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Protection for 330 kV transmission line and recommendation for Nigerian transmission system: a review

Vincent Nsed Ogar, Kelum A. A. Gamage, Sajjad Hussain
Department of Electrical and Electronic Engineering, James Watt School of Engineering, University of Glasgow, Glasgow, United Kingdom

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ABSTRACT

The transmission line is an integral part of the electrical power system; however, a fault has a negative impact on the system, like blackout, power loss, financial losses, and socio-economic impact. This fault occurs due to ageing conductors, lightning stroke, switching surge and human interference. We reviewed the protection scheme implemented in the Nigerian transmission network, which has challenges relating to the environment's terrain and a long-distance transmission line of about 20,000 km. The different approach of fault classification, detection and location was analyzed and critically summarized. This review paper proposes a hybrid artificial neural network (ANN) and distance protection scheme that can automatically identify, locate, isolate, predict, correct faults, and real-time monitor and control the entire network. It can also detect the shortest possible trip time of 0.02 s and 0.03 s of line current and fault losses, respectively, during fault to avert damage on the line. However, this method has its challenges, such as the volume of data generated from load flow analysis, training time, and the total distance covered by the network. However, these can be averted by segmenting the entire network for easy evaluation and monitoring to achieve set goals.

Corresponding Author:

Vincent Nsed Ogar
Department of Electronic and Electrical Engineering, James Watt School of Engineering, University of Glasgow
Glasgow G12 8QQ, United Kingdom
Email: v.ogar.1@research.gla.ac.uk

1. INTRODUCTION

The transmission of electric power involves the delivery of electricity to consumers from the generating station, and it serves as a middleman from the power plant to the distribution substation, which is closer to the end-users. The power system helps in transferring bulk electric power to end users, and the protection of the entire line cannot be overemphasized. This is because majority of the power system flaws occurs within the transmission line [1]–[5]. Generally, such failures are difficult to trace or detect due to some natural phenomenon such as distance, weather, vegetation and industrialization. For instance, Nigeria has a vast land mass with rivers and swamps in the South, mountains, rocks and desert in the north [6], [7]. It has become imperative for an automatic protective scheme to be designed and developed for optimum protection of the transmission line. This can only be done through careful modelling of the transmission line with modern technique to meet with global standard.

Current power generating stations are mostly built close to where raw materials are readily available. Some of these sources are waterfall for hydroelectric stations, gas and coal for thermal plant, wind and sunshine for renewable sources of electricity. Meanwhile, the end-users are found in clustered areas and mostly metropolises and industrialized zones. Therefore, to reduce power loss in the system, different voltage classes are introduced based on transmission line distance and capacity to enable a smooth transmission. For this reason, there is need for adequate protection of the system. This review paper will focus on the different fault detection, classification and localization techniques, it will also compare the various techniques based on the algorithm used, input dataset, line distance used, test system, fault extraction model and the complexity of the output result.

2. THE NIGERIAN TRANSMISSION NETWORK

The Transmission Company of Nigeria (TCN) is vested with the power of transmitting electricity to the entire country. The 330 kV transmission network is the first network that connects all generating plants and load centers in all parts of the country to a single synchronized network, hence its economic importance cannot be overemphasized [8]. This vast network is opened to both symmetrical and unsymmetrical faults. Nigeria's transmission grid is made up of full-scale (theoretical) transmission capacity of 7,500 MW and above 20,000 km of transmission lines. Currently, the transmitting size of 5,300 MW is higher than the average working generating capacity of 3,880 MW, which is below the overall generating capacity of 12,523 MW. The entire installation is typically spiral, without redundancies thus creating internal accuracy issues. At a mean of about 7.4%, the losses throughout the system are high when compared to other Nations' model of about 2 to 6%. Nigeria transmits 330 kV to 132 kV, which will be stepping down to 33 kV and 11 kV known as the distribution network.

The most common causes of transmission line fault in Nigeria include weak grounding system, the type of conductors used or ageing conductors, the geographical terrain; these consists of swamps and forest, weather/climate due to high amount of rainfall and thunderstorm. Other factors include line losses, corona effect, lack of spare part and technical human resources. Non-technical issues like vandalism and poor government policies are also some of the causes of transmission line failure in Nigeria. Considering the associated faults, protecting the transmission line is very important and this cannot be overemphasized. Firstly, it helps to identify and isolate the damaged section of the system to avoid system collapse. Secondly, it helps to protect against overload and fault current to feedback to the transformer or generators which will help to provide steady electricity to end-users.

Presently, Nigeria is using overcurrent distance protection relay system for its network. This scheme has some drawback which includes limited fault resistance measurement capacity. In Nigeria, the network as shown in Figure 1, consists of a 330 kV high voltage line with about 27 buses and ten generating stations scattered across the country. Table 1 describes the diagram in Figure 1. It shows the bus number, bus rating, transformers, generating stations and load centers. This transmission line is synchronized to a single network with a single control Centre only, at Oshogbo [9].

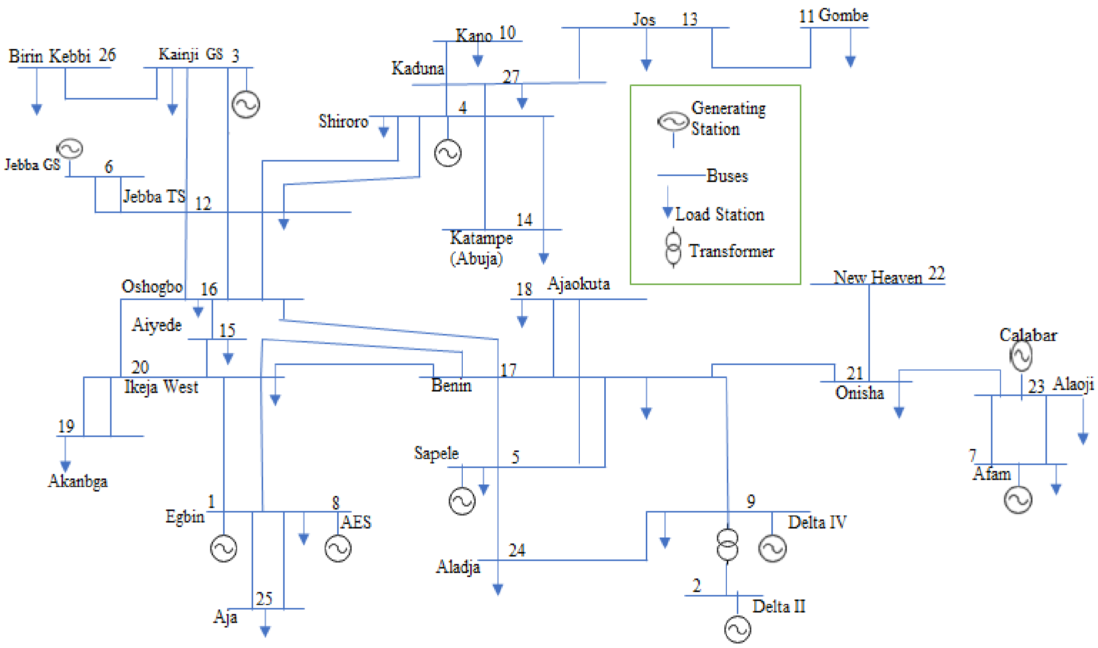

Figure 1. Single line diagram of Nigeria 330 kV line

Table 1. Bus description of Nigeria 330 kV transmission system network

Bus Number	Bus Name/Rating (MVA/MV)	Bus Number	Bus Name/Rating (MVA/MV)
1	Egbin (+800 MW)	15	Ayede (-77-j91) MVA
2	Delta (+300 MW)	16	Oshogbo (--120-j76) MVA
3	Kainji (+400 MW)	17	Benin (-161-j82) MVA
4	Shiroro (+600 MW)	18	Ajaokuta (--63-j32) MVA
5	Sapele (90 MW)	19	Akangba (-233-j119) MVA
6	Jeba GS (+300 MW)	20	IK West (-334-j171) MVA
7	Afam (+470 MW)	21	Onitsha(-131-j67) MVA
8	AES (+300 MW)	22	New Heaven (-113-j57) MVA
9	Okapi (+490 MW)	23	Alaoji(-164-j83) MVA
10	Kano (-253-j129) MVA	24	Aladja (-48-j24) MVA
11	Gombe (-74-j38) MVA	25	Aja (120-j62) MVA
12	Jeba TS (-8-j4) MVA	26	Birnin Kebi (-70-j36) MVA
13	Jos (-82-j42) MVA	27	Kaduna(-150-j77) MVA
14	Katampe (-200-j103) MVA		

3. BASIC FAULTS AND PROTECTION OF TRANSMISSION LINE

Diverse categories of fault occur in transmission line some of which are short circuit faults. This type of fault occurs when the load current is interrupted due to breakdown of installation due to sparks gap across the facility, ageing equipment, temperature change, adverse weather condition, chemical pollution, and foreign objects like trees and animals on lines. Other types of faults include phase and ground faults. Ground fault involves one phase conductor and ground while phase fault requires two or more phase conductors with or without a ground. Examples: i) line–to–ground fault (L-G), ii) line–to–line fault (L-L), and iii) three-line fault (L-L-L). Faults are classified according to the severity of occurrence, and the most common faults are the L-L and L-G faults while the most intense is the L-L-L and L-L-L-G fault.

