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Artificial Neural Network –Based Short Circuit Fault Detection And Classification Strategies In Power System Network

Aniebiet Uko Sam[1]
Dept of Electrical and Electronic Engineering
University of Uyo, Uyo. Akwa Ibom State
Uyo, Nigeria

Nseobong I. Okpura [2]
Dept of Electrical and Electronic Engineering
University of Uyo, Uyo. Akwa Ibom State
Uyo, Nigeria
nseobongokpura@uniuyo.edu.ng

Kufre M. Udofia[3]
Dept of Electrical and Electronic Engineering
University of Uyo, Uyo. Akwa Ibom State
Uyo, Nigeria

***Abstract*— In this work, short-circuit fault detection and classification on the Nigerian 330kV transmission network in the Middle Belt Region using an artificial neural network (ANN) is presented. The first step was to obtain the power system information from the National Control Center in Oshogbo and model the network in the power system environment in Simulink. The network was modeled in SIMULINK with current signal values from various classes of faults exported to Matlab environment for the development of the ANN model. The modeled ANN was inserted to the power system model in Simulink to test the efficiency of the model in detecting and classifying short circuit faults. From the outcome, the ANN model effectively detected and classified the occurrence of short circuit faults in Lines 1 and 3 with the highest classification deviation being 3.07%. However, there were concerns in line two as the maximum deviation being 20.33%. In conclusion, the use of ANN from the study adequately detected and classified the occurrence of short circuit fault in lines 1 and 3 but has a large deviation in line 2 especially in detecting the triple phase line (ABC).**

Keywords— Artificial Neural Network, Short Circuit Fault, Fault Detection, Power System Network, Fault Classification

1. INTRODUCTION

Power systems comprise transformers, generators, loads, transmission lines as well as other safety devices such as circuit breakers and relays among others [1,2]. Their mode of operation is such that the currents and voltages magnitude are distributed in equal proportions when they are in a normal state. Nevertheless, if there is a fault in the circuit, it will cause interference or a total failure that will disrupt the normal operation of the system [3]. These faults may either be symmetrical (balanced) which includes all the phases or asymmetrical (unbalanced) which consists of one or two phases [4].

Notably, fault analysis is very important in power system since it involves determining the bus voltages and line currents when various types of failures occur [5,6,7]. The influence of faults on power system operation is widely regarded as important, as it causes power supply interruption and destabilizes the entire system [8,9,10]. This analysis aids in determining the most appropriate safety precautions to take as well as the necessary protective gear, for example, choosing an appropriate fuse, the most suitable circuit breaker size, or the right kind of relay [4,11,12,13]].

Furthermore, fault detection mechanism is a vital measure to deploy in power systems as it helps to maintain the safety and reliability of these systems, as well as minimize accidents, device damage, and unexpected blackouts [14,15,16]. In power systems, many categories of faults occur and the fault categories include short circuit faults which include single-phase-to-ground faults, phase-to-phase faults, double-phase-to-ground faults, and three-phase-to-ground faults ([17,18,19]. Among the aforementioned short circuit faults, single phase to ground fault is the commonest type of fault in power systems and its detection is very important as it makes it possible to isolate the faulty section of the system [20].

Deep learning (DL) techniques have recently gained popularity for a variety of applications, including the detection of faults in power systems [21] These techniques are model-based and the popular ones are Artificial Neural

Networks (ANN), Case-Based Reasoning (CBR), and fuzzy logic among others [22]. Transmission line faults affect the safe and stable operation of power systems as the scale of power systems grows with increased enhancement in the transmission of capacity and voltage [23]. Based on professional knowledge and experience, it has been discovered that the application of deep learning methods on a large number of short-circuit fault samples are core to improving the stability of fault diagnosis [24]. Accordingly, in this work, short-circuit fault detection and classification on the Nigerian 330kV transmission network in the Middle Belt Region using an artificial neural network (ANN) is presented. The details of the case study power system network, the model development and simulation, as well as results and discussions are presented.

2 METHODOLOGY

2.1 The model development procedure and case study power network data

The major aim of this work is the detection and identification of short circuit fault (SCF) on the Nigerian 330kV transmission network using Artificial Neural Network (ANN) model. The summary of the procedure used is outlined in the flow diagram shown in Figure 1.

