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Fault mitigation in an interconnected network using artificial intelligence technique

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Abstract

The reliability of an interconnected power network is critical for maintaining a stable and efficient power supply. This research focuses on the detection, classification and mitigation of faults on the Ibom power interconnected network comprising of three synchronous generators, assuming each generator generate a 40 MW power, with a total power capacity of 120 MW power after synchronization. The network transmits it power through four transmission stations, first Afaha-Ube sub-transmission station, which has a load offtake of 60 MW, Itu sub-transmission station with 20 MW, Eket sub-transmission station with 25 MW, and Ekim sub-transmission station with 15 MW. All the sub-transmission station received 132 kV and step it down to 33kV. The system was first analyzed under normal operating conditions before various types of faults were introduced at the Afaha-Ube Substation bus, these included single line-to-ground (A-G), double line-to-ground (AB-G), and three-phase-to-ground (ABC-G), faults. To enhance fault detection, classification and system protection, current signals only were obtained through discrete wavelet transform (DWT). These signals were fed as input to train the ANFIS to properly detect and classified each fault type The ANFIS model was also trained to analyze fault current patterns and trigger a trip signal to the circuit breaker for fault isolation. Although faults persisted from 0.8 to 1.6 seconds, ANFIS was optimized to identify the fault and send a trip signal at 1.2 seconds, effectively mitigating damage and improving network stability. The result obtained shows that ANFIS successfully trip the Afaha-Ube bus station at exactly 1.2 seconds.

Keywords: Ibom Power Network; Fault Detection and Classification; Synchronous Generators; Discrete Wavelet Transform; ANFIS; Mitigation; MATLAB/Simulink

1. Introduction

Power system networks are critical infrastructures required for the generation, transmission, and distribution of electrical energy to consumers [1]. But electrical faults are common in these networks and can lead to equipment damage, power outages, and system instability if not detected and addressed quickly. Synchronous generators provide a critical foundation to power stability in integrated energy systems. A synchronous generator (also known as an alternator) is an electrical generator that converts mechanical energy to electrical energy in the form of alternating current (AC). According to [2] describe the synchronous machine is considered the more crucial part nature of the power system makeup in transmission, distribution and generation stations in the power system grid in the world. In as much as the reliability of the generation systems were high, the issues of fault occurrence in power plants have always been a major concern in the power engineering field [3, 4]. This was due to the fact that the occurrence of faults in the power generation systems results in automatic blackout except in situations where there was a backup or distribution generator [5, 6, 7].

Power system can be protected by using a relay at both ends of the power network that continuously monitor voltages and currents and react to a fault. The most commonly used power system protection method is the distance protection, which has a line safety of approximately 85% [8, 9]. Using phasor-based methods in the protection system has certain

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drawbacks: first, the delay in relay operation causes uncertainty in voltage protection; second, a communication link between the relays at the two ends of the line is required [10, 11]. Researchers have presented several methods for power system fault detection, classification and location, the broader categories are mentioned here: Conventional methods, Signal processing-based methods, and Artificial intelligence-based methods.

Conventional techniques such as the travelling wave method and the impedance measurement-based method are frequently employed for the identification, categorization, and localization of transmission line faults [12, 13]. The current and voltage signals collected from a transmission line terminal are used to suggest single-end or two-end impedance techniques [14]. The impedance-based method's fault location error is high because of the high fault impedance, line load, source characteristics, and shunt capacitance [15]. By comparing the forward and backward propagation of waves in a power system, the travelling wave-based method determines the fault's distance. Finding faults in high resistance faults is more accurate with this method. However, the difficulties that make practical use difficult are the high frequency of sampling, high cost, and computational complexity [16].

Several signal processing methods such as Fourier transform (FFT), wavelet transform (WT), multi resolution analysis (MRA), and discrete wavelet transform are the famous methods for fault detection and classification in power system. WT can detect and identify fault characteristics more accurately by using a faulty waveform's decomposed frequency components [17]. FFT signal is needed in the stationary broad sense to calculate the coefficients more proper and precise. Moreover, most signals in power systems are flexible and fluctuate over time concerning their properties [18]. Multi resolution analysis (MRA), a signal processing tool, was established in the nineties. To address several issues with Fourier, transform analysis techniques,[19, 20]. Discrete wavelet transforms (DWT), which originated from discrete variant of the wavelet transform (WT), is one of most widely use tool to analyze discrete or sampled signals. The demand for DWT techniques in digital relaying systems has been rising recently in an era of digital communication and analysis [10]. Several AI-based fault detection, classification, and Location techniques, such as ANN, Fuzzy logic, and hybrid algorithms using integrated wavelet transform ANN, SVM, and fuzzy logic, have been used for the past few years safety of power systems [21, 22].

Adaptive Neuro-Fuzzy Inference System (ANFIS), have long been effectively employed in a number of fault analysis investigations. The most valuable feature of ANFIS is its capacity for autonomous learning valuable fault feature[23].

Authors in[24] suggested an ANN base fault classification and location of power transmission lines. Different fault types such as single-phase to ground, two-phase, two-phase to ground and three-phase were considered. The variation of fault resistance was considered, too. The output of the ANN was the estimated fault location with two machine power system model and simulation carried out in PSCAD/EMTDC to obtain the mentioned voltages and currents values. The neural network toolbox of MATLAB was used for training and testing of ANN.

[25] Incorporates adaptive neuron-fuzzy inference system and back propagation neural network, for fault detections, classification, and localization in transmission lines. The IEEE 9-bus system was utilized to obtain data from one end of the transmission line to develop an ANFIS-based model. The result shows that all four techniques used performed well for fault classification, detection, and location. However, the percentage error for the ANFIS-based fault model was less compared to back propagation, self-organizing map, and discrete wavelet transform with ANFIS.