For a transmission line to be fully protected, fault must be detected and classified. The location of the fault must be accurate for quick isolation of the line to protect it from system collapse. Figure 2 represent a simplified explanation of the flow of fault correction in a network. The input signal consists of high voltage, which is sent to the current and voltage signal acquisition, which helps convert it to either analog to digital or vice versa. The next stage is the data processing unit, which helps extract the data or signal the useful information needed in the module.

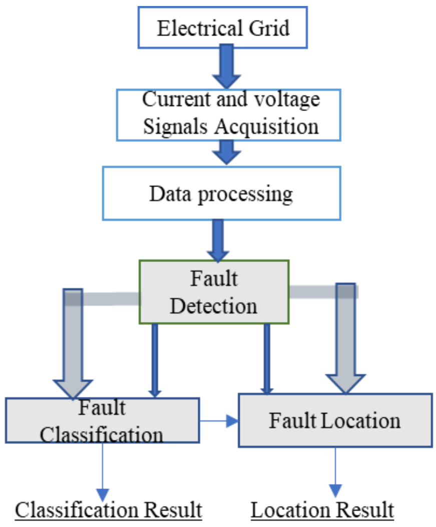

Figure 2. Fault location, detection and classification diagram [10]

The fault detection unit provides a reliable and fast relaying operation. The dominant protective relays for the transmission line are overcurrent protection relay, directional overcurrent relay, distance relay, and pilot relay. This relays helps to shield the line against symmetrical and unsymmetrical faults, although it does not guarantee full protection due to frequent short circuit fault that occurs at the distribution network [11]. The fault locator and classifier section are used to locate the exact distance of fault and determine the fault type and phase.

4. RELEVANT RESEARCH ON PROTECTION OF TRANSMISSION LINE

In this section, we will discuss some of the approaches used to protect transmission line which includes: i) distance relay approach [12], [13]; ii) wavelet approach [14], [15]; iii) the artificial neural network (ANN) approach [16]–[22], iv) fuzzy logic approach [23], [24], and v) mobile robot approach [25]–[28]. Other techniques are the hybrid method, machine learning and deep learning technique: i) neuro-fuzzy technique [24], [29]–[33], ii) wavelet and ANN technique [34]–[36], iii) wavelet and fuzzy-logic technique [37], [38], iv) wavelet and neuro-fuzzy technique [39], [40], v) machine learning approach [15], [41], [42], vi) support vector machine (SVM) [43], vii) k-nearest neighbours (KNN) and decision tree (DT) [44], and viii) principal component analysis (PCA) [45].

4.1. Distance relay approach

Using overcurrent protection relay (OCR) to determine the time it takes for the relay to trip and the current to trigger to identify fault location [11], [46]. A model with two distributed energy sources is used with seven overcurrent relays, the OCR 6 and OCR 7 were accessed in the 5 km line and were graded in terms of current-time characteristics. The pick-up current for OCR 7 was 1.8 kA and a tripping time of 0.12 s, while OCR 6 provides backup relay, and the tripping time was 0.45 s with a pick-up current of 1.8 kA. The impedance characteristics of both OCR 6 and OCR 7 relay is shown in Figure 3. With the Thevenin impedance, a higher start-up current shows a smaller radius. It was observed that OCR 6 has a trip time of 0.08 s (thick circle) is smaller than the one with 0.45 s trip time (dash circle) as shown in Figure 4. Where Ip is the fault current, $I`_p$ is the impedance pick-up current, Zo is the Thevenin impedance on the circle, Z`o is the center circle's impedance, and r and $r`$ are the change in radius. Using the inverse characteristics to determine the tripping time for the OCR 6 and OCR 7 relay. Two scenarios are used to calculate the tripping time, including energy resources and without energy resources. In the first instance, the tripping time for OCR 6=0.638 s while the tripping time for OCR 7=0.255 s. After connecting the energy resource, the pick-up current is 3.994 kA. OCR 6=0.557 kA and OCR 7=0.535 kA and the tripping time of OCR 6=0.523 s and the tripping time for OCR 7=0.205 s. The addition of the energy resource to the system reduces the time to trip to 0.115 s and 0.05 s for OCR 6 and OCR 7, respectively.

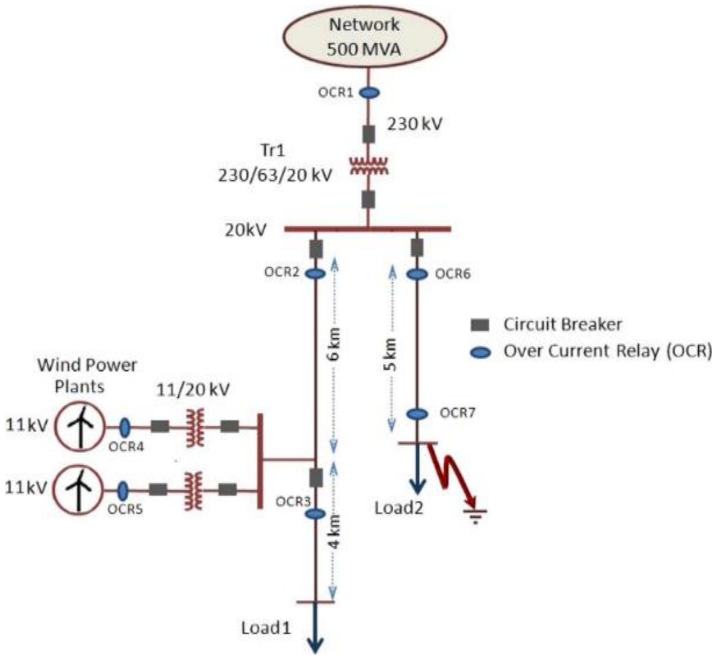

Figure 3. Power system model with two distributed energy resources

Another paper on 'the use of adaptive current protection scheme', highlights the challenges encountered in current differential protection with respect to speed, accuracy, and sensitivity. This helps to detect the fault and the unreliability if such a protection scheme arise if the shunt capacitance current is neglected in the line. Also, error may occur due to the saturation of the core with decaying direct current (DC) current [47].

A new approach for controlling restrictive areas for fast detection of fault was introduced by using the phasor approach for current differential protection with a series compensated transmission line as a reference. Electromagnetic transient program simulation was used to analyse the results [48], [49]. In [50], Thyristor controlled series capacitor (TCSC) was also introduced as a protection device for high frequency extra high voltage transmission line. The result shows that the introduction of TCSC can affect the line if it fails to operate. Using the Wavelet Transform, transient protection is used to solve the problems caused by TCSC. The analysed result proved that the appearance of TCSC in extra high voltage lines is accurate. In another paper, an extreme learning machine combined with wavelet transform technique was used to test about 28,800 faults at different locations by changing the inception angle, fault resistance, distance, load angle and percentage compensation level. MATLAB Simulink was used to simulate the result, which indicates that the approach is suitable for a wide variety in the system and operating conditions [15].

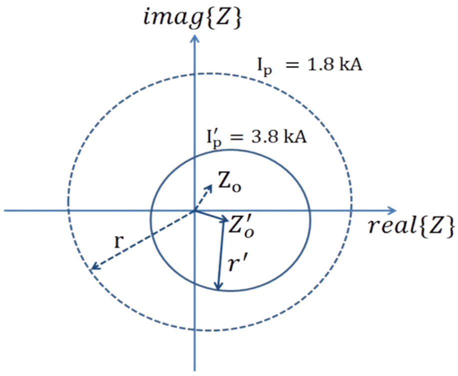

Figure 4. Pickup current on the impedance plane

4.2. Application of wavelet technique

This is one of the significant techniques used in classifying fault in a transmission line. This is explained in [14]. It recommends a system using the wavelet technique and current measurement to classify faults in the line. Analysis was carried out using MATLAB under diverse fault conditions. The stability of the line was tested using various fault criteria and the results obtained were reliable. A pilot wavelet was chosen using multi-resolution analysis (MRA) to check the signal at diverse resolution and frequency, which is helpful for low-frequency signals.

