Chopra, G. Dhiman, A. Sharma, M. Shabaz, P. Shukla, and M. Arora, "Taxonomy of adaptive neuro-fuzzy inference system in modern engineering sciences," *Comput. Intell. Neurosci.*, vol. 2021, 2021.
[18] G. Guariso and M. Sangiorgio, "Performance of implicit stochastic approaches to the synthesis of multi-reservoir operating rules," *J. Water Resour. Plan. Manag.*, vol. 146, no. 6, p. 4020034, 2020.
[19] W. Wu, Y. Zhou, and M. Leonard, "Evolutionary algorithm-based multiobjective reservoir operation policy optimization under uncertainty," *Environ. Res. Commun.*, vol. 4, no. 12, p. 121001, 2022.
[20] B. Jia, J. Zhou, X. Chen, Z. He, and H. Qin, "Deriving operating rules of hydropower reservoirs using Gaussian process regression," *IEEE Access*, vol. 7, pp. 158170–158182, 2019.

[21] Y. Liu *et al.*, “Deriving reservoir operation rule based on Bayesian deep learning method considering multiple uncertainties,” *J. Hydrol.*, vol. 579, p. 124207, 2019.

[22] K. Hussain, M. Salleh, and M. Najib, “Analysis of techniques for anfis rule-base minimization and accuracy maximization,” *ARPN J. Eng. Appl. Sci.*, vol. 10, no. 20, pp. 9739–9746, 2015.

[23] R. G. Moghadam, M. A. Izadbakhsh, F. Yosefvand, and S. Shabanlou, “Optimization of ANFIS network using firefly algorithm for simulating discharge coefficient of side orifices,” *Appl. Water Sci.*, vol. 9, no. 4, p. 84, 2019.