Authors in [26, 27] propose the use of three-phase distance relay using an adaptive neuro-fuzzy inference system algorithm (ANFIS). The proposed relay was used to protect the power transmission lines where they are subjected to faults continuously. Isolation of faulty line without affecting the other lines within the network the relays were trained using adaptive neuro-fuzzy inference system (ANFIS). The obtained results shows that the designated distance relay with (ANFIS) algorithm has the ability to detect the faults occurrence, recognize it from the cases of the disturbance and to isolate only the fault zone without affecting the work of other relays in system[28].

The combination of wavelet and adaptive neuro-fuzzy inference (ANFIS) technique for fault location and identification in a distributed system was propose in[29], discrete wavelet transform (DWT) was used to represent the signal. The extracted features from the dataset were send to the ANFIS classifier to classify all fault type that occurred in the distributed power systems. The results were compared with the existing techniques such as DWT-FFNN and DWT-RBFNN methods.

Similarly, authors in[30] suggest a protection algorithm based on the joint framework of discrete wavelet transform (DWT) and adaptive neuro-fuzzy inference system (ANFIS) for PV integrated microgrid with non-linear load. Approximate co-efficient of voltage and current signals were obtain through discrete wavelet transform (DWT). These signals were fed as input to the train the ANFIS model separately for the islanded and grid-connected mode. The test result analysis and performance comparison with ANN clearly validate the reliability and effectiveness of the scheme in imparting possible protection to the microgrid.

Author in [31] suggest a neuro-fuzzy method for examining power system fault location estimates. The aim center on creating a model for a 264 km, 132 kV, 50 Hz transmission line using MATLAB Simulink simulation software to simulate different faults. The ANFIS was trained using wavelet-processed data from the power system including the signal's fine-grained features, from both ends of the line.

Machine learning methods such as Adaptive Neuro-Fuzzy Inference System (ANFIS) was discussed in [32]. A combined Wavelet and ANN based fault location scheme was compared with ANFIS. The test results show that fault identification and location estimation was very accurate with average percentage error standing within 0.001%. In [33], the voltage and current features signals extracted using discrete wavelet transform was fed to the Adaptive neuro-fuzzy inference system (ANFIS) based fault locator to estimate the location of the fault.

Authors in [34] suggest the use of ANFIS and ANN for classification and localization of faults in a lengthy transmission line. The current and voltage data extracted from the source end were fed to ANFIS and ANN network to precisely identify fault types and pinpoint the transmission line issue. The result show that artificial intelligence-based machine learning techniques do better in specific tasks than other approaches.

Authors in [35] suggest the combination of discrete wavelet transform (DWT) and a Taguchi-based artificial neural network (ANN) for fault detection, classification, the three-phase fault voltages, and three-phase fault currents, were fed as an input to the ANN. The result shows that the ANN identifies and identifies the faulty phase and the location of the fault.

ANFIS has emerges as a promising solution in this context of fault detection, classification and location in a power system, but fault mitigation still poses a serious treat in the modern-day power system. Considering the mentioned restrictions, a new relaying technique is required for efficient fault mitigation in the power system network. This technique helps the power system to operate without complete breakdown of the system network. Therefore, this paper presents a hybrid Artificial Intelligence (AI) based technique that uses only current for fault detection, classification, and mitigation. Current signals were obtained through discrete wavelet transform (DWT). These signals were fed as input to the train the ANFIS to properly detect and classified each fault type. Ibom power plant 7-bus system that comprises of three synchronous machines assuming to generate 40MW each with a 132kV transmission line were used for the analysis.

The significance of this research will aid power engineers to determine ways of mitigating the fault impact in the power system to prevent power shut down. The study will be used as a base for further research on the importance of artificial intelligent model on fault analysis of generation plants and would aid in the improvement of the reliability of the synchronous plant inter-connected to other power system components.

2. System Studied

The Ibom power interconnected network is used as a study model in this paper. The power network consists of three synchronous generators, four transformers, five buses, four transmission lines, and four loads, the single diagram is shown in Fig. 1. It is assumed that each generator generates 40 MW power, with a total power capacity of 120 MW after synchronization. The network transmits it power through four Sub-transmission stations, first Afaha-Ube sub-transmission station, which has a load offtake of 60 MW, Itu sub-transmission station with 20 MW, Eket sub-transmission station with 25 MW, and Ekim sub-transmission station with 15 MW.Each sub-transmission station received 132 kV, which they subsequently reduced to 33 kV. To put the suggested ANFIS-based fault detection, classification, and mitigation strategies into practice, this system is simulated using MATLAB/Simulink version 2016a.

2.1. Adaptive Neuro-Fuzzy Inference System

The hybrid learning algorithm ANFIS makes optimal use of fuzzy logic and ANN. Adaptive networks are multilayer networks in which the applied data set determines the specific function that each node performs. Every node has a unique process. ANFIS is able to identify the output and distinguish between each input feature as a result. Some benefits that make ANFIS superior for complex problems include improved generalization ability, experience-based learning, and decision-making ability. These make ANFIS the most useful tool for identifying, locating, and classifying power system faults. This method outperforms other networks in terms of accuracy.

A multilayer feed forward network known as adaptive network permits each node to perform some unique function based on the incoming signals gather for set of specific parameters to that node. The node formula function may be differ from one node to another based on the set of parameters used, and the selection of each node formula function depends on the entire input and output function that the adaptive network must perform as shown in Fig. 2. In an adaptive network it should be noted that connections do not carry weights; but rather, they simply represent each signal flow direction between nodes [36].

