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Faults detection, location, and classification of the elements in the power system using intelligent algorithm

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ABSTRACT

This study proposes an intelligent protection relay design that uses artificial neural networks to secure electrical parts in power infrastructure from different faults. Electrical transformer and transmission lines are protected using intelligent differential and distance relay, respectively. Faults are categorized, and their locations are pinpointed using three-phase current values and zero-current characteristics to differentiate between non-earth and ground faults. The optimal aspects of the artificial neural network were chosen for optimal results with the least possible error. Levenberg-Marquardt was established as the ideal training technique for the suggested system comprising the differential relay. Levenberg-Marquardt was the optimal training technique for the proposed framework consisting of the differential relay. Fault detection and categorization were performed using 20 and 50 hidden layers, and the corresponding error rates were 9.9873e-3 and 1.1953e-29. In the context of fault detection by the distance relay, the hidden layer neuron counts were 400, 250, and 300 for fault detection, categorization, and location; training error rates were 7.8761e-2, 1.2063e-6, and 1.1616e-26, respectively.

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1. INTRODUCTION

It is vital to have a continuous and dependable electricity source. Electrical outages impact the economic scenario at domestic and industrial levels. Irregular and arbitrary faults in the electricity transmission system cause major power interruptions. The effects of power outages can be reduced by quickly and accurately identifying faults to enable service restoration. Several studies have addressed electrical fault location [1]–[4]. Electrical faults are dangerous for the proper operation of any electrical system because they disturb regular system operation and create instability hazards. In the context of the electrical grid, transmission lines and transformers are affected the most. Numerous works have proposed methods to detect [5]–[7], pinpoint, and categorise electrical faults in the transmission network and power transformers.

References number [8]–[10] proposed a productive method to detect, categorise, and pinpoint electric transmission system faults. The system comprised a virtual bus and neural network-based simulation to evaluate faults on the bus and transmission network. A two-port network performance technique specified an adaptive neuro-fuzzy inference system algorithm (ANFIS) devised to secure the electrical transmission system with frequent faults. Recognising and categorising AC transmission network faults was assessed by

[11] using power spectral density (PSD) and data assessment for fault-specific situations using PSD with frequency and time. Subsequently, a wavelet-covariance matrix is created to determine PSD. Researchers [12] indicated similar objectives for using evolutionary coding software (PSCAD/EMTDC) to simulate several operational and faulty situations for the high voltage transmission network. A combined method was proposed to recognise and identify faults in the transmission system comprising an interconnected network [13]. This work proposed to use phasor measurement units (PMUs) to determine positive sequence current and voltage characteristics. Fan and Liao [14] devised a system integrity preservation technique using wide-area evaluations. The approach divides the network, and the smaller networks or protection zones are fitted with current measuring instruments that help identify problems and provide a pinpointing vector for the faulty network region. The technique by [15] employs a change in sign concerning the positive-sequence current levels at line terminals to identify faults. Moreover, three-phase current values are determined locally and used to derive the transient monitor index to categorise faults.

Phasor measurement units (PMU) [16] were devised to identify faulty conditions and use circuit breakers (CBs) to safeguard and secure the network. CBs operate based on the excessive divergence of a specific network parameter. Rapid and precise fault identification prevents large-scale effects on the distribution system and reduces economic impact. Power transmission lines are vulnerable to numerous faults; however, other system components are also affected. Power transformers are the costliest components in electrical distribution systems; they must be monitored continually in order to implement protective steps with a slight delay. Power transformers are secured using differential relays. This mechanism checks current flowing in the secondary and primary sides and sends a tripping command to the CB.

Nevertheless, such relays may not be reliable during the high magnetising inrush current drawn when the transformers are switched on [17]. The primary concern about transformer protection is the rapid response offered by an effective differential relay technique that disconnects the transformers from the system, reducing damage. Ali *et al*. [18] devised an approach based on the primary and secondary current values corresponding to each phase; the ratio of the magnitude of difference and sum at both sides, and the phase-specific ratio of the magnitudes of the difference and aggregate of the primary and secondary terminal voltages are used for the protection scheme. A novel technique [19] used the integral concept to provide power transformers with differential protection. The necessary signals are computed operationally using restraining-current values for the required phases. The second harmonic is employed for more computations. Ali *et al*. [20] devised a universal technique using voltage and current ratios for primary and secondary sides, the direction of the current, and wave characteristics concerning power transformers independent of connection type (delta or star). Root cause identification is proposed in [21], considering that fault tree-based evaluation is employed to evaluate characteristics causing wrong trips. Regulation approaches can be used when the significant root issues are determined. The security framework facilitates an analytical qualification of protective model reliability. Artificial neural network (ANN) and wavelet transform based protection approach for three-phase transformers is specified in [22]. Wavelet operations are used to decompose present waves. ANN methods are employed for pattern categorisation. Numerous studies indicate the wavelet transform is appropriate for initiating feature determination for several transient scenarios. Althi *et al*. [23] proposed a safeguarding approach for open conductor and series issues concerning six-phase transmission networks. The technique starts by approximating the current characteristics from the time-domain current values at the conductor on the transmitting side. A fuzzy logic protection technique consumes the information. Das and Adhikari [24] used fuzzy logic to devise a fault identification and classification approach for a UPQC-compensated distribution line. Further, differential safeguarding for power transformers using the signal localised convolution neural network (SLCNN) is proposed [25]. Sequentially, the time and frequency coefficients are processed using the convolution approach for distinct signal localisation. The required coefficients are determined using wavelet operations concerning the differential current signal.