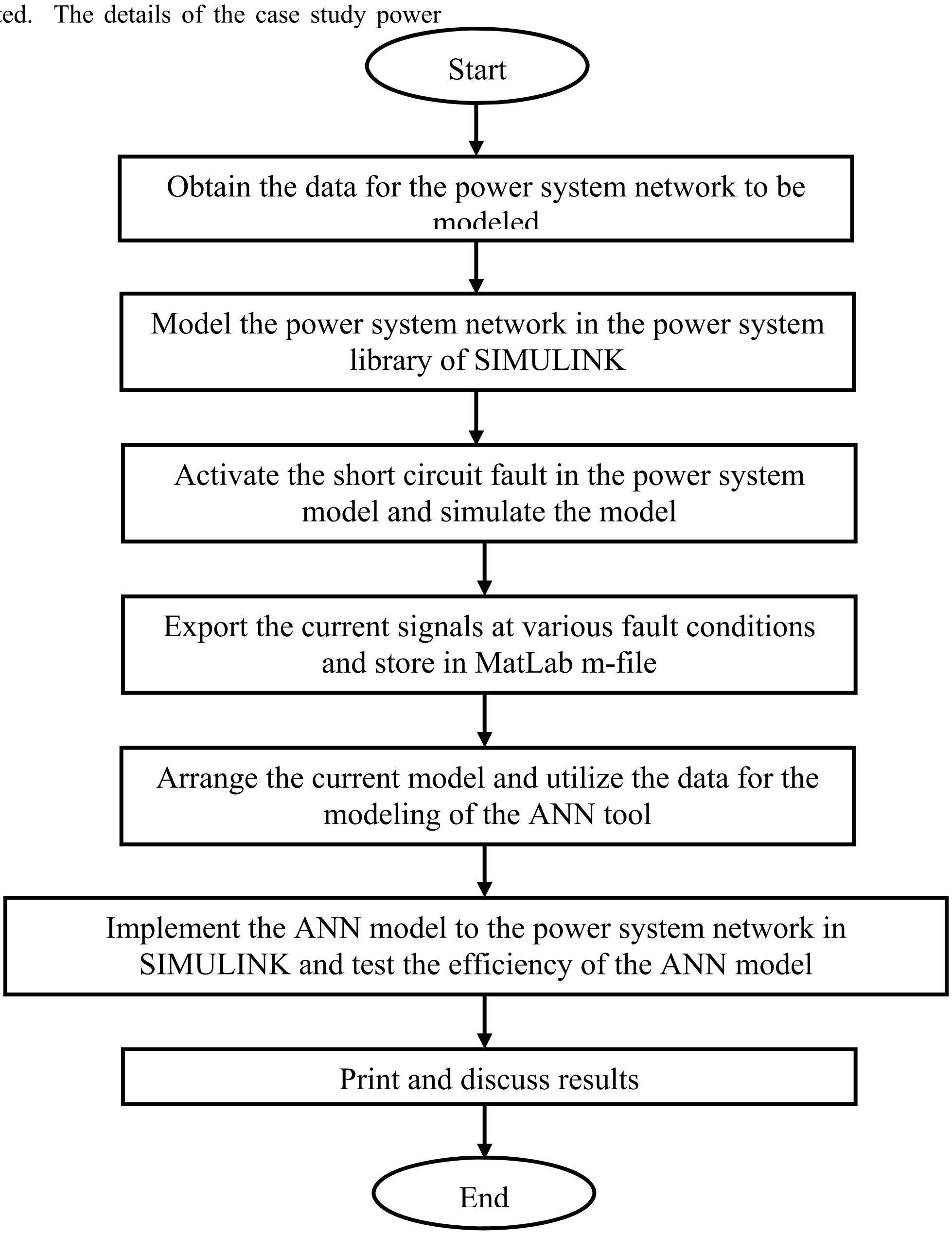

Figure 1 The summary of the research procedure used

Table 1: Bus numbering table

Bus Location	Bus Number
Shiroro GS	1
Gwagwalada TS	2
Katampe TS	3

Table 2: Transmission Line information

Line	From Bus	To Bus	Transmission Line Distance	R	X
1	1	2	144km	0.043	0.224
2	1	3	124km	0.0332	0.0431
3	2	3	60km	0.0437	0.1882

Table 3: Current signal values at fault conditions

Condition of Fault	Line 1			Line 2			Line 3		
	A	B	C	A	B	C	A	B	C
Normal	180	172	160	181	177	164	165	169	172
LG (Ag)	20	151	158	22	159	152	21	155	160
LL (A-B)	320	340	180	335	349	188	352	330	154
LLG (ABg)	14	13	172	10	11	161	24	17	180
LLL	290	323	331	340	301	307	311	303	319
LLLG	17	12	15	10	22	17	9	16	29

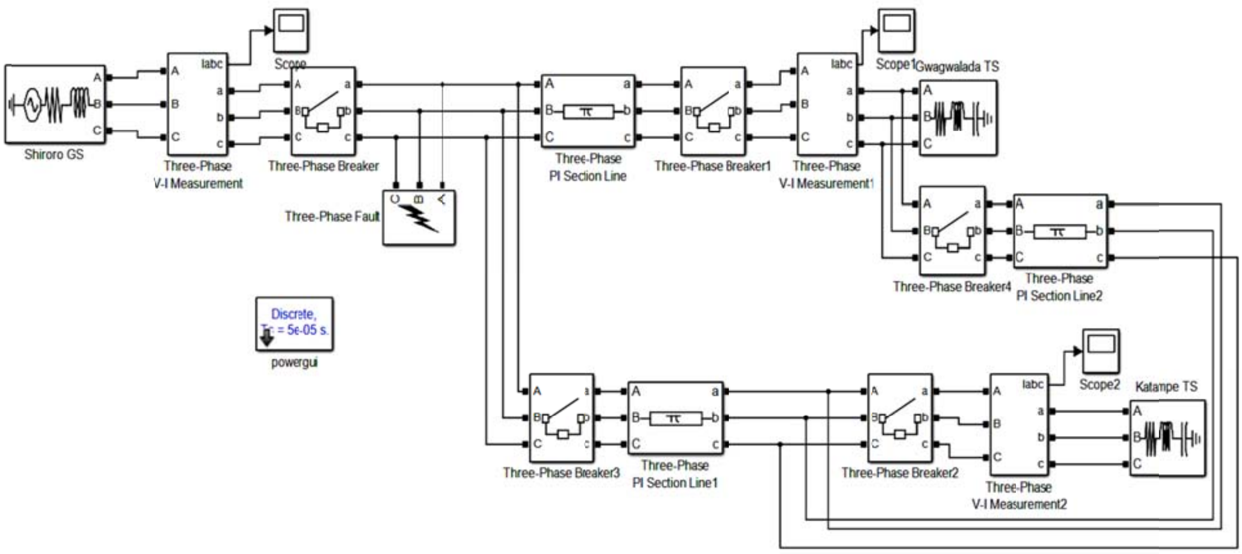

Figure 2: Power system SIMULINK model

The data in Table 3 were used as the independent (input) data for the modeling of the ANN for the short circuit fault detection and classification of the power system network.