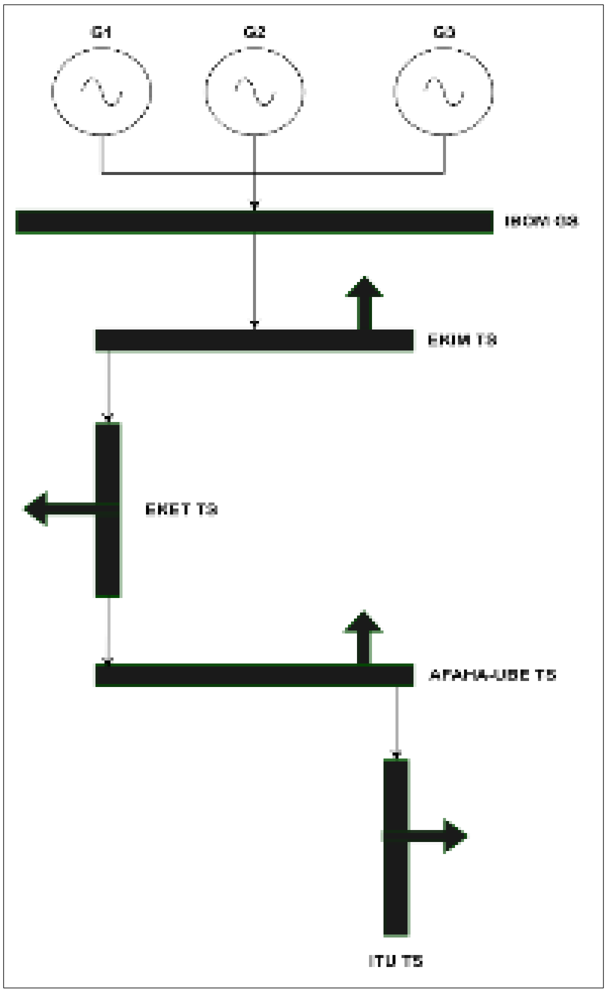

Figure 1 Ibom power interconnected network

ANFIS construction is made up of Fuzzy Interface System (FIS) whose membership function of parameters was altered using various methods, such as the back propagation algorithm or the least squared approach as shown in Fig. 2. ANFIS is significantly more sophisticated compared to fuzzy inference systems, that offered only by all fuzzy system possibilities.

ANFIS exclusively used the Sugeno-type fuzzy rule to map out neural network architectures and training mechanism. The number of output features are compatible with the Sugeno-type fuzzy rule because it is easier to optimize using gradient descent and other learning algorithms.

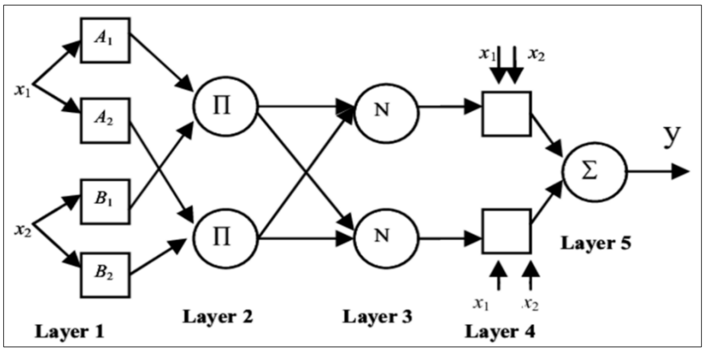

Figure 2 ANFIS architecture with input features [36]

The mathematical expression of an Adaptive Neuro-fuzzy inference system with one prediction (output) y and four inputs x1(current A) x2(current B) x3(current C) x4(current G) is defined below [37]

2.1.1. If the rule base has four Takagi and Sugeno-type fuzzy then rules are

Rule 1

$$f\ x_1\ is\ A_1, x_2\ is\ B_1, x_3\ is\ C_1, x_4\ is\ D_{1,}$$

Then

$$f_1 = p_1 x_1, + q_1 x_2 + r_1 x_3 + s_1 x_4 + t_1$$

Rule 2

$$if\ x_1\ is\ A_2, x_2\ is\ B_2, x_3\ is\ C_2, x_4\ is\ D_{2,}$$

Then

$$f_2 = p_2 x_1, + q_2 x_2 + r_2 x_3 + s_2 x_4 + t_2$$

Rule 3

$$if\ x_1\ is\ A_3, x_2\ is\ B_3, x_3\ is\ C_3, x_4\ is\ D_{3,}$$

Then

$$f_3 = p_3 x_1, + q_3 x_2 + r_3 x_3 + s_3 x_4 + t_3$$

Rule 4

$$if\ x_1\ is\ A_4, x_2\ is\ B_4, x_3\ is\ C_4, x_4\ is\ D_{4,}$$

Then

$$f_4 = p_4 x_1, + q_4 x_2 + r_4 x_3 + s_4 x_4 + t_4$$

2.1.2. The ANFIS structure with five layers is given as follows

Layer 1

Each node has a node function i in this layer. An adaptive node is present in this labeling. The membership grade of an input layers executes the output, which is given as follows

$$O_{i,1} = \mu A_1(x_1), \qquad \mu B_1(x_2), \qquad \mu c_1(x_3), \qquad \mu D_1(x_4),$$

where A represent the linguistic label connected to this node while $O_{i,1}$ is the membership function of $\mu A_1(x_1)$. Each membership function (MF) is changed according to the layer's parameter

Layer 2

The nodes in layer two are fixed, with the node symbol π, this denotes and perform function as a multiplier. Each input signals represent multiplies of each node layer; the firing strength of each rule can be determined before sending the result out. The equation is given as follows

$$O_{i,2} = w_i = \pi_{j=1}^{m} \mu A_1(x)$$

Layer 3

As can be seen in Fig. 2, this layer is likewise a fixed nodes layer, and the firing strength has been normalized from the previous layer. The marked node is indicated by N. The following is the equation for this layer

$$O_{i,3} = \overline{\omega} = \frac{w_i}{w_1 + w_2}$$

Layer 4

Layer four is an adaptive layer node, where the output parameters are modified. The first-order polynomial is combined with the normalized firing strength to serves as an output, which, can be processed for each node in the layer. The layer's outputs are then provided as follows

$$O_{i,4} = \overline{W}_i f_i = \overline{W}_i (p_i x_1 + q_i x_2 + r_1 x_3 + s_1 x_4 + t_i) i = 1, 2, 3 \ldots.$$

Layer 5

In layer five, the previous layer is imported together to get all the predicted inputs and output values. All of the layers' output is provided by

$$O_{i,5} = \sum_i y_i$$

$$O_{i,5} = \sum_i \overline{\omega}_i f_i = \overline{\omega}_1 (p_1 x_1) + \overline{\omega}_1 (q_1 x_2) + (\overline{\omega}_1 r_1) + \overline{\omega}_2 (p_2 x_2) + \overline{\omega}_2 (q_2 x_2) + (\overline{\omega}_2 r_2)$$

The final equation can be expressed as follows: In this last layer, the following parameters can be solved using a least squares technique

$$y = [w_1 x_1 w_1 x_2 w_1 w_2 x_2 w_2] \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} = XW$$

The flow diagram for ANFIS techniques is shown in Fig. 3. The following steps are taken for the ANFIS model.