The approach proposed in this study can accurately predict fault distance for line-to-ground (LG) and line-to-LG (LLG) ground faults. However, this approach cannot pinpoint faults for open conductors, line-to-line (LL), and LL-to-line (LLL). This work presents a power network fault detection, categorisation, and localisation approach that helps estimate with high precision the fault location in the transmission network.

The study aims and objectives are devising an intelligent distance relay-based technique powered by artificial neural networks to safeguard power transmission lines. Devise an ANN-based intelligent differential protection approach to safeguard electrical power transformers. A two-related system is proposed to differentiate higher load and work scenarios for issues that affect the network but prevent CBs from tripping during electrical faults. Estimate fault location in the network using an ANN model trained using the present power network fingerprint. Classify system fault types using present power network fingerprint to train three artificial neural networks.

2. METHOD AND TOOLS

Smart relays have been built to protect the electrical network. ANN based techniques help determine issues. Furthermore, it is feasible to differentiate between faults and acceptable overload. Figure 1 depicts the fault location categories and specifications for SLG, LL, LLG, and LLLG that could affect an electrical power network. Table 1 display the power network characteristics in this work.

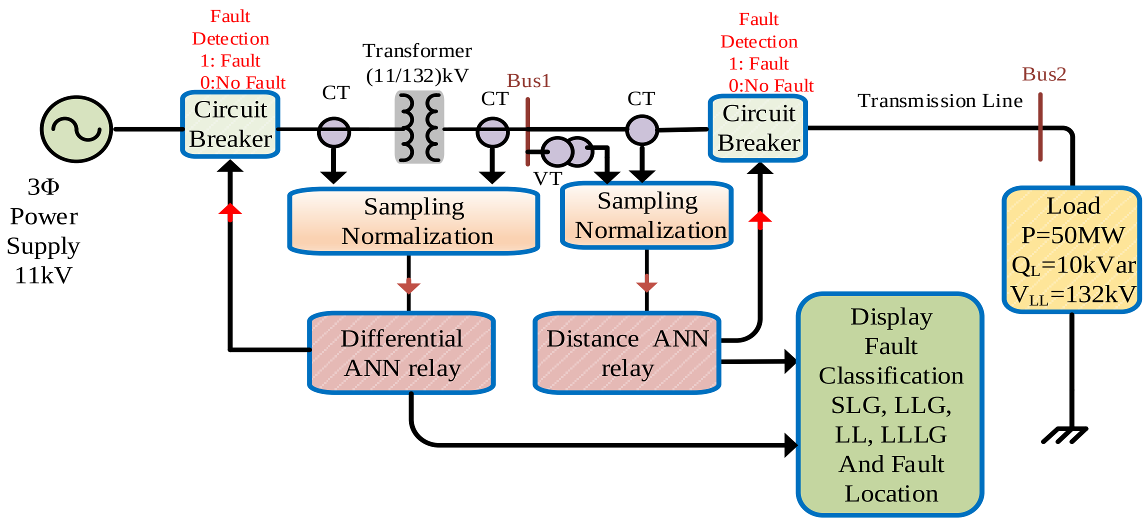


Figure 1. Power system with smart relays

Table 1. Power network characteristics

Elements	Data
Power supply	3 phases, Vp-p=16.5 kV, S=100 MVA, f=60 Hz
Power transformer	3 phases, S=100 MVA, V1=16.5 kV, V2=230 kV, Yg/Yg
Load	3 phases Yg, Vp.p=230 kV, f=60 Hz, P=90 MW, QL= 30 KVar
Transmission line	R1 [Ω/km]=0.08993, Ro [Ω/km]=0.224825, L1 [mH/km]=1.29, Lo [mH/km]=3.22, C1 [nf/km]=7.922, Co [nF/km]=4.74, Line length=200 Km

The protection mechanism is devised with an intelligent distance relay to determine transmission network faults. The system is equipped with a smart differential safeguarding mechanism to protect the electrical transformer. Relays are designed considering the neural network; moreover, hidden layer neuron count is optimised to provide acceptable outcomes. The study also considers the training techniques required for the two relays. The differential phase considers current values and differences concerning the secondary and primary sides.

Figure 2 depicts an intelligent distance relay that uses neural networks to safeguard the electrical network from faults. System voltage and current values comprise relay input; the framework is used to determine the impedance of the transmission line. The ANN technique works to determine the inductance and resistance of the electrical line, thereby identifying faults. A trip command is asserted to the CB to safeguard the network from an electrical fault.

Figure 3 depicts the intelligent differential relay that relies on an artificial neural network to safeguard power transformers from electrical faults. The currents flowing in the secondary and primary sides of the three-phase transformer are used as relay input. Subsequently, the current difference between the two sides is fed into the network, considering the transformer conversion factor to allow the ANN to identify transformer fault and send the trip signal to allow the CB to isolate the transformer from the network.

Hence, any difference indicates the presence of transformer faults. Currents on the three phases of the primary and secondary sides are used as neural network inputs. Table 2 specifies the characteristics of the neural network-based fault detection system. Table 3 lists information about the neural network framework used to determine and classify issues relating to electrical transformers.