4.3. Inspection robot approach

The use of an inspection robot in a transmission line to check for mechanical damage has helped to reduce cost in terms of outages and man-hour wastage due to fault [51]–[53]. The three main robots used for inspection are climbing, flying and hybrid robots. The research proposed hybridizing two robots into a single robot as a better model to power transmission line monitoring. Some of the drawbacks of the paper include poor battery capacity, electromagnetic shielding and advanced control for uncertainties such as wind disturbance [27]. Another research based on a mobile robot was designed with the help of a controller, a programmable device, an integrated circuit card, a monitor for the development network, and a mobile robot. The robot is placed on the transmission line, which assists in detecting mechanical faults on the transmission line [54]. This robot will send the information to the controller, and it will appear on the screen. Also, another article on the multi-unit serial inspection robot the transmission network focused on designing a four tri-arm inspection robot mechanism that has an obstacle crossing ability and makes use of fewer motors and is lightweight for motor and cable [55]. The article did not discuss lightening fault (overcurrent fault) and other symmetrical faults such that full protection is not provided.

Figure 5 shows a block diagram of a mobile robot that comprises a power source, a controller that operates under two types of control, one for approximate motion and the other for accurate positioning. Data and commands are being programmed into the robot through the offline computer. The robot sensor sends feedback data from precision positioning. All these components are assembled and are placed on the transmission line to sense faults [51]. Other advanced monitoring robots consist of advanced sensing and imaging system that can detect and jump over an obstacle, and the information will be monitored on a screen. The device consists of three main parts: the robot motion control unit, communication control unit, and remote monitoring control unit [28].

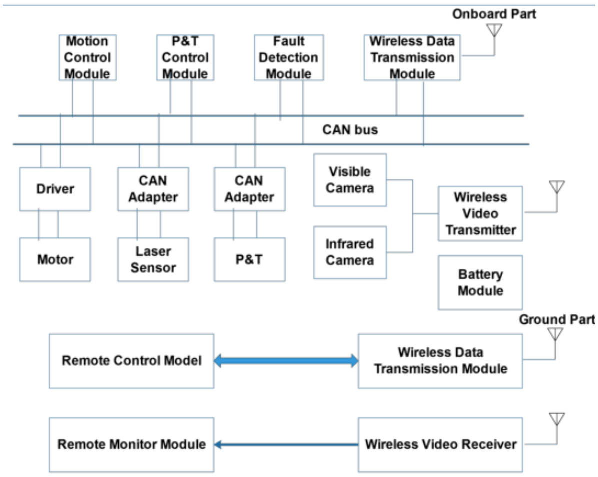

Figure 5. Mobile robot function configuration

4.4. The use of artificial neural network (ANN) technique

This paper explains how ANN is used to protect power systems for pattern recognition and classification to detect quantities like noise absorption and fault tolerance. These will not affect the variation in system parameters, which include system voltage and line current. This technique was applied in the power system, and positive feedback has been attained [16], [56]. A 230 kV, three-phase, two-machine power system was used to analyze the measurement of the transmission line problem. The training pattern was developed by simulating the various faults on the network. Parameters like fault location, fault type, resistance and initiation time were varied to achieve the practice template to cover a large array of fault conditions. A total of 3,600 models and a transmission line distance of 100 km was initiated in training ANN distance relay [57]. Some of the significant areas that ANN can be used include fault detection and classification, and in this method, a three-phase voltage and current are fed at one end. The feed-forward ANN propagation design was introduced to identify and classify faults of each of the three phases. These faults are simulated with diverse parameters to test the efficiency of the process using MATLAB [58].

In another article titled application of ANN in protective relaying of the transmission line, the writer used the adaptive linear neuron (ADALINE) model to explain the use of ANN in transmission line protection, considering the distance relay. The model was able to locate the operating point correctly in the decision space. The ANN is used as a conversational relay with two inputs, which is current and voltage, and the suggested quantity can be used to model the microprocessor framework [19]. Another article on Investigation of Faults on the Nigerian power system transmission line using ANN focuses on performing three functions: detection, classification, and isolation of faults. It detects two signals and chooses the best signal with the least error as output; it also classifies signals based on preference and isolates the signal with the most severe fault [59], [60].

ANN technique has been used to model the Nigerian network. The article focused on evaluating the performance of ANN-based relay linked to both ends of the line using the feed-forward non-linear managed back-propagation method. Power systems computer aided design/electromagnetic transients program (PSCAD/EMTP) software was used to model the network. The fault was generated from both sides of the transmission line, and two different power sources were fed into the system with different fault inception angles, locations, and resistance. The fault current will be analyzed and used for the testing and training of data using MATLAB. The result was simulated and confirmed using actual data obtained from a microprocessor-based Relay connected to the network. This shows that ANN accurately identifies, classify, and localize the genuine fault on the transmission line with more precision [59]. The analysis was also carried out using regression analysis and the mean square error (MSE). Regression analysis is used to test and analyze the system and the output of the system. If regression is 1, then there is a closed relationship between the output and target, but if regression is zero, it means that the system has not yet converged, and their difference is still huge, which shows that the network needs to be checked.

On the other hand, the MSE tests the average square difference between normalized output and the target. When MSE is zero, it shows that there is no error in the process, but if it is more significant than 0.4, it means the error is higher. Therefore, for a sound system, MSE should be within the range of 0.0000 to 0.4000 [60]. Also, in [61] backpropagation technique was used to detect and identify fault on the network, and it was trained with conjugate gradient backpropagation with high accuracy and low percentage error.

5. REAL-TIME PROTECTION WITH PHASOR MEASUREMENT UNIT TECHNIQUE

Monitoring of transmission line and its parameters (resistance, inductance, capacitance and shunt conductance) is necessary for transmission line protection in [62]. The synchrophasor based real-time transmission line parameter is used to monitor the system by tracking the parameter using an estimation algorithm model to get accurate data from the network. Real-time data were gathered from the utility network and simulated with the new algorithm proposed. It was observed that it performed better under unfavourable conditions. However, some of the traditional methods such as the supervisory control and data accusation systems [63], digital fault recorders [64], and travelling wave fault locator [65] were also used. Other monitoring systems are based on informing the operator of the problem and fault in the network, so the introduction of multi-agent systems has an intelligent response and self-troubleshooting of the system using MATLAB/Simulink to simulate the model. When an outage is detected, the system can disconnect the transmission line, clear the fault and provide flexible protection alternative and fast response to a fault.

Another important technique used in the monitoring transmission line is the phasor measurement unit (PMUs) technique. This device produces the harmonized measurement of real-time phasor of voltage and current. Harmonization is accomplished by sampling voltage and current waveform using timing signals from global positioning system (GPS) satellite. PMU provides the magnitude and phase angle of the system in real-time [66]. Dorf [67] proposed fault monitoring methodology, which is used as alternative monitoring of the power grid. This module can classify and detect faults in a transmission line. This is achieved using PMU while studying the equivalent power factor angle (EPFA) variation helps detect a fault in the network.