2.2. Modeling of the ANN for Short Circuit Fault Detection and Classification

The input data for the ANN model in Matlab are the current signals of the various short circuit fault conditions shown in Table 3 while the target data are the fault classification code presented in Table 4. From the SCF classification code shown in Table 4, it simply means that when the power system network is at normal condition, the classification code is zero (0); when the SCF is single phase to ground (in this case, Ag fault is modeled), the classification code is one (1). The same approach is applied to the remaining SCFs listed in Table 4.

The current signal values had a total of six (6) datasets (known as data samples in ANN). For this study, 70% of the data was used for training, 15% for validation and 15% for testing as shown in Figure 3. The architecture of the ANN model is shown in Figure 3 showing that the ANN model has 3 input neurons in the input layer, 5 hidden neurons in the hidden layer and 1 output neuron in the output layer. The training of the network was done with levenberg maquart back propagation network.

Table 4: Fault classification code

S/N	Fault Condition	Coded Value
1	Normal	0
2	LG	1
3	LL	2
4	LLG	3
5	LLL	4
6	LLLG	5

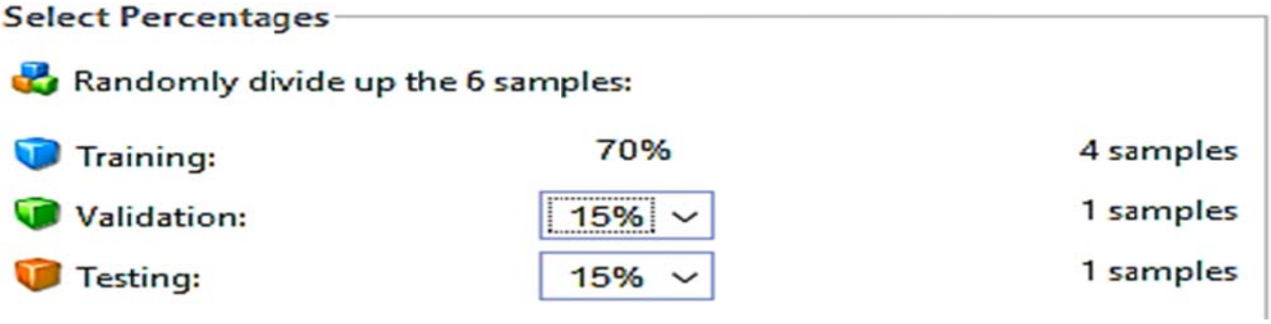

Figure 3: Data sample split

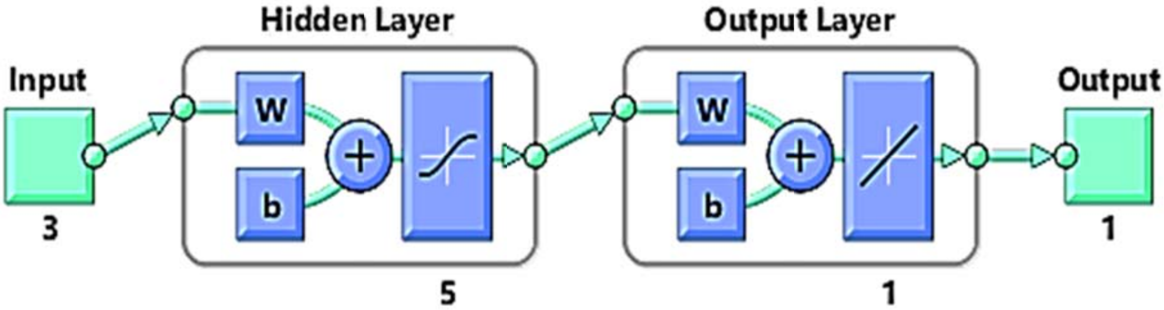

Figure 4: ANN model structure

3 RESULTS AND DISCUSSION

The sine wave of the current signal at normal condition for the generating station in Shiroro is shown in Figure 5; it shows a perfect signal due to the absence of distortion on the current phases and this implies that there is absence of fault in this location. Hence, the system would be described to be in normal condition.

The current signal with LG classified fault is shown in Figure 6 and it shows the current signal with a single phase line to ground fault occurrence. The fault occurred on phase A for each of the transmission line. The current signal for t phase was low due to the presence of the fault and the phase A transmission line are distorted with the current signal values appearing to be below 30 Amps.