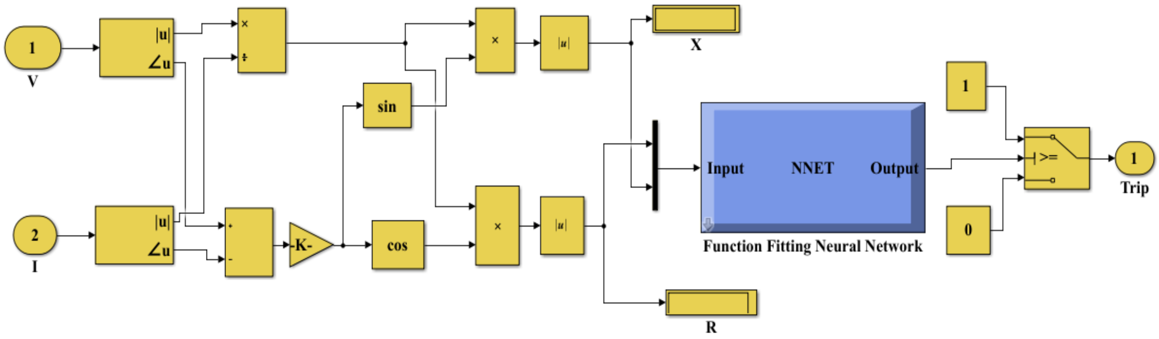


Figure 2. Intelligent distance relay model

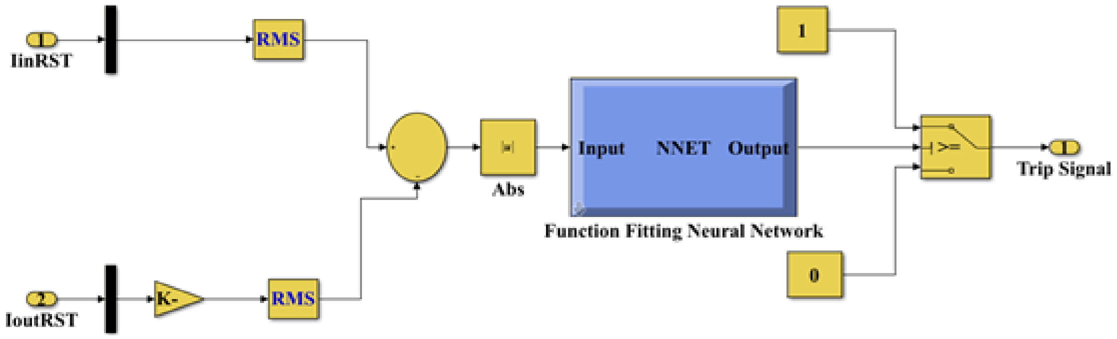


Figure 3. Schematic of a smart differential relay

Table 2. Specifications of the neural network for identifying transformer faults

ANN–Parameters	Characteristics
Training–Algorithm	Levenberg–Marquardt
Epochs	10
Training-Goal (MSE)	9.9873e-3
Inputs	**3**
Output–Neurons	1
Neurons-Hidden Layer	20

Table 3. Neural network building blocks to categorise transformer faults

ANN- Parameters	Characteristics
Training –Algorithm	Levenberg–Marquardt
Epochs	4
Training- Goal (MSE)	1.1953e-29
Inputs	4
Output-Neurons	1
Neurons-Hidden Layer	50

The distance relay protects the electrical line; it compares the measured line impedance against the nominal value to identify faults. If the determined impedance is below the nominal value for the line, a fault is indicated. Phase-specific voltage and current values are critical inputs to assess faults. Fault categorisation and location is based on the current flowing in the three phases; these values are used by the neural network system, as specified in Tables 4-6, respectively.

The put forward technique begins by determining current flow in the secondary and primary sides of the transformer. If there is a difference between the two sides, the transformer has a fault, whereby the CB isolates the faulting system through a trip command. Subsequently, the fault is located and categorised. If the current values on the two sides are the same, the impedance is determined for the line and compared against the nominal value for a normal no-fault situation.

If the determined line impedance is below the nominal value, a fault might exist in the system, and the CB is sent the trip signal to protect the system. Subsequently, the faulty system is isolated, the faults are classified, and locations are pinpointed using the neural network. Figure 4 explain the Training, Testing and Validation graphs for detection faults by intelligent differential relay. Figure 5 explain the Training, Testing and Validation graphs for detection faults by intelligent distance relay.

The safeguarding system mechanism is depicted in the flowchart presented in Figure 6. It depicts the issue detection and categorisation technique for fault location and type in the transmission network. The system measures the primary (Ip) and secondary (Is) current values for the transformer; subsequently, it gauges the voltage and current levels in the three-phase transmission system. Transmission network and transformer values and angles are computed. Initially, a phase-wise comparison is made for the primary and secondary current values.

Table 4. Neural network aspects to identify transmission line faults

ANN- Parameters	Characteristics
Training- Algorithm	Levenberg– Marquardt
Epochs	13
Training -Goal (MSE)	7.8761e-2
Inputs	2
Output -Neurons	1
Neurons - Hidden Layer	400

Table 5. Neural network aspects to categorise transmission line faults

ANN -Parameters	Characteristics
Training-Algorithm	Levenberg– Marquardt
Epochs	4
Training-Goal (MSE)	1.2063e-6
Inputs	**4**
Output-Neurons	1
Neurons-Hidden Layer	250

Table 6. Neural network aspects to identify transmission line fault location

ANN Parameters	Characteristics
Training Algorithm	Levenberg– Marquardt
No. of Epochs	6
Training Goal (MSE)	1.1616e-26
No. of Inputs	**4**
No. of Output Neurons	1
No. of Neurons Hidden Layer	300