The angular variation between the three-phase voltage phasor *(V_s)* and a corresponding three-phase current phasor *(I_s)* is called EPFA ϕ. This is highlighted in Figure 6. The *ds* and *qs* axis show the static source frame in which the voltage phasor VR, VY, VB and current phasor IR, IY, IB are shown. The free reference frame d_s^e and q_s^e rotate at steady speed with respect to the frequency of the system ω_s. At steady-state conditions, both system frequency ω and ω_s are equal as shown in Figure 6. The parameters of d_s^e and q_s^e axis components of voltage and current are also explained in the paper. From (1) $\underset{V_s}{\rightarrow}$ is the voltage phasor while $\underset{I_s}{\rightarrow}$ is the current phasor, called EPFA ϕ, can be calculated using (1).

$$\phi = \tan^{-1}\left(\frac{V^e q^s}{V^e d^s}\right) = \tan^{-1}\left(\frac{I^e q^s}{I^e d^s}\right) \quad (1)$$

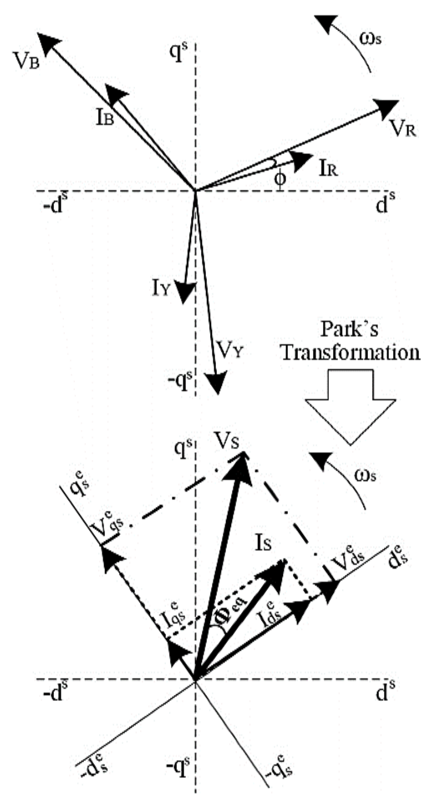

Figure 6. Diagram showing the power factor angle of a transmission line [65]

Figure 7 represents a block diagram of a western system coordinating council (WSCC) which was modelled as a case study in [68]. The system line parameter was represented in [67]. The transmission line connected to bus 4 and 5 is taken as a case study. The fault was introduced at separate intervals of 20 km from bus 4. The equivalent power factor angle of generator one was selected for fault monitoring at a reasonable condition and had a constant value. In contrast, a line to ground fault occurs in loop 4-5 (20 km at bus 4) at 0.04 s with R of Zero ohms and fault inception angle (FIA) of 0^0. In [69], it analyses the deviation of transient power and relationship between the network specification during the fault. This is achieved by aligning voltage and current at both ends of the line to identify internal and external fault in the line and DC fault.

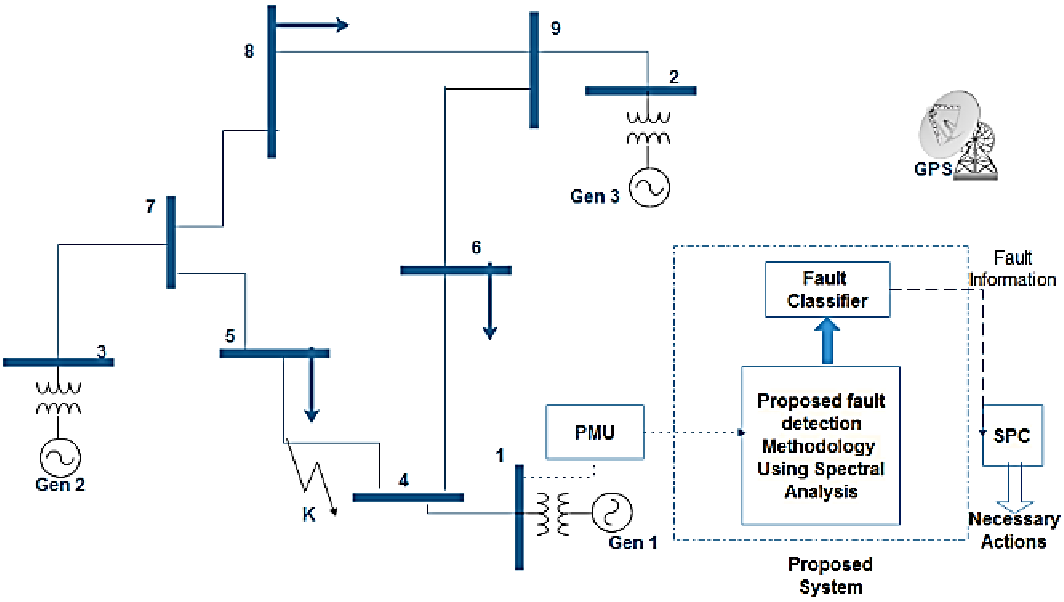

Figure 7. Proposed fault classification methodology

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6. COMPARING THE DIFFERENT PROTECTIVE SCHEMES IN THE NIGERIAN 330 kV TRANSMISSION LINE

The various protection schemes have their advantages and disadvantages due to configuration and type of fault there are programmed to protect, as illustrated in Table 2. While Table 3 comparing input and output data on the various technique. These are classified based on the technique used in implementation, the method used, transmission line length and fault resistance, the advantages and disadvantages of their percentage accuracy, precision and percentage error. Also, some of these techniques focus on either fault classification, detection or localization. For a proper fault management system, the fault must be detected and classified. The exact location of the fault must be identified for appropriate isolation and circuit breaker reclosure for adequate protection. In Table 3, the percentage error and accuracy of some selected techniques shows that the ANN had the lowest percentage accuracy ranging from 78%-99.9%. In comparison, the wavelet transform (WT) and SVM had about 100% accuracy for Gaussian and Polynomial Kernel functions though SVM alone had 99.833% accuracy.

Table 2. Comparing the different protection scheme

Protection Type	Method Used	Advantages	Disadvantages
Series compensated transmission line.	The use of KR9 1 and EM9 1 Relay	Initiation of the trip after fault.	No-fault identification
Current differential protection	dynamic phasor and series compensated TL	Speed and accuracy in detecting faults	No-fault correction and isolation
Thyristor controlled series capacitor	Thyristor controlled series capacitor (TCSC)	Fault location and identification fault isolation	No-fault isolation
Wavelet Approach	Uses wavelet transform and discrete wavelet transform (DWT)	Fault classification and detection	No-fault isolation and Relay reclose
Artificial Neural Network Approach	Uses ANN, Distributed and hierarchal Neural Network, Backpropagation	Fault classification, detection and identification	No-fault isolation
Fuzzy Logic Approach	Fuzzy logic	Fault identification	No-fault isolation and reclose
Fuzzy Neural Network Approach	ANN, Fuzzy logic and Fuzzy set approach	Fault classification and identification	No-fault correction
Wavelet and ANN Approach	DWT, ANN and continuous wavelet transform (CWT)	Fault identification, classification and location	No-fault correction
Monitoring robot technique	Uses sensor Robot	Fault location and mechanical fault or cable damage	Cannot detect symmetrical and unsymmetrical fault
Phasor Measurement Unit technique	Uses equivalent power factor angle (EPFA) GPS monitoring	Detect the exact location and fault classification	No-fault classification and fault correction
The transient Power measurement technique	Phasor Measurement Unit	Fault isolation and identification	No-fault correction
Distance Relay technique	Distance Relay, Microprocessor-based distance relay	Fast and accurate detection of fault and isolation	No accurate monitoring of fault location
The extreme Learning machine technique	Extreme learning technique, WT-ELM, DWT.	Fault identification and selection	Lack of fault isolation

Table 3. Comparing input and output data on the various technique

Technique used	Line length (KM)	Fault resistance (Ω)	Input data	% Error	Accuracy	Output	Reference
ANN	100	0-100	Fault current and voltage	Min. 1.472, max. 7	78% - 99.9%	Detection, classification	[70]
SVM	200	0-50	LLL fault current	0.015 – 0.7	99.833%	Detection, location	
WT and SVM	330	0.01-50	Fault current		100% for Gaussian and Polynomial kernel function	Classification, detection	[43]
Extreme learning machine (ELM)	100	0-100	Fault current signal	1.3%-4.8%	98%	Classification	[41]
PCC	150	0.0585	Single line fault	0.011%-2.413%	99.129%	Localization	[45]
T-transform and PNN	300	0-100	Fault current signal	-	90% to 100%	Classification and detection	[71]
SRC AND RDRP	300	0.1148-44.92	Three phase fault voltage	-	99.3% to 99.6%	Classification	[72]

7. CRITICAL ANALYSIS AND LIMITATION OF THE DIFFERENT SCHEMES

The various methods mentioned above have their setbacks; therefore, this paper aims to address them by providing better methods in fault detection, classification and localization. The main noticeable observation is the inability of most of the papers to explain extensively fault localization, thereby making it difficult to isolate or take on significant fault repairs within the shortest possible time. Also, in discrete wavelet transform (DWT) and decision tree (DT) [44]. It has limited time resolution capability and low performance for high-performance fault. In wavelet and data mining [73], K-nearest neighbours (KNN) and decision tree (DT) fault location are not measured. In [73], the S-transform technique, fault location and classification were not determined. Differential and Hibert-Huang transmission (HHT) technique is costly and has no-fault direction. Also, the mathematical morphology and recursive least-square (RLS) method [70] has high calculation and technical standards that need an expert to implement. Another shortcoming from these techniques already explained was the inability to focus more on fault localization. Localization of fault assists in quick diagnosing and restoration of power during fault. The ANN technique can identify exact fault types. The application is easy; it helps in real-life problems; it can be easily practiced with few parameters like voltage and current as input. However, the training process is complicated for serious dimension problems and shows slow convergence, which is also replicated for other techniques.