- Step 1 Decide which power system region to study. For this investigation, the region between the Itu and Afaha-Ube sub-transmission stations has been chosen.
- Step 2 Create a fault between the sub-transmission stations Itu and Afaha-Ube, then record the current values from one end.
- Step 3 All fault conditions should be applied, including ABC-G, ABC, AB-G, AC-G, BC-G, AB, AC, BC, A-G, B-G, C-G, and no-fault.
- Step 4 Extract both the faulty and no-fault current data using DWT for ANFIS training.
- Step 5 identifies the faulty current data.
- Step 6 Select the structure of ANFIS for fault detection and classification.

- Step 7 Define the fuzzy interface structure (FIS) for proper testing and training.

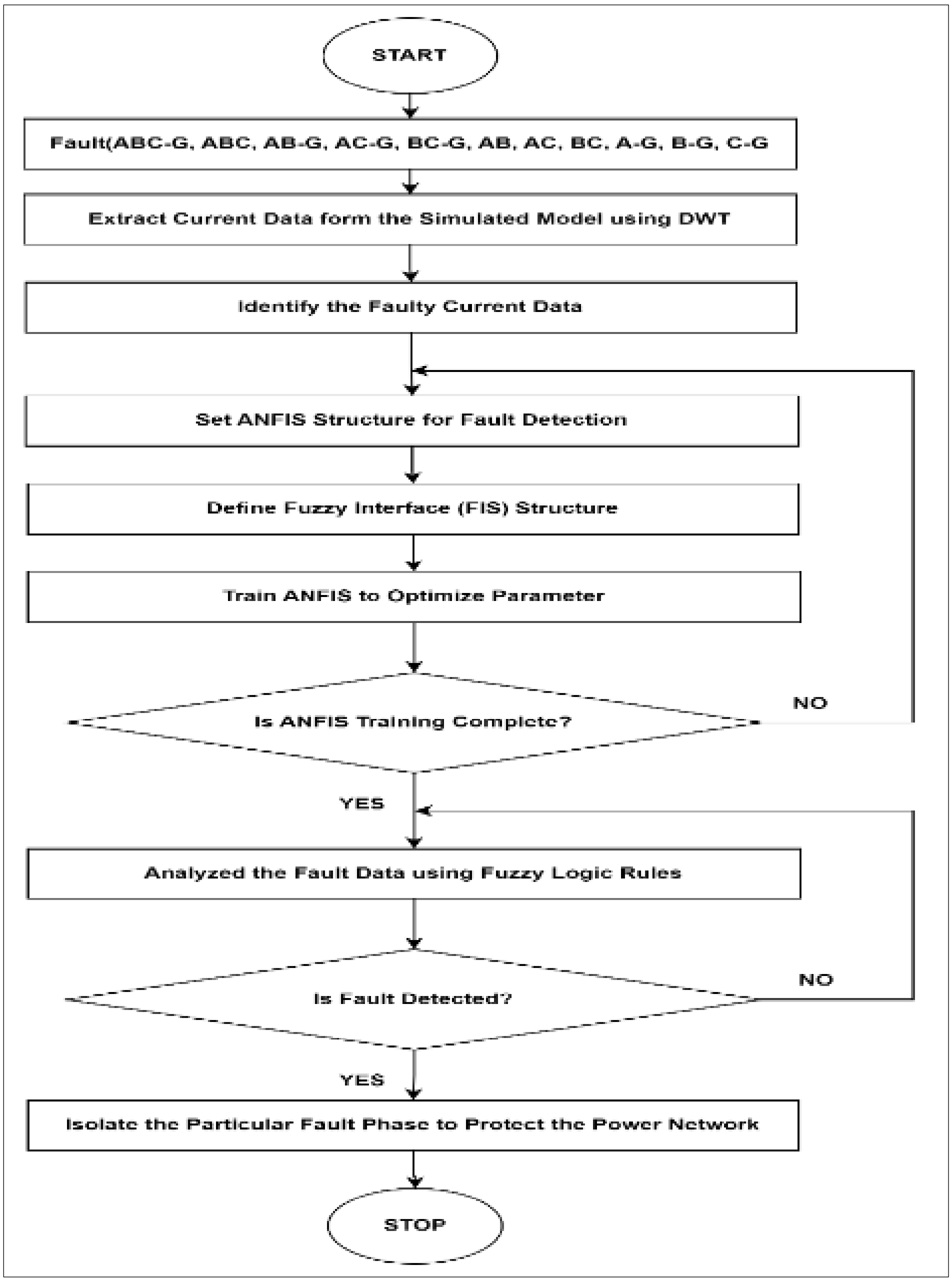

Figure 3 Flow diagram for ANFIS technique

- Step 8. Train ANFIS with the dataset.
- Step 9. After training, analyzed the data to see if fault is detected.
- Step 10. If fault is detected and classify, isolate the particular fault phase in other to protect the power system.

3. Material and methods

3.1. Data Acquisition

The data acquired includes three synchronous generators at each generating 40MW with a total of 120MW when synchronize together and transmitting at 132kV. There are four transmission stations on the interconnected network that send to the Ekim 132/33kV sub-transmission station with a 15MW load offtake. These transmission stations pass through the Eket 132/33kV sub-transmission station with a 25MW load offtake, the Afaha-Ube 132/33kV sub-transmission station with a 60MW load offtake, and the Itu 132/33kV sub transmission station with a 20MW load offtake. Tables 1 and 2 display the bus data and bus numbering for the power system.