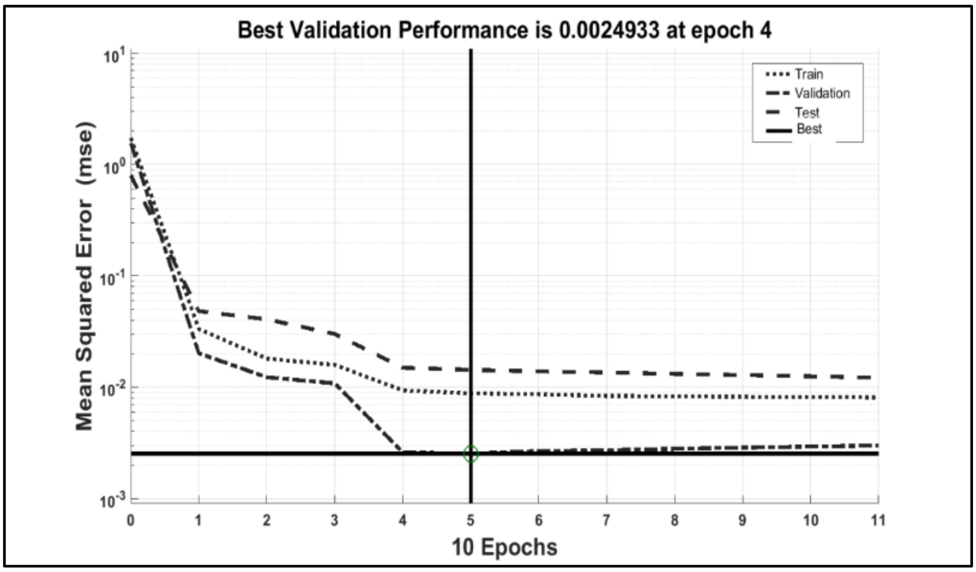


Figure 4. Testing and validation graphs for detection faults by intelligent differential relay

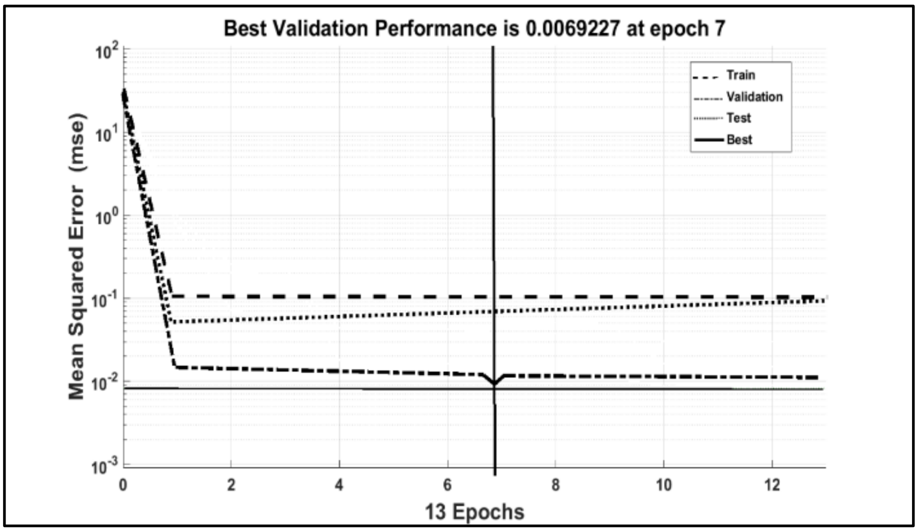


Figure 5. Testing and validation graphs for detection faults by intelligent differential relay