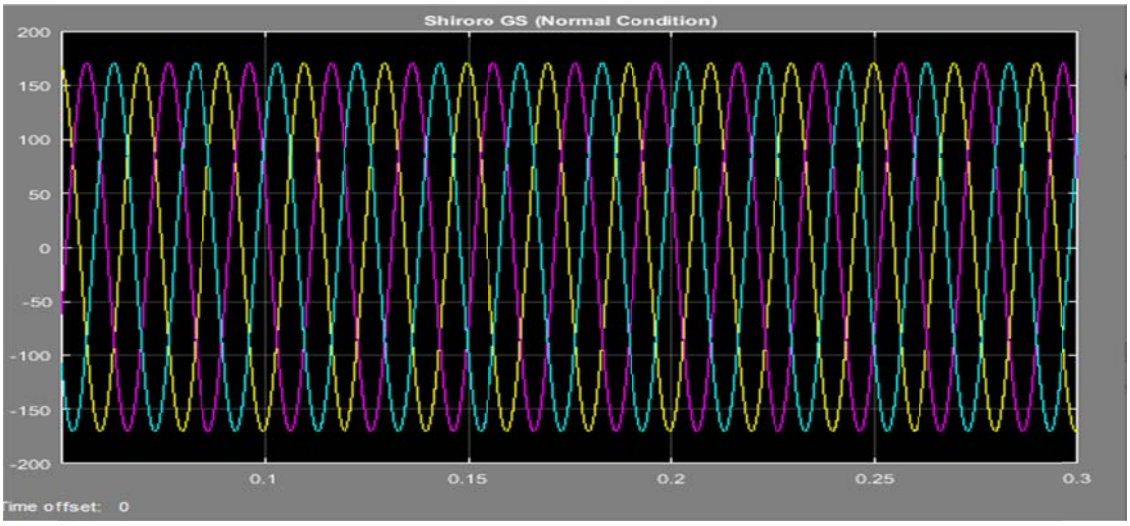

Figure 5: Normal condition at lines (measure from Shiroro GS).

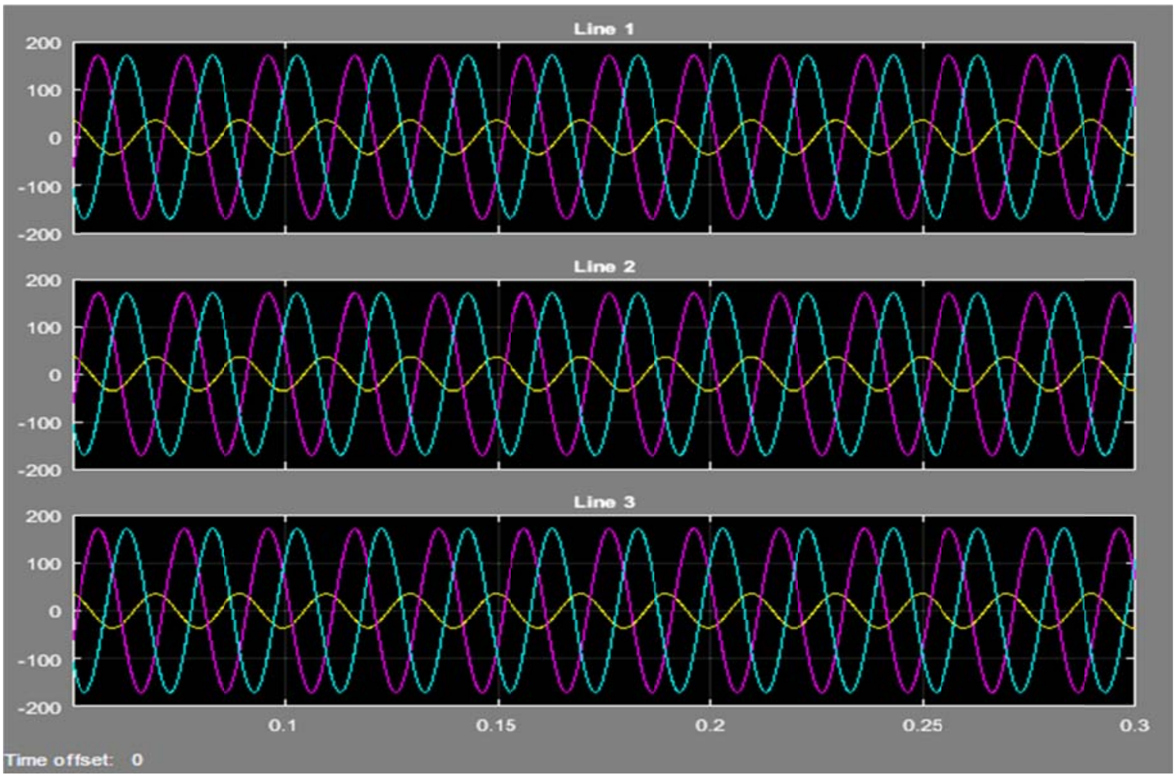

Figure 6: Current signal for LG (Ag) fault.

The current signal for the line to line fault (AB) was shown in Figure 7 and it shows that when short circuit occurs leading to line to line fault, the current signal would increase. This is evidence in phase A and B of Figure 7. The current signal values are above 250 Amps which shows the occurrence of line to line short circuit fault on all the lines of the power system network.

The occurrence of double line to ground fault (ABg) is shown in Figure 8. and it shows the current signal values are below 25 Amps which indicates the occurrence of double line to ground short circuit fault.