Table 1 Bus Data of the Ibom power network used as input for the Simulation

Bus Identification		Voltage (kV)	Generator		Load	
Name	No		MW	Mvar	MW	Mvar
Bus	1	132	40.00	15.00	0.00	0.00
Bus	2	132	40.00	15.00	0.00	0.00
Bus	3	132	40.00	15.00	0.00	0.00
Bus	4	33	00.00	00.00	15.00	5.00
Bus	5	33	00.00	00.00	25.00	10.00
Bus	6	33	00.00	00.00	60.00	20.00
Bus	7	33	00.00	00.00	20.00	5.00

Table 2 Bus Numbering of the Ibom Power System

Bus location	Bus number	Bus voltage (kV)
Ibom power plant	1	132
Afaha-Ube	2	132/33
Itu	3	132/33
Eket	4	132/33
Ekim	5	132/33

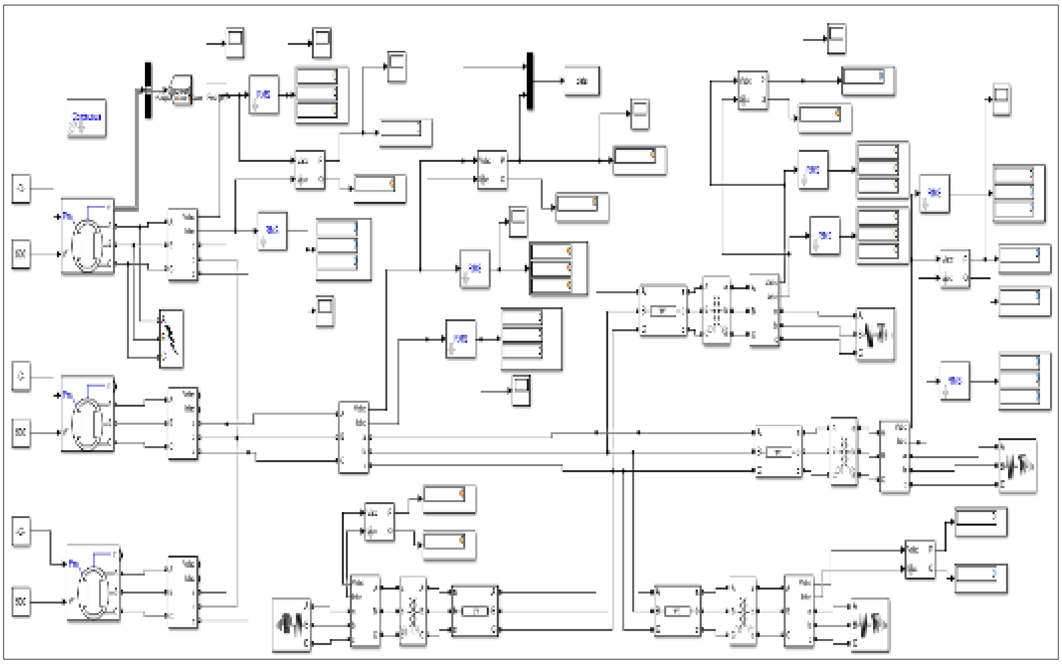

Figure 4 Ibom Power Interconnected Network

The Ibom power interconnected network was modeled in MATLAB/Simulink simulation software using the obtained data in table 1 and 2. The network consists of three synchronous generators at each generating 40MW. The generators are synchronized together to give a total output power of 120MW as presented in Fig 4. The generated power is then transmitted to four sub-transmission station at different offtake. The current signal of the transmission network at healthy and faulty condition was obtain.

3.2. Training and Testing Data

For training neural network models, input and targets need to be organized for a given task. Training and testing namely are the two fundamental procedures in a Neural network with the input data and target data to predict the future, in that case, the fault detection, and fault classification. Table 3 describes the input and output data used for training and testing. ANFIS-based models were trained using data obtained from bus number 4 in the Ibom power connected system after simulating eleven types of disturbances and normal condition. A-G, B-G, C-G, AB, BC, CA, AB-G, BC-G, CA-G ABC, and ABC-G faults are the eleven fault cases consider. All these faults were created at Afaha-ube sub-transmission station in between bus no. 3 and bus no. 4 in interconnected network model at its best in MATLAB/Simulink platform.

Training and testing data, in the form of root mean square values of three-phase current obtain through DWT, were collected and preprocessed for the next step. For the development of ANFIS-based fault detection, classification, and mitigation models, a Fuzzy C-mean (FCM) Clustering algorithm is used. The total clusters used are 50, and the total membership for each cluster is 50, too. The Gaussian input membership function is further used as a membership function for input

After generating a trained ANFIS network for fault detection, classification, and mitigation, the trained network was saved and used with the simulated model to get the results.

Table 3 Sample data set for the ANFIS-based fault detection, classification, and mitigation

	Input	**data**			**output**	**data**
Fault	Ia	Ib	Ic	Ig	detection	classification
ABC-G	1.609e+2	1.602e+2	1.609e+2	1.502e+2	1	1
ABC	1.607e+2	1.605e+2	1.607e+2	120.534	1	2
AB-G	1.079e+2	1.133e+2	119.524	1.262e+2	1	3
AC-G	1.980e+2	135.564	1.973e+2	1.973e+2	1	4
BC-G	103.985	1.172e+2	1.148e+2	1.161e+2	1	5
AB	1.080e+2	1.033e+2	119.564	130.520	1	6
AC	1.336e+2	135.560	1.343e+2	130.434	1	7
BC	103.985	1.075e+2	1.087e+2	130.341	1	8
A-G	1.352e+2	103.984	119.524	1.418e+2	1	9
B-G	103.985	1.102e+2	119.564	1.123e+2	1	10
C-G)	103.987	103.984	1.409e+2	1.503e+2	1	11
No faults	103.957	103.944	104.926	104.935	0	0

3.3. Fault Type Classification

For efficient fault classification, various types of faults are considered in this paper as shown in table 4. Proper fault classification provides and insight of various types of faults that can occur in electrical power system. It also helps to diagnose and manage the fault more effectively in other to ensure power system stability. The most frequent and usually easiest to identify and fix are single line-to-ground faults, whereas line-to-line, double line-to-ground, and three lines-to-ground faults are more severe and can cause major disruptions. Each fault type represents a distinct scenario of electrical disturbance.