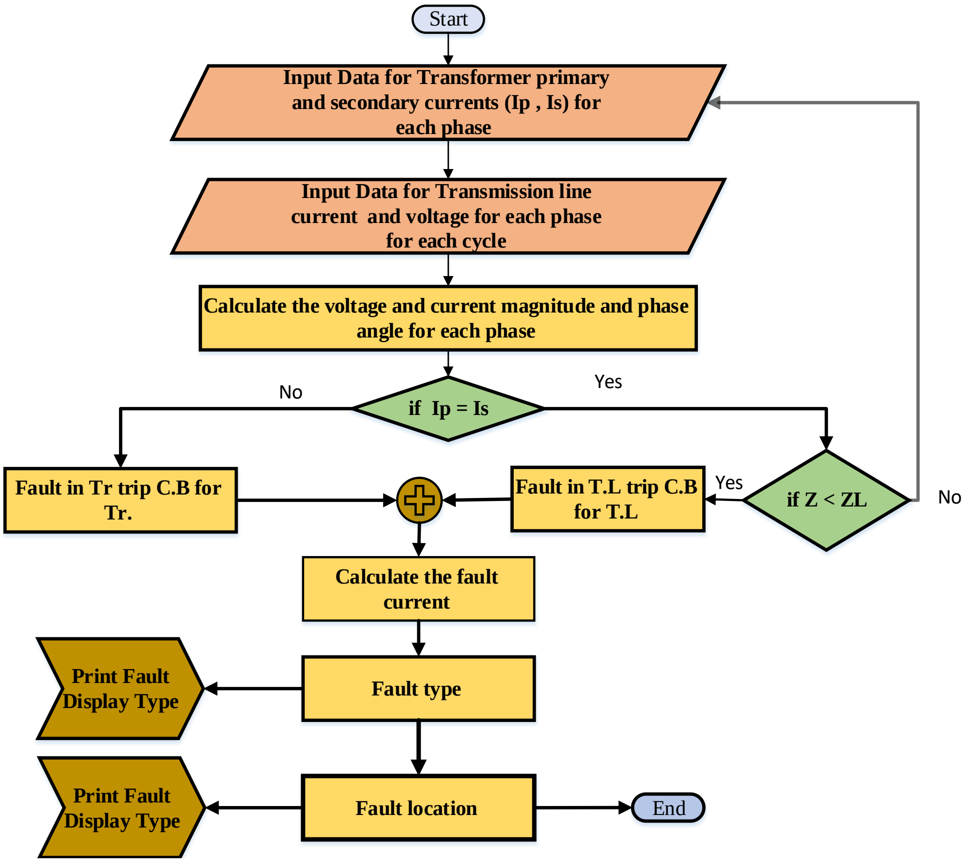


Figure 6. Power system flowchart for the intelligent protection relay function

A transformer fault is indicated if the values differ, and a trip signal is asserted to the CB to isolate the transformer from the network. Subsequently, the fault category is determined. However, if the currents on the two transformer sides are the same, the electrical line impedance (Z) is computed using the current and voltage values on every phase. Normal condition (ZL) is reported if the values are nominal. However, if the values are below the nominal values, a transmission fault is indicated, and a trip signal is asserted to the CB to isolate the transmission system. Subsequently, the fault type and location are determined using the proposed ANN technique.

3. RESULTS AND DISCUSSION

Figure 1 depicts a MATLAB/Simulink simulated electrical power network with different fault categories. A typical case is increased electrical load, and it does not require the differential relays to issue the trip command to CBs. However, when the power transformers witness issues, the differential relays send commands to trip the CBs. Moreover, when the transmission line experiences different faults, the distance phase for safeguarding the transmission network is used to trip the CBs. Numerous scenarios were considered, and faults were simulated within the power system, as specified in Table 7. Furthermore, to clarify the numerous faults which can happen in the system, the categories of these faults were presented in the proposed model as shown in Table 8. Table 9 lists the fault location error on the transmission network using the neural network when the middle of the line experiences faults.

Table 7. System faults used in this study

Case-1	The system is normal without a fault or overload.
Case-2	The system is in case of overload.
Case-3	The system has a phase-to-ground (A-G) fault in the power transformer on the primary side.
Case-4	The system has a phase-to-ground fault (B-G) in the power transformer on the primary side.
Case-5	The system has a phase-to-ground (C-G) fault in the power transformer on the primary side.
Case-6	The system had a two-phase to ground (AB-G) fault in the power transformer on the primary side.
Case-7	The system has a two-phase to ground (BC-G) fault in the power transformer on the primary side.
Case-8	The system had a two-phase to ground (AC-G) fault in the power transformer on the primary side.
Case-9	The system had a three-phase to ground fault (ABC-G) in the power transformer on the primary side.
Case-10	The system had a phase-to-ground fault (A-G) in the transmission line at a distance of 25% of the length of the line.
Case-11	The system had a phase-to-ground fault (B-G) in the transmission line at a distance of 50% of the length of the line.
Case-12	The system had a phase-to-ground fault (C-G) in the transmission line at a distance of 75% of the length of the line.
Case-13	The system had a two-phase fault to the ground (AB-G) in the transmission line at a distance of 25% of the length of the line.
Case-14	The system had a two-phase to ground fault (BC-G) in the transmission line at a distance of 50% of the length of the line.
Case-15	The system has a two-phase to ground fault (AC-G) in the transmission line at a distance of 75% of the length of the line.
Case-16	The system had a three-phase to ground fault (ABC-G) in the transmission line at a distance of 50% of the length of the line.

Table 8. System fault categories

Cases	Maximum current in phase A for primary transformer [KA]	Maximum current in phase B for primary transformer [KA]	Maximum current in phase C for primary transformer [KA]	Maximum current in phase A for secondary transformer [KA]	Maximum current in phase B for secondary transformer [KA]	Maximum current in phase C for secondary transformer [KA]	Maximum current in phase A for transmission line [KA]	Maximum current in phase B for transmission line [KA]	Maximum current in phase C for transmission line [KA]	Trip signal C.B for transformer	Trip signal C.B for transmission line
1	3.7	3.7	3.7	3.7	3.7	3.7	0.266	0.266	0.266	No trip	No trip
2	5	5	5	5	5	5	0.363	0.363	0.363	No trip	No trip
3	22.3	3.7	3.7	3.7	3.7	3.7	0.266	0.266	0.266	Trip	No trip
4	3.7	19.8	3.7	3.7	3.7	3.7	0.266	0.266	0.266	Trip	No trip
5	3.7	3.7	9.7	3.7	3.7	3.7	0.266	0.266	0.266	Trip	No trip
6	22.3	19.8	3.7	3.7	3.7	3.7	0.266	0.266	0.266	Trip	No trip
7	3.7	19.8	9.74	3.7	3.7	3.7	0.266	0.266	0.266	Trip	No trip
8	22.3	3.7	9.7	3.7	3.7	3.7	0.266	0.266	0.266	Trip	No trip
9	22.3	19.8	9.7	3.7	3.7	3.7	0.266	0.266	0.266	Trip	No trip
10	16.2	3.7	3.7	16.2	3.7	3.7	1.16	0.266	0.266	No trip	Trip
11	3.7	15.2	3.7	3.7	15.2	3.7	0.266	1.02	0.266	No trip	Trip
12	3.7	3.7	8.05	3.7	3.7	8.05	0.266	0.266	0.56	No trip	Trip
13	17	15.6	3.7	17	15.6	3.7	1.22	1.11	0.266	No trip	Trip
14	3.7	15.4	8.3	3.7	15.4	8.3	0.266	1.6	0.598	No trip	Trip
15	15.9	3.7	7.96	15.9	3.7	7.96	1.14	0.266	0.52	No trip	Trip
16	16.5	15.8	8.21	16.5	15.8	8.21	1.19	1.13	0.589	No trip	Trip