The deep learning technique is fast growing in terms of research because it can be applied in different scenarios like the time series, convolutional neural network (CNN), recurrent neural network (RNN) and long-short term memory. Though it is expensive, and it takes weeks to train with high technicality. For the Nigerian transmission network to measure with other grids globally, there must adopt a better approach in tackling the protection of the system. One proposed method is a hybrid and automated process of the digital relay protection scheme and ANN technique. This scheme will comprise two or more of the already existing models to form a hybrid system that will solve fault isolation and control, Relay re-closure, and faults correction. The effect of the fault on the radial line reduces the sensitiveness of the protection scheme in identifying faults. Other faults that can be corrected include arc resistance, tower resistance, footing resistance, ground return path, and fault resistance in looped and lone lines. It will also serve as real-time monitoring and control of the entire network using GPS.

8. ANALYSING, SCRUTINISING THE ANN AND FOURIER ALGORITHM IN TERMS OF TRIPPING AND SETTLING TIME

Comparing tripping time of the protective relay at different kilometers using ANN and Fourier algorithm in Tables 4 and 5 highlights both the time it takes the relay to trip and settle back to normal, and about 32 cases were analyzed for all the voltage levels and line length. At the end of every voltage level, it shows the percentage of faults where the Fourier algorithm is slower than the ANN [74]. From Table 4, the ANN-based algorithm performs better than the Fourier algorithm for transmission lines with a range of 345 kV. Also, this is more reliable than the ANN-based algorithm for cases where the voltage level of transmission lines is higher than 345 kV. Also, the impact of fault resistance on the accuracy of the evaluated impedance was analyzed. It was discovered that the reactance and the fault resistance of the measured Relay depend on the line to the fault load [74].

Table 4. Comparing the medium time of tripping in milliseconds for ANN and Fourier algorithm technique

Voltage level	Algorithm	50 km	74 km	150 km
138 Kv	ANN	6.88	8.16	6.90
	Fourier Algorithm	14.20	15.63	13.70
	No. of Cases	97	100	100
345 Kv	ANN	11.40	10.55	9.75
	Fourier Algorithm	16.70	16.20	15.40
	No. of Cases	100	100	100
500 Kv	ANN	7.60	6.77	6.17
	Fourier Algorithm	13.06	12.43	12.56
	No. of Cases	97	97	97

Table 5. Comparing the medium time for settling in milliseconds for ANN and Fourier algorithm technique

Voltage level	Algorithm	50 km	74 km	150 km
138 Kv	ANN	12.28	13.65	12.17
	Fourier Algorithm	17.97	18.75	18.12
	No. of Cases	94	97	100
345 Kv	ANN	17.15	17.57	18.46
	Fourier Algorithm	19.50	18.30	18.53
	No. of Cases	75	69	100
500 Kv	ANN	36.85	35.03	44.42
	Fourier Algorithm	16.85	17.00	16.93
	No. of Cases	41	47	35

Fuzzy logic-based protection system is easy to implement, and the results are accurate under the assumption of fault distance, fault resistance, line length and pre-fault power flow. Although accuracy cannot be guaranteed in large networks, therefore, the fuzzy-neuro approach is introduced because of its reliable relaying algorithm during the execution and classification of the fault. This sensitive change requires a massive dataset for training and many neurons, which affects their accuracy and speed in protecting an extensive network [33]. For optimal performance of the hybrid system, the Nigerian 330 kV line was modelled, and different faults were initiated to the network.

ANN technique was used to detect and isolate fault by modelling the protection scheme with the help of distance relay protection. The results were evaluated to detect the line loss in Figure 8, fault current in Figure 9, and percentage accuracy of iteration in Figure 10. Power flow data analysis was conducted by considering the metrics of all the bus data voltage, voltage angle, load (MW, MVar), power generated (MV, MVar) and injected voltage (MVar) values. Analysis of line flow data was also carried out to establish the line loss. The total line loss was about 15.999 MVA and 18.929 MW. The Load was pitched at 1293 MV and 652 MVar. From the result, it is evident that the line has a lot of losses which makes it inefficient. Figure 10 shows the percentage accuracy of the system, which was about 95% and affirmed that the system could function better with the use of ANN technique. We considered that all the metrics are bus data voltage, voltage angle in degrees, load (MW, Mvar), generation (MW, Mvar) and injected Mvar value. Also, the line flow data analysis was carried out to determine the power at various buses and line flow in MW, Mvar and MVA, line loss (MW, Mvar) value. Fault was identified, detected and isolated using ANN technique, and the trip time of the circuit breaker using the distance relay protection and the fault current and line loss was identified and the line isolated as fast as 0.02 s and 0.03 s, respectively compared to other results gotten from using only distance relay protection.