Table 4 Type of Faults

Type of Faut	Phase A	Phase B	Phase C	Ground G
ABC-G	√	√	√	√
ABC	√	√	√	×
AB-G	√	√	×	√
AC-G	√	×	√	√
BC-G	×	√	√	√
AB	√	√	×	×
AC	√	×	√	×
BC	×	√	√	×
A-G	√	×	×	√
B-G	×	√	×	√
C-G	×	×	√	√
No faults	×	×	×	×

The most severe fault in an electrical power system is three-phase fault, it causes a major power outages or equipment damage to the power system or end user when occur. This classification will aid to design a suitable protective relays or fault management systems, to quickly and accurately identify, classify and mitigate the fault in the power system in other for the power system to maintain stability.

3.4. Fault Detection

The fault is detected by the ANFIS based fault-detection model during processing of the three-phase current signal.The three-phase post-fault current RMS values used in the fault detection model.The output state of FDM is defined as two binary (1) or (0).That indicates a fault, and a similar 0 will indicate no fault too.Given four inputs (three-phase current with ground) and one output to indicate the fault, a detection problem is being described.

4. Simulation results and discussions

4.1. Simulation and Analysis of the Model System Without

The design, simulation and analysis of the power generation station using synchronous machines was carried out to analyze the performance of the system in terms of generation, synchronization, and power distribution without fault. -The simulation results shown that without fault, the efficiency of the system maintain a stable operation by ensuring the required power is delivered to each substation. The system consists of three synchronous generators; each rated at 40 MW. The simulation verified that each generator operates at its maximum capacity, delivering an active power output of 40 MW. This indicates proper excitation and synchronization within the generators. The result presented in Fig. 4 shows that during no-fault condition, the power system operates under normal steady-state conditions, and the three-phase current waveforms remain stable and balanced. Since no disturbances are present in the system, the current flow follows the expected sinusoidal pattern, with no significant fluctuations or distortions.

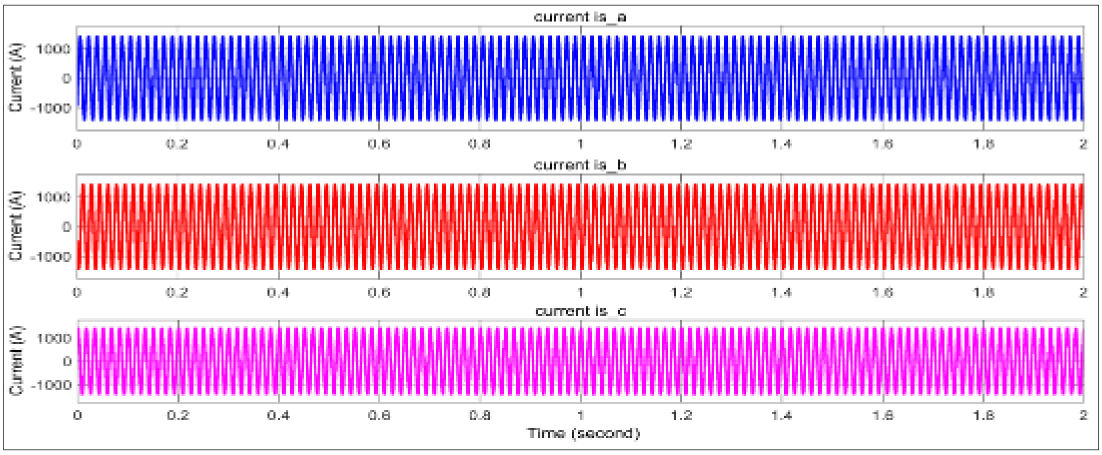

Figure 5 Simulation result of the model system without fault

As seen in Fig. 4, the three-phase currents (Phase A, Phase B, and Phase C) maintain their expected sinusoidal shape and magnitude, indicating that the system is operating efficiently. There are no significant deviations or sudden spikes in the current waveforms, confirming that there are no faults or disturbances affecting the network

4.2. Simulation and Analysis of the Model System with Fault (Current)

To assess the performance and resilience of the power system under fault conditions, the output waveform of the current was analyzed with different fault case such as single line-to-ground fault (L-G), double line to ground fault (L-L-G), and three lines to ground fault (L-L-L-G), using the Afaha-Ube Substation as the case study. The fault scenario was analyzed over a 2-second simulation time, divided into three phases. Pre-fault condition (0-0.8 second), the system operated normally with no faults. Fault condition (0.8-1.6 seconds), three types of faults were injected into the system. Post-fault condition (1.6-2 seconds), the fault was cleared, and the system returned to normal operation as seen from Fig (6-8).

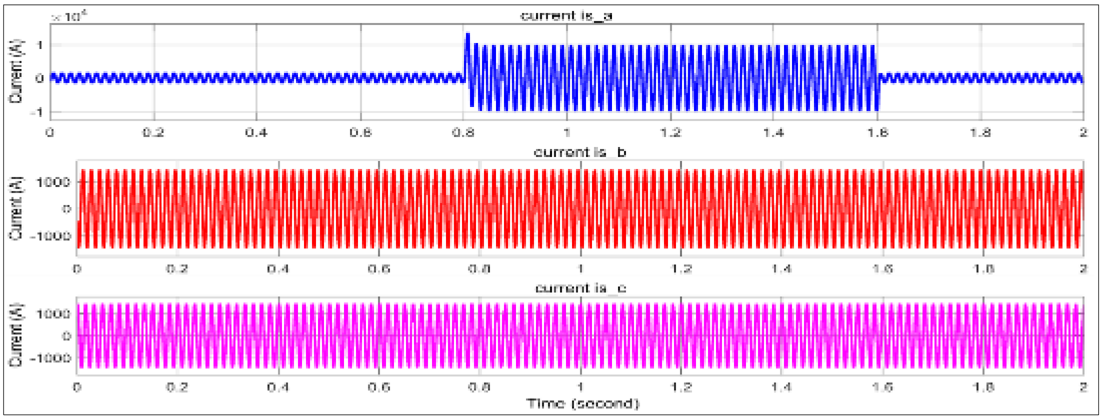

Figure 6 Simulation result of the model system single line-to-ground (A-G) fault

As seen in Fig. 4. At 0.8 seconds, the phase A current suddenly spikes, indicating that a fault has occurred, while phase B and phase C currents remain normal, as they are not directly involved in the fault. At 1.6 seconds, the fault was cleared, with phase A current returning to normal operating condition, restoring balance in the system.