Table 9. Fault location detection error rate

Cases	Actual fault location in transmission line [km]	Estimate fault location in transmission line using ANN [km]	Error [%]
10	50	49	1
11	100	98	1
12	150	151	-0.5
13	50	50	0
14	100	95	2.5
15	150	149	0.5
16	100	100	0

The following diagrams indicate the current and voltage plots corresponding to a three-phase system under failure at time t=0.2 sec. The electrical line and both transformer sides are under the fault scenario. Figure 7 depicts the current and voltage plots for the three transmission phases where two phases have a ground fault (AB-G) at time t=0.2 sec, and phases A and B have higher current values. Figure 8 depicts the disconnect signals issued by the differential and distance relays to disconnect the circuit. Considering that the transmission line had faults, the distance relay asserted the trip command since the transformer is normal, but the line is faulty.

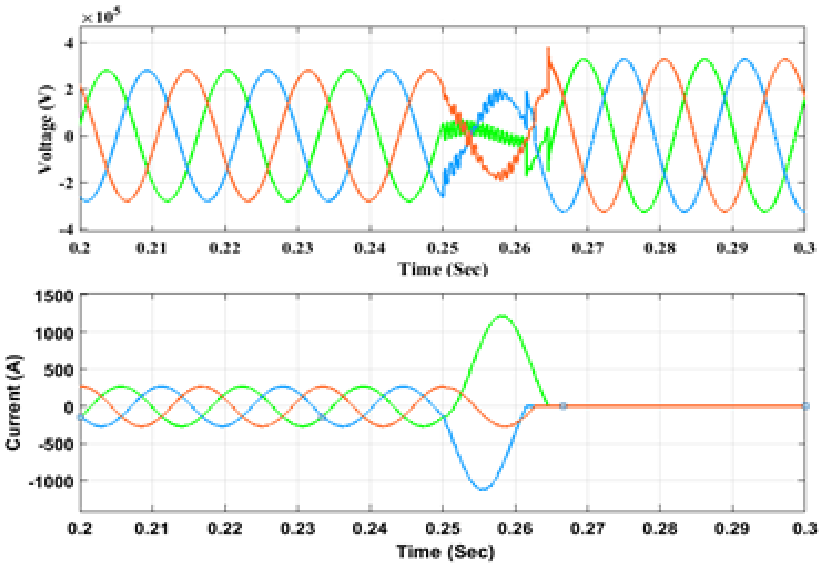


Figure 7. Current and voltage plots for a two-phase-to-earth (AB-G) line fault

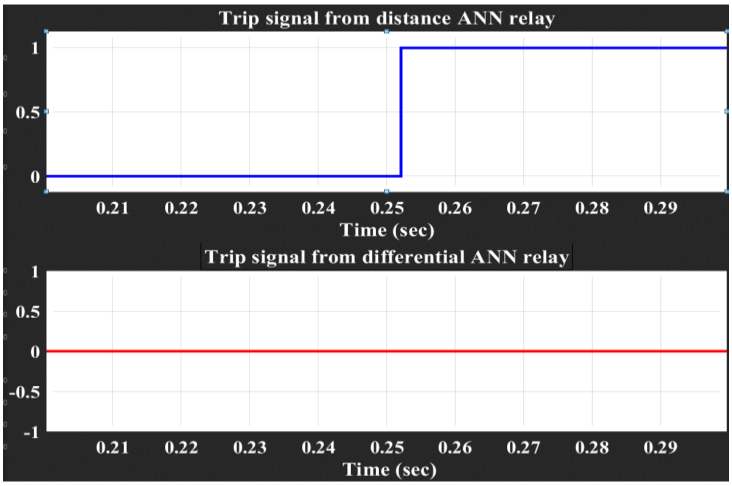
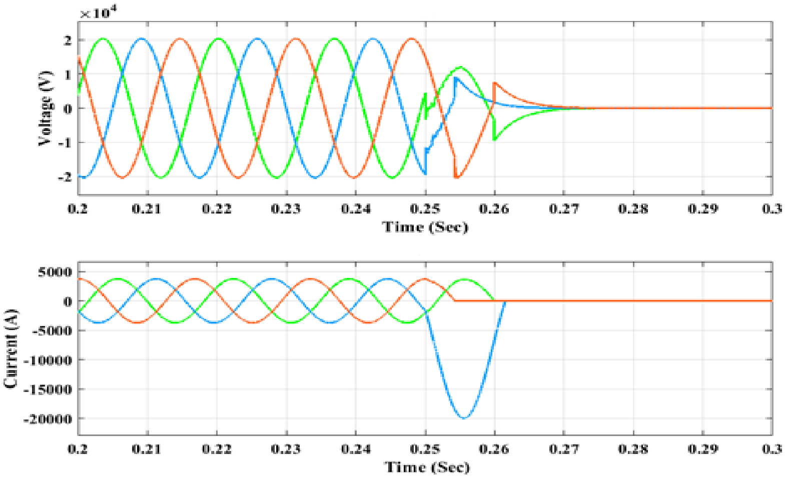
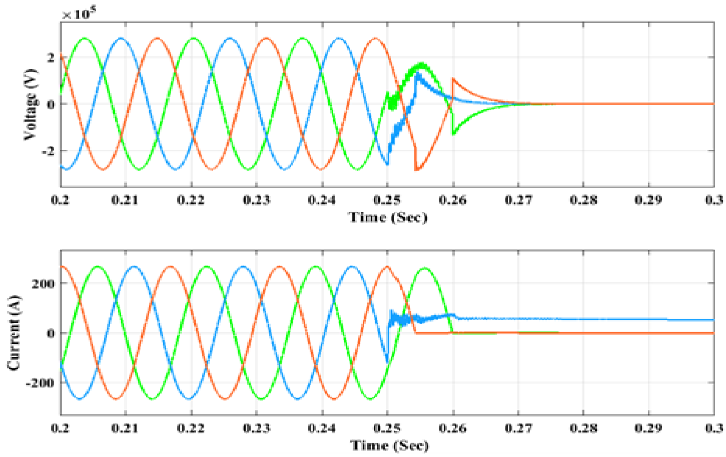