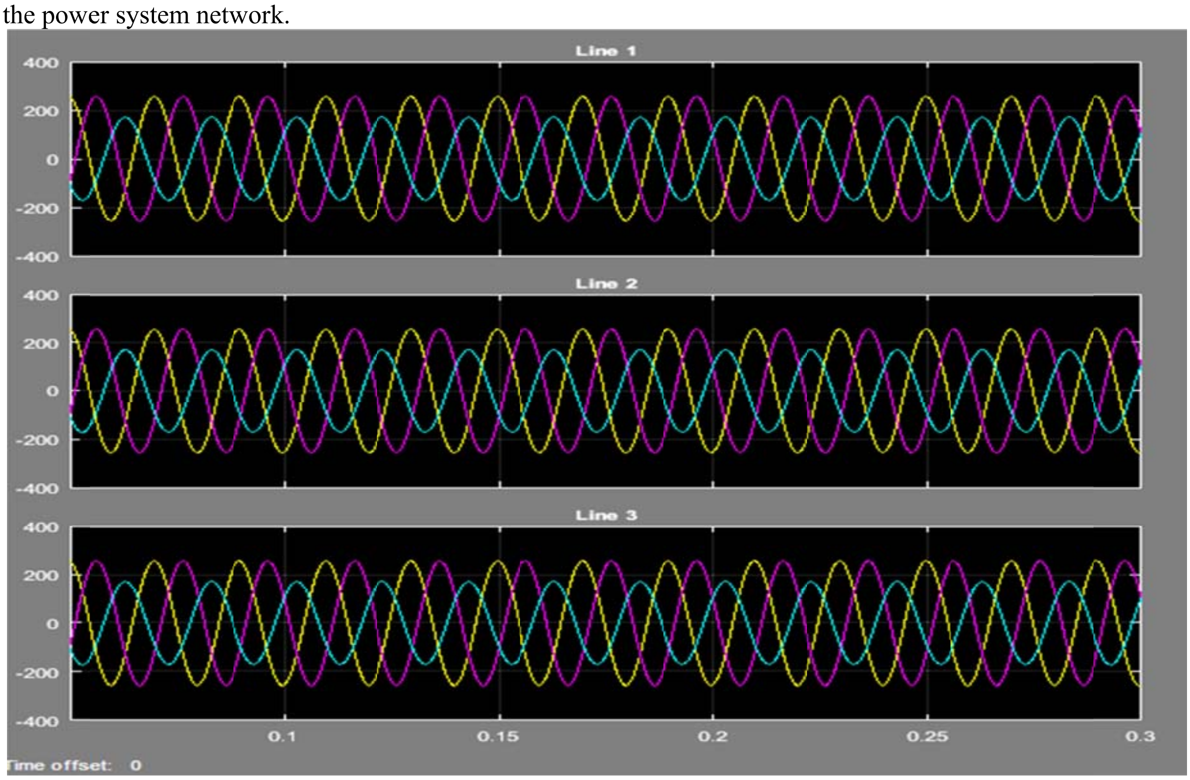

Figure 7: Current signal with line to line fault on phases AB.

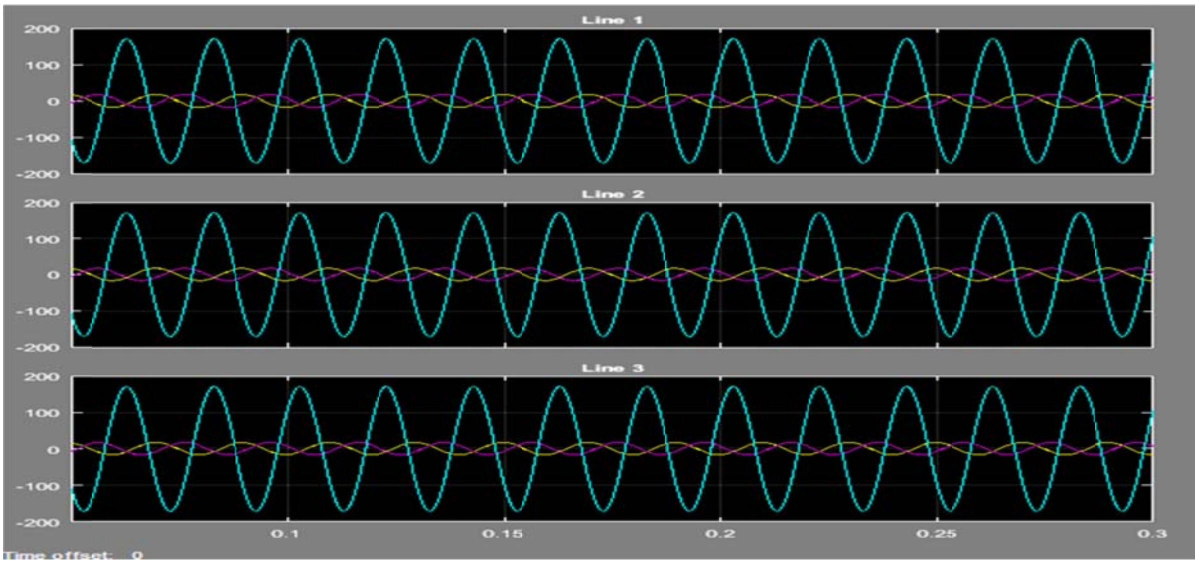

Figure 8: Current signal indicating the occurrence of double line to ground fault (ABg)

The current signal with the occurrence of triple phase line fault was shown in Figure 9. The occurrence of three phase fault on the transmission line led to rise of current signals of the three phases of the transmission line. The outcome in Figure 9 suggests the occurrence of short circuit fault on the transmission line of the network.

The occurrence of three-phase to ground fault is presented in Figure 10 which shows the current signal when three phase to ground fault occurs. Specifically, the current signal observed is low with current signal values lower than 20 amps and this depicts the presence of the faults.

The fault classification outcome with ANN model for the transmission lines are shown in Figure 11. The results of the percentage deviation of the fault classification carried out with ANN from the actual classification code employed are shown in Table 5 for all the transmission lines and all the class of faults. The results in Table 5 show that the ANN from adequately detected and classified the occurrence of short circuit fault in lines 1 and 3. However, it is not that adequate for line 2 given that the maximum error deviation occurred at line 2 while detecting the occurrence of triple phase fault with percentage deviation of 20.33%.