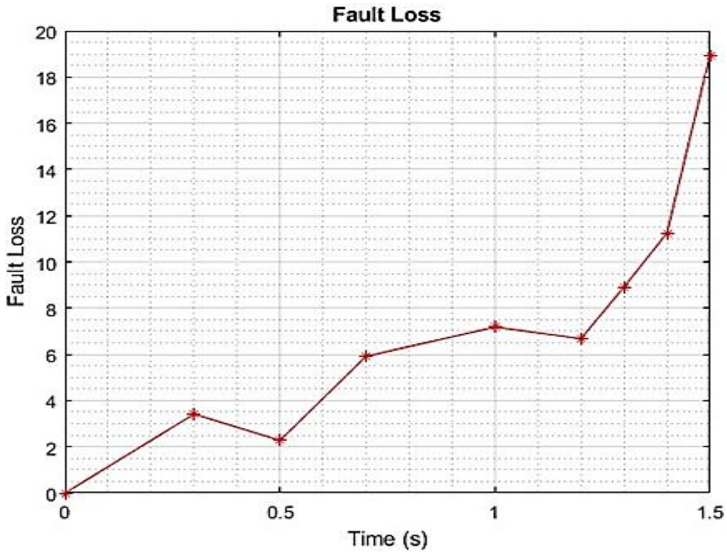

Figure 8. Line loss on 330 kV transmission line

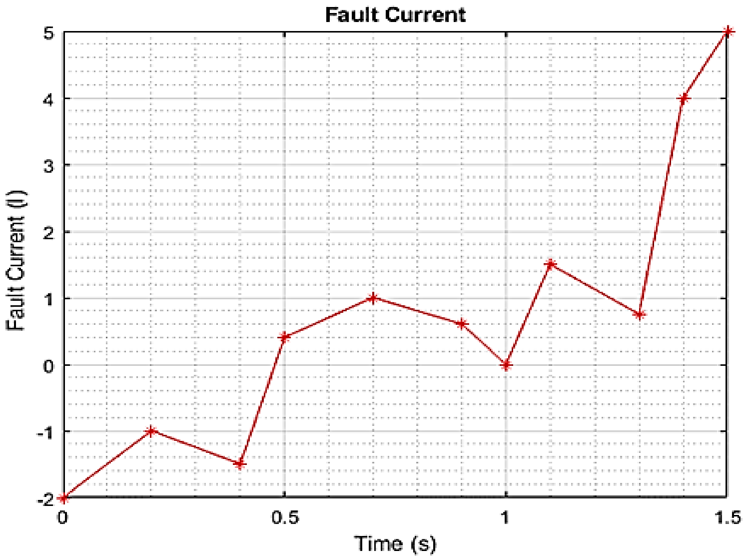

Figure 9. Fault current on the 330 kV transmission line

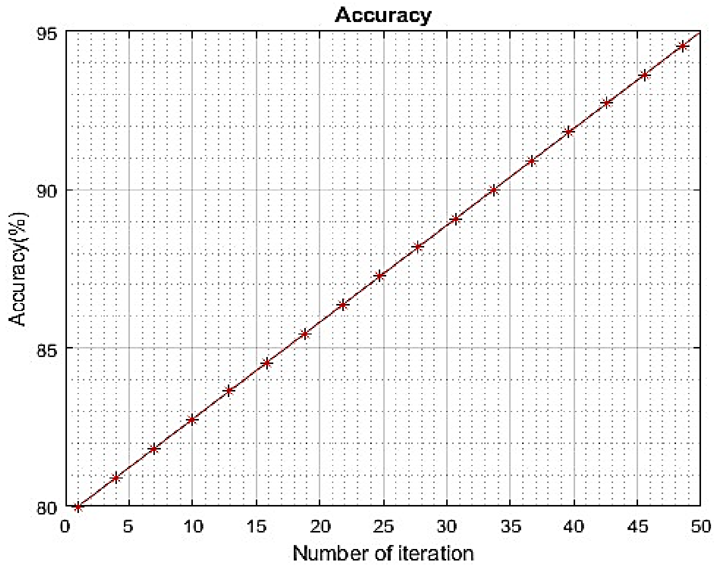

Figure 10. Percentage accuracy on the 330 kV transmission line due to ANN

9. CONCLUSION

The paper discussed a review of fault detection, classification, and location in transmission lines, specifically the Nigerian scenario. It explained the Nigerian transmission network, the major types of faults and the causes. Some of the techniques analyzed include using the wavelet approach, overcurrent and distance relay approach, fuzzy logic, and monitoring robot. Others are artificial neural network, machine learning, neuro-fuzzy, wavelet and ANN, wavelet and neuro-fuzzy, wavelet and fuzzy-logic and fault monitoring approach to protect and monitor transmission line system. Machine learning and deep learning technique such as CNN, RNN, SVM, and DT were also discussed. The focus was also on the comparison of the various approaches with respect to their viability and response time to fault, features, input and output data, the complexity of training. This paper will form a better strategy and research guide for fault location, detection and classification technique in transmission line systems. Developing an automated control system that involves a hybrid scheme of ANN and distance relay protection techniques is recommended for the proper functioning of the network. Finally, this review paper will guide the design of the transmission line protection scheme and the best approach and technique to use in power system protection.

REFERENCES

[1] J. Katrasnik, F. Pernus, and B. Likar, "A survey of mobile robots for distribution power line inspection," *IEEE Transactions on Power Delivery*, vol. 25, no. 1, pp. 485–493, Jan. 2010, doi: 10.1109/TPWRD.2009.2035427.

[2] K. Toussaint, N. Pouliot, and S. Montambault, "Transmission line maintenance robots capable of crossing obstacles: State-of-the-art review and challenges ahead," *Journal of Field Robotics*, vol. 26, no. 5, pp. 477–499, May 2009, doi: 10.1002/rob.20295.

[3] O. Menendez, F. A. Auat Cheein, M. Perez, and S. Kouro, "Robotics in power systems: enabling a more reliable and safe grid," *IEEE Industrial Electronics Magazine*, vol. 11, no. 2, pp. 22–34, Jun. 2017, doi: 10.1109/MIE.2017.2686458.

[4] M. F. A. Jalal, K. S. M. Sahari, A. Anuar, A. D. M. Arshad, and M. S. Idris, "Conceptual design for transmission line inspection robot," *IOP Conference Series: Earth and Environmental Science*, vol. 16, no. 1, Jun. 2013, doi: 10.1088/1755-1315/16/1/012094.

[5] B. Jalil, G. R. Leone, M. Martinelli, D. Moroni, M. A. Pascali, and A. Berton, "Fault detection in power equipment via an unmanned aerial system using multi modal data," *Sensors*, vol. 19, no. 13, Jul. 2019, doi: 10.3390/s19133014.

[6] R. Zhi-bin, R. Yi, L. Zheng, and Y. Yong, "Motion planning of inspection robot suspended on overhead ground wires for obstacle-navigation," in *2009 Chinese Control and Decision Conference*, Jun. 2009, pp. 1322–1326, doi: 10.1109/CCDC.2009.5192699.

[7] G. Wu, T. Zheng, H. Xiao, and C. Li, "Navigation, location and non-collision obstacles overcoming for high-voltage power transmission-line inspection robot," in *2009 International Conference on Mechatronics and Automation*, Aug. 2009, pp. 2014–2020, doi: 10.1109/ICMA.2009.5245998.

[8] A. A. Elbaset and T. Hiyama, "Fault detection and classification in transmission lines using ANFIS," *IEEJ Transactions on Industry Applications*, vol. 129, no. 7, pp. 705–713, 2009, doi: 10.1541/ieejias.129.705.

[9] C. J. Nnonyelu and T. C. Madueme, "Power system contingency analysis: a study of Nigeria's 330KV transmission grid," *Energy Source for Power Generation*, vol. 4, pp. 1–9, 2013.

[10] W. H. Conley and R. J. Deferrari, "Principles and applications," *The Journal of Higher Education*, vol. 23, no. 4, Apr. 1952, Art. no. 225, doi: 10.2307/1976787.

[11] A. Rahmati, M. A. Dimassi, R. Adhami, and D. Bumblauskas, "An overcurrent protection relay based on local measurements," *IEEE Transactions on Industry Applications*, vol. 51, no. 3, pp. 2081–2085, May 2015, doi: 10.1109/TIA.2014.2385933.

[12] Z. Y. Xu *et al.*, "A distance protection relay for a 1000-kV UHV transmission line," *IEEE Transactions on Power Delivery*, vol. 23, no. 4, pp. 1795–1804, Oct. 2008, doi: 10.1109/TPWRD.2008.919038.

[13] K. Ravishankar and D. Thukaram, "Analysis of distance relay trip regions for EHV and UHV transmission lines," in *2011 International Conference on Power and Energy Systems*, Dec. 2011, pp. 1–6, doi: 10.1109/ICPES.2011.6156630.

[14] A. Prasad and J. B. Edward, "Application of wavelet technique for fault classification in transmission systems," *Procedia Computer Science*, vol. 92, pp. 78–83, 2016, doi: 10.1016/j.procs.2016.07.326.

[15] V. Malathi, N. S. Marimuthu, S. Baskar, and K. Ramar, "Application of extreme learning machine for series compensated transmission line protection," *Engineering Applications of Artificial Intelligence*, vol. 24, no. 5, pp. 880–887, Aug. 2011, doi: 10.1016/j.engappai.2011.03.003.

[16] T. Dalstein and B. Kulicke, "Neural network approach to fault classification for high speed protective relaying," *IEEE Transactions on Power Delivery*, vol. 10, no. 2, pp. 1002–1011, Apr. 1995, doi: 10.1109/61.400828.

[17] A. Prasad and J. B. Edward, "Importance of artificial neural networks for location of faults in transmission systems: A survey," in *2017 11th International Conference on Intelligent Systems and Control (ISCO)*, Jan. 2017, pp. 357–362, doi: 10.1109/ISCO.2017.7856016.

[18] K. Lout and R. K. Aggarwal, "A feedforward artificial neural network approach to fault classification and location on a 132kV transmission line using current signals only," in *2012 47th International Universities Power Engineering Conference (UPEC)*, Sep. 2012, pp. 1–6, doi: 10.1109/UPEC.2012.6398574.

[19] L. L. Lai, "Application of neural networks to fault classification and protection," in *APSCOM-97. International Conference on Advances in Power System Control, Operation and Management*, 1997, vol. 1997, pp. 72–76, doi: 10.1049/cp:19971807.

[20] B. Y. Vyas, B. Das, and R. P. Maheshwari, "Improved fault classification in series compensated transmission line: comparative evaluation of chebyshev neural network training algorithms," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 8, pp. 1631–1642, Aug. 2016, doi: 10.1109/TNNLS.2014.2360879.

[21] P. B. Osofisan and C. N. Nwaeke, "Application of artificial neural network (ANN) for short-term load forecasting (case study on national control centre (PHCN) Oshogbo, Osun State, Nigeria)," *Journal of Engineering and Applied Sciences*, vol. 5, no. 2, pp. 78–83, Feb. 2010, doi: 10.3923/jeasci.2010.78.83.

[22] A. Swetapadma and A. Yadav, "An artificial neural network-based solution to locate the multilocation faults in double circuit series capacitor compensated transmission lines," *International Transactions on Electrical Energy Systems*, vol. 28, no. 4, Apr. 2018, doi: 10.1002/etep.2517.

[23] A. Ferrero, S. Sangiovanni, and E. Zappitelli, "A fuzzy-set approach to fault-type identification in digital relaying," *IEEE Transactions on Power Delivery*, vol. 10, no. 1, pp. 169–175, 1995, doi: 10.1109/61.368401.

[24] R.-A. Tirnovan and M. Cristea, "Advanced techniques for fault detection and classification in electrical power transmission systems: An overview," in *2019 8th International Conference on Modern Power Systems (MPS)*, May 2019, pp. 1–10, doi: 10.1109/MPS.2019.8759695.