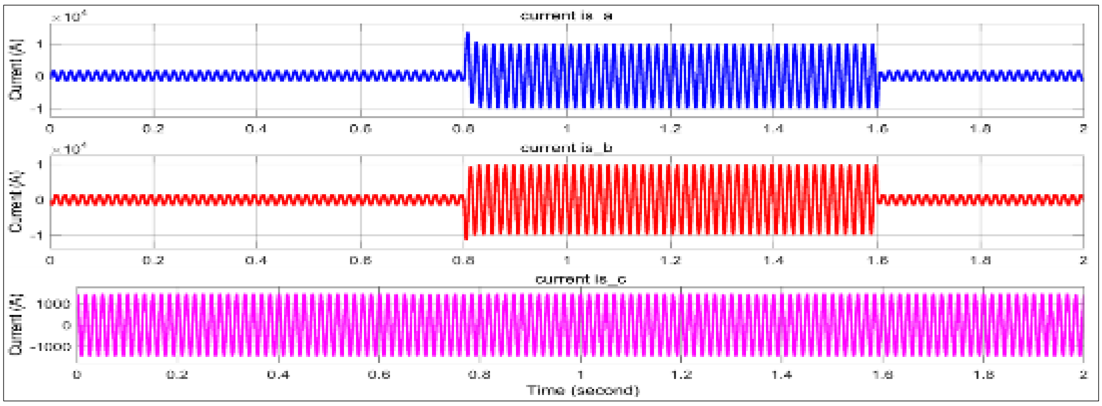

Figure 7 Simulation result of the model system double line-to-ground fault (AB-G)

As seen in Fig. 6. When a phase A and B to Ground (AB-G) fault was introduced, both phase A and phase B experienced a sudden spike in current, while Phase C remained unaffected. This type of fault occurs when two phases come into direct contact with the ground, creating a low-impedance path for fault current.

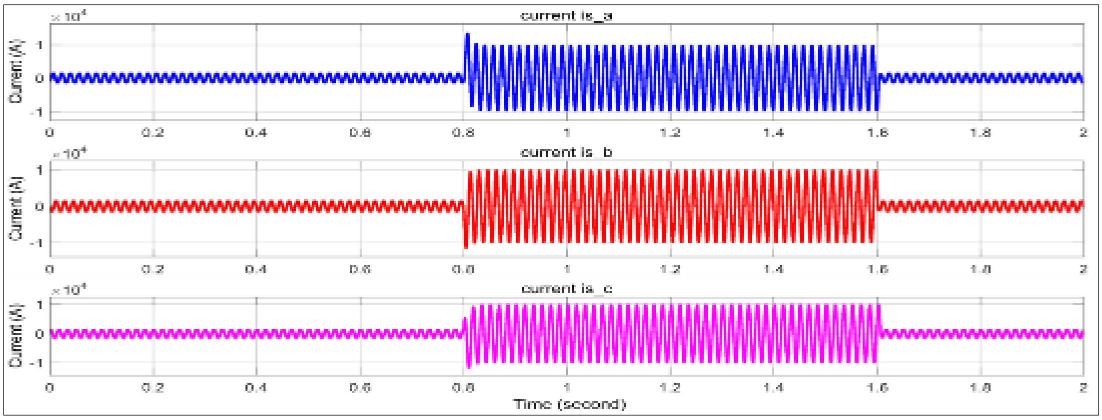

Figure 8 Simulation result of the model system three line-to-ground fault (ABC-G)

As seen in Fig. 7, when a three-phase to Ground (ABC-G) fault was introduced, all three phases (A, B, and C) experienced a sudden spike in current, indicating a highly severe fault condition. This type of fault occurs when all three phases come into direct contact with the ground, creating a very low impedance path for fault current, making it one of the most dangerous faults in a power system.

At 1.6 seconds, the fault was cleared, and the phase A, phase B, and phase C currents return to normal, and system balance was restored. The power system resumes its normal operation, ensuring power stability and continuous supply to all substations.

4.3. Fault Mitigation and Protection Using ANFIS

To enhance the stability and reliability of the power system, Adaptive Neuro-Fuzzy Inference System (ANFIS) was implemented for fault mitigation and protection. ANFIS combines the learning capabilities of Artificial Neural Networks (ANNs) with the rule-based reasoning of Fuzzy Logic, allowing for an intelligent and adaptive fault detection and response system. After successfully training the Adaptive Neuro-Fuzzy Inference System (ANFIS) for fault detection and classification, the trained system was integrated into the power network as a protective relay mechanism. The ANFIS model was configured to detect, classify, and respond to faults by sending a trip signal to the circuit breaker when critical faults occurred. The trained ANFIS Network is presented in Fig.9.