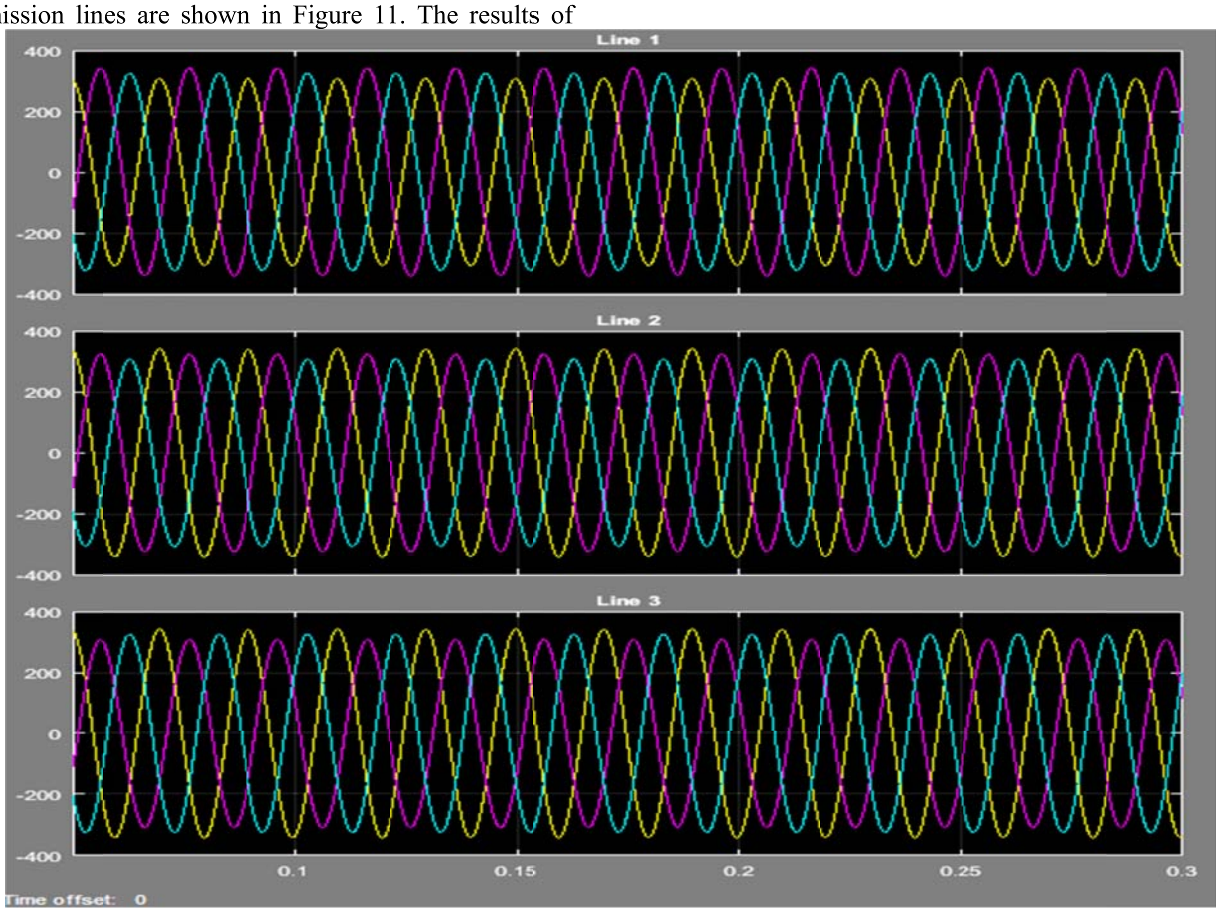

Figure 9: Current signal showing the occurrence of triple line phase fault

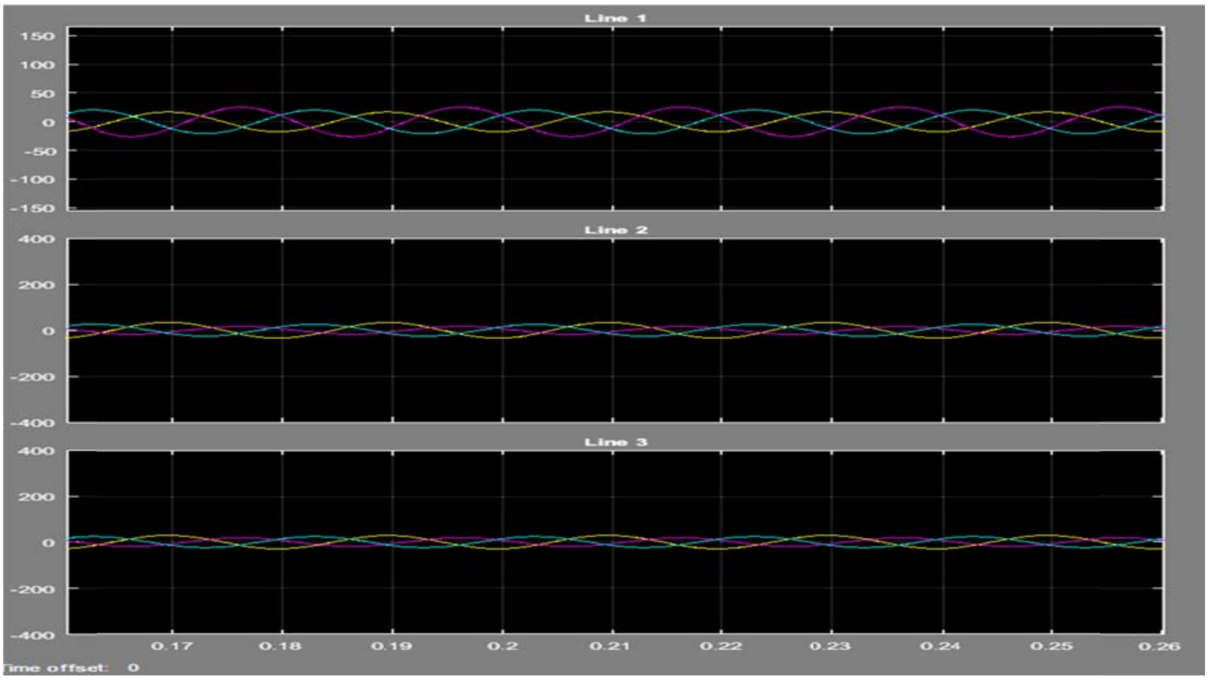

Figure 10: Current signal with triple phase fault to ground

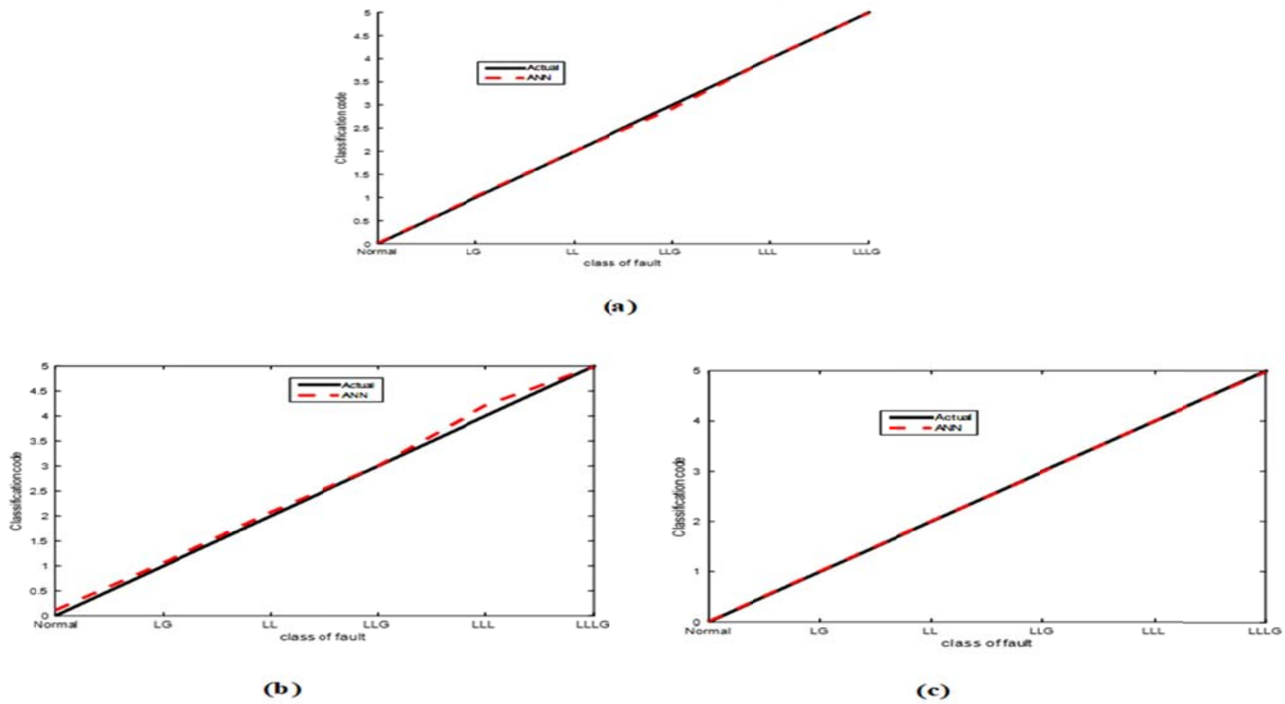

Figure 11 the results of the classification of fault with ANN for (a) line 1 (b) line 2 and (c) line 3

Table 5. : Short circuit fault detection and classification deviation with ANN model

Class of fault	Line 1 (%)	Line 2 (%)	Line 3 (%)
Normal	0.04	10.33	0.012
LG (Ag)	0.09	5.22	0.033
LL (AB)	0.076	4.11	0.021
LLG (ABg)	3.07	0.97	0.014
LLL (ABC)	0.14	20.33	0.092
LLG (ABCg)	0.092	1.09	0.066

4. CONCLUSION

The main emphasis in this study is the detection and classification of short circuit fault on the transmission lines connecting three power system stations in the Nigerian 330kV station. The network was modeled in SIMULINK with current signal values from various classes of faults exported to Matlab environment for the modeling of ANN. The modeled ANN was inserted to the power system model in Simulink to test the efficiency of the model in detecting and classifying short circuit faults. From the outcome, the ANN model effectively detected and classified the occurrence of short circuit faults in transmission lines 1 and 3 with minimal classification deviation However, there were concerns in transmission line 2 as the classification deviation was relatively high In conclusion, the use of ANN from the study adequately detected and classified the occurrence of short circuit fault in lines 1 and 3 but has a large deviation in transmission line 2 especially in detecting the triple phase line (ABC).