[25] S. Fu *et al.*, "Structure-constrained obstacles recognition for power transmission line inspection robot," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct. 2006, pp. 3363–3368, doi: 10.1109/IROS.2006.282513.

[26] G. Rui, Z. Feng, C. Lei, and Y. Jun, "A mobile robot for inspection of overhead transmission lines," in *Proceedings of the 2014 3rd International Conference on Applied Robotics for the Power Industry*, Oct. 2014, pp. 1–3, doi: 10.1109/CARPI.2014.7030054.

[27] A. B. Alhassan, X. Zhang, H. Shen, and H. Xu, "Power transmission line inspection robots: A review, trends and challenges for future research," *International Journal of Electrical Power & Energy Systems*, vol. 118, Jun. 2020, doi: 10.1016/j.ijepes.2020.105862.

[28] S. Montambault and N. Pouliot, "About the future of power line robotics," in *2010 1st International Conference on Applied Robotics for the Power Industry (CARPI 2010)*, Oct. 2010, pp. 1–6, doi: 10.1109/CARPI.2010.5624466.

[29] H. Wang and W. W. L. Keerthipala, "Fuzzy-neuro approach to fault classification for transmission line protection," *IEEE Transactions on Power Delivery*, vol. 13, no. 4, pp. 1093–1104, 1998, doi: 10.1109/61.714467.

[30] P. K. Dash, A. K. Pradhan, and G. Panda, "A novel fuzzy neural network based distance relaying scheme," *IEEE Transactions on Power Delivery*, vol. 15, no. 3, pp. 902–907, Jul. 2000, doi: 10.1109/61.871350.

[31] A. Raza, A. Benrabah, T. Alquthami, and M. Akmal, "A review of fault diagnosing methods in power transmission systems," *Applied Sciences*, vol. 10, no. 4, Feb. 2020, doi: 10.3390/app10041312.

[32] A. Prasad, J. Belwin Edward, and K. Ravi, "A review on fault classification methodologies in power transmission systems: Part—I," *Journal of Electrical Systems and Information Technology*, vol. 5, no. 1, pp. 48–60, May 2018, doi: 10.1016/j.jesit.2017.01.004.

[33] K. Babu, M. Tripathy, and A. Singh, "Recent techniques used in transmission line protection: A review," *International Journal of Engineering, Science and Technology*, vol. 3, no. 3, Jul. 2011, doi: 10.4314/ijest.v3i3.68416.

[34] S. K. Shukla, E. Koley, and S. Ghosh, "A hybrid wavelet–APSO–ANN-based protection scheme for six-phase transmission line with real-time validation," *Neural Computing and Applications*, vol. 31, no. 10, pp. 5751–5765, Oct. 2019, doi: 10.1007/s00521-018-3400-x.

[35] K. C. Wakhare and N. B. Wagh, "Review of various algorithms for protection of transmission line," *International Journal Of Engineering Research & Technology (IJERT)*, vol. 4, no. 1, pp. 346–351, 2015.

[36] F. B. Costa, K. M. Silva, B. A. Souza, K. M. C. Dantas, and N. S. D. Brito, "A method for fault classification in transmission lines based on ANN and wavelet coefficients energy," in *The 2006 IEEE International Joint Conference on Neural Network Proceedings*, 2006, pp. 3700–3705, doi: 10.1109/IJCNN.2006.247385.

[37] O. A. S. Youssef, "Combined fuzzy-logic wavelet-based fault classification technique for power system relaying," *IEEE Transactions on Power Delivery*, vol. 19, no. 2, pp. 582–589, Apr. 2004, doi: 10.1109/TPWRD.2004.826386.

[38] M. Jayabharata Reddy and D. K. Mohanta, "A wavelet-fuzzy combined approach for classification and location of transmission line faults," *International Journal of Electrical Power & Energy Systems*, vol. 29, no. 9, pp. 669–678, Nov. 2007, doi: 10.1016/j.ijepes.2007.05.001.

[39] C. K. Jung, K. H. Kim, J. B. Lee, and B. Klöckl, "Wavelet and neuro-fuzzy based fault location for combined transmission systems," *International Journal of Electrical Power & Energy Systems*, vol. 29, no. 6, pp. 445–454, Jul. 2007, doi: 10.1016/j.ijepes.2006.11.003.

[40] A. Hossam-Eldin, A. Lotfy, M. Elgamal, and M. Ebeed, "Combined traveling wave and fuzzy logic based fault location in multi-terminal HVDC systems," in *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*, Jun. 2016, pp. 1–6, doi: 10.1109/EEEIC.2016.7555591.

[41] H. Wu, J. Yang, L. Chen, and Q. Wang, "A new method for identifying a fault in T-connected lines based on multiscale S-

transform energy entropy and an extreme learning machine," *PLOS ONE*, vol. 14, no. 8, Aug. 2019, doi: 10.1371/journal.pone.0220870.

[42] C. A. Andresen, B. N. Torsæter, H. Haugdal, and K. Uhlen, "Fault detection and prediction in smart grids," in *2018 IEEE 9th International Workshop on Applied Measurements for Power Systems (AMPS)*, Sep. 2018, pp. 1–6, doi: 10.1109/AMPS.2018.8494849.

[43] B. Bhalja and R. P. Maheshwari, "Wavelet-based fault classification scheme for a transmission line using a support vector machine," *Electric Power Components and Systems*, vol. 36, no. 10, pp. 1017–1030, Sep. 2008, doi: 10.1080/15325000802046496.

[44] S. Netsanet, J. Zhang, and D. Zheng, "Bagged decision trees based scheme of microgrid protection using windowed fast Fourier and wavelet transforms," *Electronics*, vol. 7, no. 5, May 2018, doi: 10.3390/electronics7050061.

[45] A. Mukherjee, P. K. Kundu, and A. Das, "A supervised principal component analysis-based approach of fault localization in transmission lines for single line to ground faults," *Electrical Engineering*, vol. 103, no. 4, pp. 2113–2126, Aug. 2021, doi: 10.1007/s00202-021-01221-9.

[46] M. S. Almas, R. Leelaruji, and L. Vanfretti, "Over-current relay model implementation for real time simulation & Hardware-in-the-Loop (HIL) validation," in *IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society*, Oct. 2012, pp. 4789–4796, doi: 10.1109/IECON.2012.6389585.

[47] P. K. Gangadharan, T. S. Sidhu, and A. Klimek, "Influence of current transformer saturation on line current differential protection algorithms," *IET Generation, Transmission & Distribution*, vol. 1, no. 2, 2007, doi: 10.1049/iet-gtd:20060138.

[48] M. Biswal, "Adaptive distance relay algorithm for double circuit line with series compensation," *Measurement*, vol. 53, pp. 206–214, Jul. 2014, doi: 10.1016/j.measurement.2014.03.036.

[49] S. Dambhare, S. A. Soman, and M. C. Chandorkar, "Adaptive current differential protection schemes for transmission-line protection," *IEEE Transactions on Power Delivery*, vol. 24, no. 4, pp. 1832–1841, Oct. 2009, doi: 10.1109/TPWRD.2009.2028801.

[50] Q. Liu, Z. Wang, and Y. Xu, "Research on the influence of TCSC to EHV transmission line protection," in *2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, Apr. 2008, pp. 2258–2261, doi: 10.1109/DRPT.2008.4523786.

[51] T. Disyadej, J. Promjan, K. Poochinapan, T. Mouktonglang, S. Grzybowski, and P. Muneesawang, "High voltage power line maintenance & inspection by using smart robotics," in *2019 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, Feb. 2019, pp. 1–4, doi: 10.1109/ISGT.2019.8791584.

[52] T. Disyadej, J. Promjan, P. Muneesawang, K. Poochinapan, and S. Grzybowski, "Application in O&M practices of overhead power line robotics," in *2019 IEEE PES GTD Grand International Conference and Exposition Asia (GTD Asia)*, Mar. 2019, pp. 347–351, doi: 10.1109/GTDAsia.2019.8715886.

[53] G. Wu *et al.*, "A novel self-navigated inspection robot along high-voltage power transmission line and its application," in *Lecture Notes in Computer Science*, 2008, pp. 1145–1154.

[54] J. Sawada, K. Kusumoto, Y. Maikawa, T. Munakata, and Y. Ishikawa, "A mobile robot for inspection of power transmission lines," *IEEE Transactions on Power Delivery*, vol. 6, no. 1, pp. 309–315, 1991, doi: 10.1109/61.103753.