Figure 8. The intelligent distance relay issuing the trip signal during transmission line faults

Figure 9 depicts the current and voltage plots for the primary and secondary sides of the transformer (Figures 9(a) and 9(b)). The primary side witnessed faults; Figure 9 depicts a one-phase-to-ground (B-G) fault at time t=0.2 sec using the primary and secondary current difference. Figure 10 depicts the signals issued by the differential and distance relays to disconnect the CB. In the case of a power transformer fault, Figure 10 indicates the differential relay issuing the disconnect command because the transformer was faulty, but the line was normal.



(a)



(b)

Figure 9. Power transformer phase-to-ground (B-G) fault (a) primary side voltage and current plot and (b) secondary side voltage and current plot

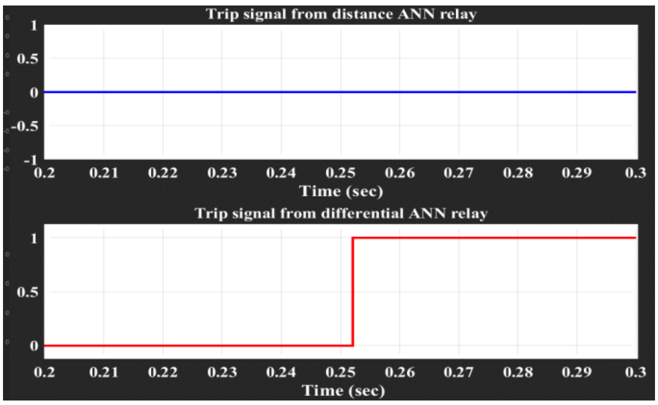


Figure 10. The trip signal issued by the differential relay during a fault at the power transformer

4. CONCLUSION

This paper discusses intelligent distance and differential relays to safeguard the electrical transmission line and power transformer, respectively. Fault categories were created, and their location in the power network was identified by employing the ANN. Transmission faults are determined by determining transmission line impedance and comparing it with the nominal values during regular operation. In the transformer case, the primary and secondary current values are compared; a transformer fault is indicated if they differ. If the measured transmission impedance falls below the nominal value, the line is faulty. This study uses three algorithms to train the system: Bayesian-Regularisation, Levenberg-Marquardt, and scaled conjugate gradient. The Levenberg-Marquardt technique was best suited for this study.

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REFERENCES

[1] I. I. Alnaib, O. S. Alyozbaky, and A. Abbawi, "A new approach to detecting and classifying multiple faults in IEEE 14-bus system," *Eastern-European Journal of Enterprise Technologies*, vol. 5, no. 8, pp. 6–16, Oct. 2020, doi: 10.15587/1729-4061.2020.208698.

[2] M. R. Javed, U. S. Virk, A. Waleed, and M. Y. Jamal, "The performance comparison of artificial intelligence based distance relays for the protection of transmission lines," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 3, pp. 1177–1185, Jun. 2022, doi: 10.11591/eei.v11i3.3305.

[3] O. W. Chuan, N. F. A. Aziz, Z. M. Yasin, N. A. Salim, and N. A. Wahab, "Fault classification in smart distribution network using support vector machine," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 18, no. 3, p. 1148, Jun. 2020, doi: 10.11591/ijeecs.v18.i3.pp1148-1155.

[4] A. M. S. Omar, M. K. Osman, M. N. Ibrahim, Z. Hussain, and A. F. Abidin, "Fault classification on transmission line using LSTM network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 1, p. 231, Oct. 2020, doi: 10.11591/ijeecs.v20.i1.pp231-238.

[5] T. T. Hoang and T. H. Le, "Intelligent fault diagnosis for power distribution system-comparative studies," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 2, p. 601, Feb. 2022, doi: 10.11591/ijeecs.v25.i2.pp601-609.

[6] P. P. Mawle, G. A. Dhomane, and P. G. Burade, "Application of artificial intelligence in early fault detection of transmission line-a case study in India," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 6, p. 5707, Dec. 2022, doi: 10.11591/ijece.v12i6.pp5707-5716.