REFERENCES

1. Anderson, P. M., Henville, C. F., Rifaat, R., Johnson, B., & Meliopoulos, S. (2022). *Power system protection*. John Wiley & Sons.
2. Horowitz, S. H., Phadke, A. G., & Henville, C. F. (2022). *Power system relaying*. John Wiley & Sons.
3. Osman, M. and Habiballah, I. O. (2021). A review of short-circuit fault analysis and novel fault detection methods. *International Journal of Engineering Research and Technology (IJERT)*, 10(12): 36 – 44.
4. Ogar, V. N., Abara, D. N., and Akpama, E. J. (2017). Symmetrical and unsymmetrical faults analysis: Using Nigeria 330-KV grid as case study. In *2017 IEEE 3rd International Conference on Electro-Technology for National Development (NIGERCON)*, pp. 1 – 7.
5. Ukil, A., Yeap, Y. M., & Satpathi, K. (2020). *Fault analysis and protection system design for DC grids*. Berlin: Springer.
6. Gjorgiev, B., & Sansavini, G. (2022). Identifying and assessing power system vulnerabilities to transmission asset outages via cascading failure analysis. *Reliability Engineering & System Safety*, *217*, 108085.
7. Abu-Siada, A., Mosaad, M. I., & Mir, S. (2020). Voltage–current technique to identify fault location within long transmission lines. *IET Generation, Transmission & Distribution*, *14*(23), 5588-5596.
8. Mahapatra, S., and Singh, M. (2016). Analysis of symmetrical fault in IEEE 14 bus system for enhancing over current protection scheme. *International Journal of Future Generation Communication and Networking*, 9(4): 51 – 62.
9. Ghiasi, M., Niknam, T., Wang, Z., Mehrandezh, M., Dehghani, M., & Ghadimi, N. (2023). A comprehensive review of cyber-attacks and defense mechanisms for improving security in smart grid energy systems: Past, present and future. *Electric Power Systems Research*, *215*, 108975.
10. Ti, B., Li, G., Zhou, M., & Wang, J. (2021). Resilience assessment and improvement for cyber-physical power systems under typhoon disasters. *IEEE Transactions on Smart Grid*, *13*(1), 783-794.
11. Stephans, R. A. (2022). *System safety for the 21st century*. John Wiley & Sons.
12. Gjorgiev, B., & Sansavini, G. (2022). Identifying and assessing power system vulnerabilities to transmission asset outages via cascading failure analysis. *Reliability Engineering & System Safety*, *217*, 108085.
13. Shi, Z., Yao, W., Li, Z., Zeng, L., Zhao, Y., Zhang, R., ... & Wen, J. (2020). Artificial intelligence techniques for stability analysis and control in smart grids: Methodologies, applications, challenges and future directions. *Applied Energy*, *278*, 115733.
14. Haes Alhelou, H., Hamedani-Golshan, M. E., Njenda, T. C., & Siano, P. (2019). A survey on power system blackout and cascading events: Research motivations and challenges. *Energies*, *12*(4), 682.
15. Aminifar, F., Abedini, M., Amraee, T., Jafarian, P., Samimi, M. H., & Shahidehpour, M. (2021). A review of power system protection and asset management with machine learning techniques. *Energy Systems*, 1-38.
16. Perumalsamy, N., Sivasankar, G., Elavarasan, R. M., Kumar, S., & Khan, B. (2022). Design of Faulty Switching Detection and Alert System to Prevent Fatality of Servicemen During Transformer Maintenance. *IEEE Access*, *10*, 77362-77374.
17. Liu, K., Zhang, S., Li, B., Zhang, C., Liu, B., Jin, H., & Zhao, J. (2021). Flexible grounding system for single-phase to ground faults in distribution networks: A systematic review of developments. *IEEE Transactions on Power Delivery*, *37*(3), 1640-1649.
18. Wang, X., Zhang, H., Shi, F., Wu, Q., Terzija, V., Xie, W., & Fang, C. (2019). Location of single phase to ground faults in distribution networks based on synchronous transients energy analysis. *IEEE Transactions on Smart Grid*, *11*(1), 774-785.
19. Barik, M. A., Gargoom, A., Mahmud, M. A., Haque, M. E., Al-Khalidi, H. and Oo, A. (2018). A decentralized fault detection technique for detecting single phase to ground faults in power distribution systems with resonant grounding. *IEEE Transactions on Power Delivery*, 33(5): 2462 – 2473.
20. Ma, J., Yan, X., Fan, B., Liu, C., and Thorp, J. S. (2015). A novel line protection scheme for a single phase-to-ground fault based on voltage phase comparison. *IEEE Transactions on Power Delivery*, 31(5): 2018 – 2027.
21. Cunha, R. G. C., da Silva Jr, E. T., and de Sá Medeiros, C. M. (2021). Machine learning and multiresolution decomposition for embedded applications to detect short-circuit in induction motors. *Computers in Industry*, 129: 103461.
22. Masrur, M. A., Chen, Z., and Murphey, Y. (2010). Intelligent diagnosis of open and short circuit faults in electric drive inverters for real-time applications. *IET Power Electronics*, 3(2): 279 – 291.
23. Dong, Q., and Liu, Z. (2013, October). The method of short circuit fault identification and location in high-voltage transmission line. In *2013 Sixth International Conference on Advanced Computational Intelligence (ICACI)*, pp. 150-154.
24. Li, Y., Wang, Y., Zhang, Y., and Zhang, J. (2021). Diagnosis of inter-turn short circuit of permanent magnet synchronous motor based on deep learning and small fault samples. *Neurocomputing*, 442: 348 – 358.