[55] G. Tao and L. Fang, "A multi-unit serial inspection robot for power transmission lines," *Industrial Robot: the international journal of robotics research and application*, vol. 46, no. 2, pp. 223–234, Mar. 2019, doi: 10.1108/IR-09-2018-0195.

[56] G. Chawla, M. S. Sachdev, and G. Ramakrishna, "Design, implementation and testing of an artificial neural network based admittance relay," *IFAC Proceedings Volumes*, vol. 39, no. 7, pp. 125–130, 2006, doi: 10.3182/20060625-4-CA-2906.00027.

[57] M. Sanaye-Pasand and H. Khorashadi-Zadeh, "An extended ANN-based high speed accurate distance protection algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 28, no. 6, pp. 387–395, Jul. 2006, doi: 10.1016/j.ijepes.2006.01.003.

[58] M. Dehghani, M. H. Khooban, and T. Niknam, "Fast fault detection and classification based on a combination of wavelet singular entropy theory and fuzzy logic in distribution lines in the presence of distributed generations," *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 455–462, Jun. 2016, doi: 10.1016/j.ijepes.2015.11.048.

[59] U. Uzubi, A. Ekwue, and E. Ejiogu, "Artificial neural network technique for transmission line protection on Nigerian power system," in *2017 IEEE PES PowerAfrica*, Jun. 2017, pp. 52–58, doi: 10.1109/PowerAfrica.2017.7991199.

[60] V. Ogboh and T. C. Madueme, "Investigation of faults on the nigerian power system transmission line using artificial neural network," *International Journal of Research in Management, Science & Technology*, vol. 2, no. 4, pp. 87–95, 2015.

[61] K. A. Jokhio, A. A. Sahito, A. M. Soomro, and S. M. Jiskani, "Transmission line fault detection and identification using artificial neural network," *International Journal of Electrical Engineering & Emerging Technology*, vol. 4, no. 1, pp. 1–7, 2021.

[62] D. R. Gurusinghe and A. D. Rajapakse, "Efficient algorithms for real-time monitoring of transmission line parameters and their performance with practical synchrophasors," *IET Generation, Transmission & Distribution*, vol. 11, no. 5, pp. 1134–1143, Mar. 2017, doi: 10.1049/iet-gtd.2016.0830.

[63] S. C. Patel and P. Sanyal, "Securing SCADA systems," *Information Management & Computer Security*, vol. 16, no. 4, pp. 398–414, Oct. 2008, doi: 10.1108/09685220810908804.

[64] M. Chantler, P. Pogliano, A. Aldea, G. Tornielli, T. Wyatt, and A. Jolley, "The use of fault-recorder data for diagnosing timing and other related faults in electricity transmission networks," *IEEE Transactions on Power Systems*, vol. 15, no. 4, pp. 1388–1393, 2000, doi: 10.1109/59.898117.

[65] M. A. Baseer, "Travelling waves for finding the fault location in transmission lines," *Journal Electrical and Electronic Engineering*, vol. 1, no. 1, 2013, doi: 10.11648/j.jeee.20130101.11.

[66] J. Li, Y. Zhang, C. Ma, and C. Cheng, "Research on multifunctional automatic transmission line automatic robot system," *Journal of Physics: Conference Series*, vol. 1074, Sep. 2018, doi: 10.1088/1742-6596/1074/1/012010.

[67] P. Gopakumar, B. Mallikajuna, M. Jaya Bharata Reddy, and D. K. Mohanta, "Remote monitoring system for real time detection and classification of transmission line faults in a power grid using PMU measurements," *Protection and Control of Modern Power Systems*, vol. 3, no. 1, Dec. 2018, doi: 10.1186/s41601-018-0089-x.

[68] X. Zheng, T. Nengling, Y. Guangliang, and D. Haoyin, "A transient protection scheme for HVDC transmission line," *IEEE Transactions on Power Delivery*, vol. 27, no. 2, pp. 718–724, Apr. 2012, doi: 10.1109/TPWRD.2011.2179321.

[69] S. Tom and J. Thomas, "HVDC transmission line protection based on transient power," *Procedia Technology*, vol. 25, pp. 660–668, 2016, doi: 10.1016/j.protcy.2016.08.158.

[70] A. Jain, A. S. Thoke, and R. N. Patel, "Double circuit transmission line fault distance location using artificial neural network," in *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC)*, 2009, pp. 13–18, doi: 10.1109/NABIC.2009.5393593.

[71] S. R. Samantaray and P. K. Dash, "Transmission line distance relaying using machine intelligence technique," *IET Generation,*

Transmission & Distribution, vol. 2, no. 1, p. 53, 2008, doi: 10.1049/iet-gtd:20070160.
[72] L. Cheng, L. Wang, and F. Gao, "Power system fault classification method based on sparse representation and random dimensionality reduction projection," in *2015 IEEE Power & Energy Society General Meeting*, Jul. 2015, pp. 1–5, doi: 10.1109/PESGM.2015.7286147.
[73] D. P. Mishra, S. R. Samantaray, and G. Joos, "A combined wavelet and data-mining based intelligent protection scheme for microgrid," *IEEE Transactions on Smart Grid*, vol. 7, no. 5, pp. 2295–2304, Sep. 2016, doi: 10.1109/TSG.2015.2487501.
[74] R. C. dos Santos and E. C. Senger, "Transmission lines distance protection using artificial neural networks," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 3, pp. 721–730, Mar. 2011, doi: 10.1016/j.ijepes.2010.12.029.

BIOGRAPHIES OF AUTHORS

Vincent Nsed Ogar A research student at the James Watt School of Engineering, Department of Electronic and Electrical Engineering, University of Glasgow. He is currently working on the design of Nigerian 330 kV transmission line protective scheme. He attended Cross River University of Technology Calabar, Nigeria where he obtained a BSc in Electrical and Electronic Engineering. MSc in Electrical System and Network at the Donetsk National Technical University, Ukraine. He is also a lecturer at the Department of Electrical and Electronic Engineering, Cross River University of Technology, Calabar, Nigeria. He can be contacted at email: v.ogar.1@research.gla.ac.uk.

Kelum A. A. Gamage is a Senior Lecturer (Associate Professor) in the School of Engineering at the University of Glasgow. He is the School Learning & Teaching Enhancement Officer and the Co-Director of the Centre for Educational Development and Innovation. Dr Gamage is a Visiting Academic in the Engineering Department at Lancaster University and, holds the position of Visiting Professor at the University of Electronic Science and Technology of China (UESTC) and Sri Lanka Technological Campus (SLTC). He is an academic accreditor for the IET, and also a Professional Registration Advisor (PRA), where he gives specialist advice to candidates who are seeking professional registration (CEng/IEng) with EC (UK) through the IET. He is the External Examiner for BEng/MEng Electrical and Electronic Engineering programs, School of Computing, Engineering & Mathematics, University of Brighton; BEng/MEng Electronic Engineering programs, Department of Engineering, Design and Mathematics at the Faculty of Environment and Technology, UWE Bristol; BEng Electrical & Electronic Control Systems Engineering (UCP) programme at Anglia Ruskin University. He is an Editor for Radiation Protection and Dosimetry Journal (Publisher: Oxford University Press), Sensors (Publisher: MDPI, Switzerland, ISSN 1424-8220), Education Sciences (Publisher: MDPI, Switzerland, ISSN 2227-7102), Energy & Power Engineering Journal (ISSN: 1934-8975) and an active reviewer for leading international peer-review journals. A Fellow of the IET, a Fellow of Royal Society of Arts and a Senior Member of IEEE. He can be contacted at email: Kelum.Gamage@glasgow.ac.uk.

Sajjad Hussain An Associate Professor (Senior Lecturer) at the James Watt School of Engineering. He is currently serving as Program Director, Electronic and Electrical Engineering with Information Engineering program at Glasgow College UESTC. He has previously served at the Electrical Engineering Department, Capital University of Science and Technology (CUST), Islamabad, Pakistan as Associate Professor. I did my masters in Wireless Communications in 2006 from Supelec, Gif-sur-Yvette and PhD in Signal Processing and Communications in 2009 from the University of Rennes 1, Rennes, France. He is a senior membership IEEE and fellowship of Higher Education Academy. I am an Associate Editor IEEE Access. I have won the College of Science and Engineering, University of Glasgow 2019 Teaching Excellence Award. He can be contacted at email: Sajjad.Hussain@glasgow.ac.uk.