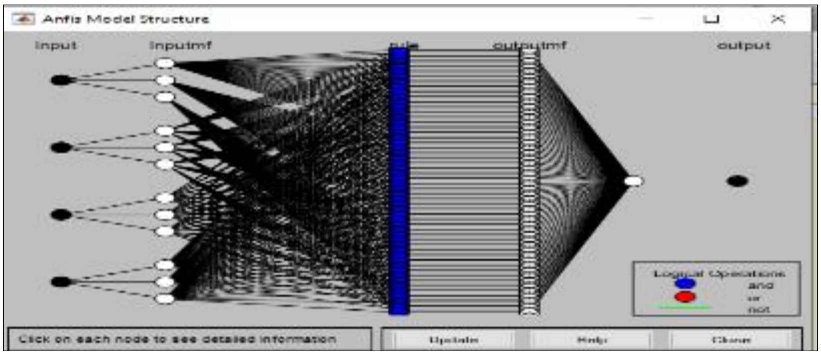

Figure 9 ANFIS Structure with 4 inputs output showing all the 5 layers in ANN architecture

The system operated normally from 0 to 1 second. Faults were introduced at 1.0 seconds, and it persisted until 1.6 seconds. The trained ANFIS system was configured to send a trip signal at 1.4 seconds, ensuring timely disconnection of the faulty section to protect the network as presented from Fig (10-12)

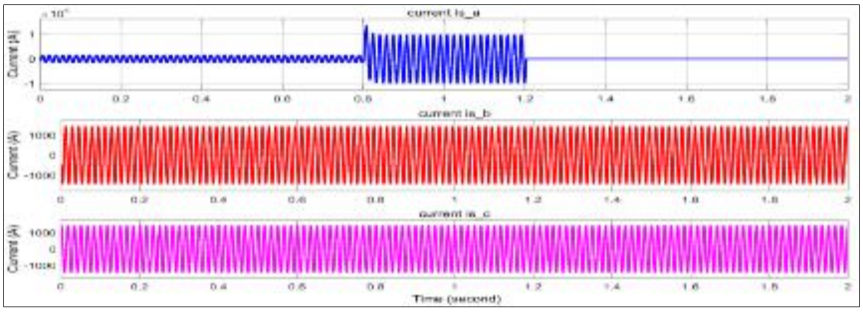

Figure 10 Single line-to-ground (A-G) fault with ANFIS protection

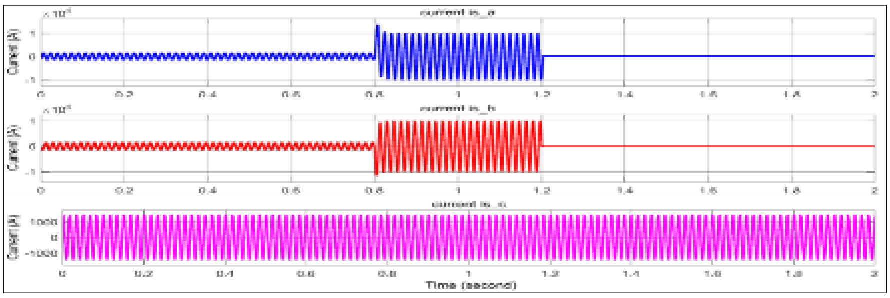

Figure 11 Double line-to-ground (AB-G) fault with ANFIS protection

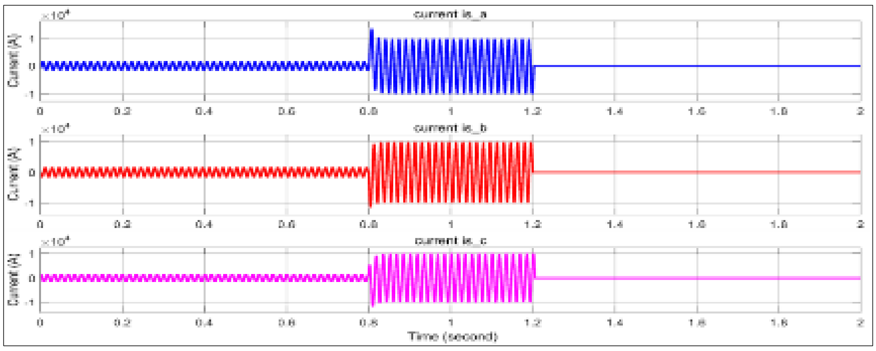

Figure 12 Three line-to-ground (ABC-G) fault with ANFIS protection

As seen from Fig (9-11), the integration of the ANFIS-based protection system significantly improved fault response in the power network. By classifying faults in real-time and sending a timely trip signal at 1.2 seconds, the system effectively prevented prolonged damage and ensured operational stability. This demonstrated the effectiveness of AI-based protection in modern power systems.

5. Conclusion

This research successfully investigated the mitigation of faults on synchronous generators in an interconnected power network using an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based protection scheme. The study followed a structured approach to achieve the outlined objectives, leading to significant findings that contribute to enhanced fault detection, classification, and protection in power systems.

First, data acquisition was carried out, detailing the network configuration, which includes three synchronous generators (each generating 40 MW, totaling 120 MW) and four transmission stations feeding multiple substations. This data was used to develop a Simulink model of the interconnected network, ensuring an accurate representation of real-world power system dynamics.

The system was simulated under normal conditions, confirming its stable operation. Various fault scenarios, including single line-to-ground (L-G), double line-to-ground (L-L-G), and three-phase-to-ground (L-L-L-G) faults, were then introduced and analyzed the system behavior with current.

To enhance fault detection and classification, ANFIS was implemented to intelligently identify and classify faults based on the maximum current coefficients of each phase and the ground. The trained ANFIS model demonstrated high accuracy in detecting faults and effectively sending a trip signal to the circuit breaker at 1.2 seconds, minimizing the impact of faults that persisted from 0.8 to 1.6 seconds. The trained ANFIS model was use to mitigate the fault

Additionally, ANFIS-based mitigation strategies were applied to protect the power system network at current output only. The system demonstrated improved fault isolation and recovery times, reducing the likelihood of prolonged disruptions and potential damage to the generators and transmission infrastructure.

In conclusion, this research successfully achieved its objectives, demonstrating that ANFIS is an effective tool for fault detection, classification, and mitigation in synchronous generator-based interconnected power networks. The findings highlight the potential of AI-driven protection systems in enhancing grid reliability, reducing downtime, and improving the overall stability of modern power systems.

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