[7] M. A. AL-Yoonus and O. S. A. Alyozbaky, "Detection of internal and external faults of single-phase induction motor using current signature," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 4, p. 2830, Aug. 2021, doi: 10.11591/ijece.v11i4.pp2830-2841.

[8] F. Wang, E. Babulak, and Y. Tang, "On detecting and identifying faulty internet of things devices and outages," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 6, pp. 3127–3136, Dec. 2021, doi: 10.11591/eei.v10i6.2698.

[9] A. Z. Jidin, R. Hussin, L. W. Fook, and M. S. Mispan, "A review paper on memory fault models and test algorithms," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 6, pp. 3083–3093, Dec. 2021, doi: 10.11591/eei.v10i6.3048.

[10] M. Saini, A. A. M. Zin, M. W. Mustafa, A. R. Sultan, and R. Nur, "Algorithm for Fault Location and Classification on Parallel Transmission Line using Wavelet based on Clarke's Transformation," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 8, no. 2, p. 699, Apr. 2018, doi: 10.11591/ijece.v8i2.pp699-710.

[11] D. Guillen *et al.*, "Fault detection and classification in transmission lines based on a PSD index," *IET Generation, Transmission &amp$\mathsemicolon$ Distribution*, vol. 12, no. 18, pp. 4070–4078, Sep. 2018, doi: 10.1049/iet-gtd.2018.5062.

[12] M. Singh, B. K. Panigrahi, and R. P. Maheshwari, "Transmission line fault detection and classification," in *2011 International Conference on Emerging Trends in Electrical and Computer Technology*, Mar. 2011, doi: 10.1109/icetect.2011.5760084.

[13] A. Q. Khan, Q. Ullah, M. Sarwar, S. T. Gul, and N. Iqbal, "Transmission Line Fault Detection and Identification in an Interconnected Power Network using Phasor Measurement Units," *IFAC-PapersOnLine*, vol. 51, no. 24, pp. 1356–1363, 2018, doi: 10.1016/j.ifacol.2018.09.558.

[14] W. Fan and Y. Liao, "Wide area measurements based fault detection and location method for transmission lines," *Protection and Control of Modern Power Systems*, vol. 4, no. 1, Mar. 2019, doi: 10.1186/s41601-019-0121-9.

[15] S. Biswas and P. K. Nayak, "A Fault Detection and Classification Scheme for Unified Power Flow Controller Compensated Transmission Lines Connecting Wind Farms," *IEEE Systems Journal*, vol. 15, no. 1, pp. 297–306, Mar. 2021, doi: 10.1109/jsyst.2020.2964421.

[16] P. Ray and S. Beura, "Accurate Fault Detection of Distribution Network with Optimal Placement of Phasor Measurement Unit," in *2019 International Conference on Intelligent Sustainable Systems (ICISS)*, Feb. 2019, doi: 10.1109/iss1.2019.8908029.

[17] A. Ahmad, M. L. Othman, K. K. B. Zainab, and H. Hizam, "Adaptive ANN based differential protective relay for reliable power transformer protection operation during energisation," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 8, no. 4, p. 307, Dec. 2019, doi: 10.11591/ijai.v8.i4.pp307-316.

[18] E. Ali, A. Helal, H. Desouki, K. Shebl, S. Abdelkader, and O. P. Malik, "Power transformer differential protection using current and voltage ratios," *Electric Power Systems Research*, vol. 154, pp. 140–150, Jan. 2018, doi: 10.1016/j.epsr.2017.08.026.

[19] D. Bejmert, M. Kereit, F. Mieske, W. Rebizant, K. Solak, and A. Wiszniewski, "Power transformer differential protection with integral approach," *International Journal of Electrical Power &amp$\mathsemicolon$ Energy Systems*, vol. 118, p. 105859, Jun. 2020, doi: 10.1016/j.ijepes.2020.105859.

[20] E. Ali, O. P. Malik, A. Knight, S. Abdelkader, A. Helal, and H. Desouki, "Ratios-based universal differential protection algorithm for power transformer," *Electric Power Systems Research*, vol. 186, p. 106383, Sep. 2020, doi: 10.1016/j.epsr.2020.106383.

[21] A. Zitouni, "Power Transformer Differential Relay Reliability Assessment Using False Trip Root Cause Analysis," in *2020 International Conference on Electrical Engineering (ICEE)*, Sep. 2020, doi: 10.1109/icee49691.2020.9249781.

[22] R. N. Bhargavi, M. L. Swarupa, and M. Rajitha, "Power Transformer Protection using ANN and Wavelet Transforms," in *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Mar. 2021, doi: 10.1109/icaccs51430.2021.9441828.
[23] T. R. Althi, E. Koley, and S. Ghosh, "Fuzzy Logic based Fault Detection and Classification scheme for Series Faults in Six Phase Transmission Line," in *2021 7th International Conference on Electrical Energy Systems (ICEES)*, Feb. 2021, doi: 10.1109/icees51510.2021.9383768.
[24] S. Das and S. Adhikari, "Fuzzy logic based fault detection and classification in Unified Power Quality Conditioner (UPQC)-compensated distribution line," in *2020 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*, Dec. 2020, doi: 10.1109/pedes49360.2020.9379334.
[25] S. K. Murugan, S. P. Simon, and R. R. Eapen, "A Novel Signal Localized Convolution Neural Network for Power Transformer Differential Protection," *IEEE Transactions on Power Delivery*, vol. 37, no. 2, pp. 1242–1251, Apr. 2022, doi: 10.1109/tpwrd.2021.3080927.

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