International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys.14, No.1 (Jul-23)

http://dx.doi.org/10.12785/ijcds/140104

Identifying Type and Location of a Fault in a Distributed Generation System

Saurabh Awasthi[1], Gagan Singh[2] and Nafees Ahamad[3]

[1,2,3]*Dept. of Electrical Engineering, Dit university, Dehradun, India*

Received 14 Oct. 2022, Revised 6 May. 2023, Accepted 8 May. 2023, Published 1 Jul. 2023

Abstract: There are numerous advantages of distributed generation system over conventional generation systems, still protection has always been one major challenge in a distributed generation system. However, from the protection point of view, a distributed generator requires special attention on account of stability loss, failure re-closure, fluctuations in voltage, etc. The situation becomes even more challenging with a short circuit fault. And thereby, it becomes substantially more important to exactly locate and determine the fault type without delay, particularly for a small distributed generation system, which otherwise impacts the operation of the system. Several techniques, like the traveling wave methodology, impedance-based, genetic algorithm (GA),fuzzy logic, and support vector machine (SVM) had been discussed in the past to identify the type and location of a fault. However, the accuracy of all these methods has always been a major issue when incorporating them into a real system. The methodology proposed here uses a shallow artificial neural network-based structure that can be trained with real fault and steady-state data for locating and identifying the specific fault type. An elementary system containing two distributed generators and a utility grid has been considered for data recording purposes. Firstly, the training of the system through the recorded simulation data is carried out, followed by the validation and testing through an artificial neural network tool. After successful training and validation, the same data is tested for any given set of conditions. The modeling of the test system has been carried out in Simulink itself. The overall result shows an unprecedented zero percent error in identifying the type of fault.

Keywords: Distribution Network, Distributed Generation, Fault identification, Neural Network, Renewable Energy systems

1. INTRODUCTION

In a developing country, particularly India, where the demand for electrical energy has increased manifold over the last few decades, it becomes imperative to identify other sources of generating electrical energy. Although 80 % of the total energy is fulfilled by fossil fuels, the generation through them is non-sustainable owing to their reserves and environmental impacts. After the recent environmental summit held in Paris, the countries were asked to reduce their carbon footprint. One of the ways of achieving it is by penetrating renewable energy resources.

Electrical power can be produced in two different ways: centralised generation and distributed generation (DG) systems [1]. Under Conventional Centralized generation system, electricity is produced at certain sizable power plants largely using traditional resources like coal, hydropower, nuclear power, etc., which are then transmitted to the consumer end via the transmission and distribution network. Although such a system produces the majority of the electrical energy demand, it also introduces some of the major environmental and economic constraints, like an increase in carbon footprint, pollution, increased transmission and distribution expenses, and the depletion of fossil fuel reserves. This leads to the weakening of large centralized generation systems and forces the paradigm towards a novel technology called distributed generation systems, whereby small units located close to the load centres typically use renewable energy sources for generating Electrical power [2]. This type of generation not only eliminates the power losses occurred in a transmission network but also makes use of readily available renewable energy technologies.

When compared to a traditional system, a distributed generating system has several benefits, including lower transmission and distribution costs, minimal environmental impact,higher dependability and security, increased energy efficiency, enhancement in rural electrification, simplicity in installation. Despite the several advantages offered by distributed generation systems, one of the major challenges that power system engineers face is the protection and fault identification that occurs within a distribution system when incorporating DG, as not only does it cause the healthy components to be disconnected but also imposes a hindrance while carrying out switchgear schemes. [3], [4]. In addition to the above-mentioned issue, the DG system also leads to harmonics, transients, and regulation-related issues [5]. The major issues with the use of distribution sys-

E-mail address: saurabh.awasthi@dituniversity.edu.in, gagan.singh@dituniversity.edu.in, nafees.ahamad@ dituniversity.edu.in

tems involve fault re-closure, is-landing operation protection under reach, clearing of faults, and sympathetic tripping [6], [7].

In recent years, many authors have proposed several optimization algorithms and artificial intelligence tools like graph theory, genetic algorithms, fuzzy logic, and AI techniques based on artificial neural networks for solving optimization problems because of their simplicity and faster response. A method wherein the direction of the current is taken as input for fault identification is proposed by Calderaro et al. [8]. However, the method requires an umpteen number of sensors for localizing faults, even in smaller sections. Further, Localization of fault has not been carried out.

Javadian et al. [9] propose a multi-layer perceptron orthodox method of splitting the system into different radial zones, in which the protection of each such zone is to be carried out using a circuit breaker. Hence, the scheme requires major alteration for better results. Haizhu Yang et al. [10] proposed a golden section method for locating a particular fault that occurs within a distribution network. The method predicts the location where fault reactance is minimum. In comparison to the conventional method, the search speed through the Golden Section method improves considerably. The method used in this paper is an enhances trapezoidal iterative power flow technique that considers all the nodes at all the locations. However, the type of a particular fault along with its location were not carried out.

In literature, there are a large number of methods for identifying and locating fault that can occur in a distribution network when incorporated with DG [11]–[14]. Even so, the particular problem still requires extensive and reliable methods for better results. The majority of such methods focus on measurements of current and voltage corresponding to different DGs. For distribution systems incorporated with distributed generation systems only via laterals. Pérez et al. propose a methodology to identify the fault location using support vector mechanics and smart meters [15]. The method has an overall accuracy of above 90 % for all types of faults. Even during the testing stage, this accuracy was above 87 %.

Dashtdar et. al. proposed a methodology for identifying location using an artificial neural network in a distribution system [11]. To train a neural network, particular attributes of the fault data were used through wavelet transformation on three-phase currents and sequences. Overall the results show satisfactory performance in identifying the location in a distribution system however the method lags in accuracy in fault type identification.

Adewole et al. suggested a new composite method that combines the features of artificial neural networks and discrete wavelet transform. It helps in identifying the fault section as well as the location of the fault when used for a power distribution system [12]. The method is applied on a standard IEEE 34-node bus system for testing purposes. Mora-Flórez et al. proposed a method that focuses on load uncertainty, types of fault, and impedance corresponding to different faults [13]. The method makes use of current & voltage measurements only corresponding to substations located at the DG end. Thus, it is easier to imply the said approach in a practical distribution system.

In this paper, the system used is a distributed generation system consisting of two generators that are located at the load end. Such systems are difficult to protect in the event of a fault, as conventional relaying cannot be easily adapted for a distributed generation system in distribution networks. The work aims here to localise and determine the fault type in such a network and can help in mitigating protection-related challenges.

MATLAB Simulink is used to represent the system in an equivalent manner. Afterward, the next stage would be to collect the steady-state and fault data, followed by training, testing and validation of the Artifical neural network. The next step would be to perform classification and localization of the type and location of the fault, which would finally remove the affected part from the remaining healthy system [14].

A. *Power System Faults*

Electrical faults in an existing power system may be defined as imperfections in the normal operation of various equipment or as unexpected deviations from standard operating conditions. As a result of this, the fault current is likely to deviate from its designated route. A fault may also be defined as an abnormal condition resulting in the weakening of the insulation strength of the dielectric/insulator existing between conductors or between conductors and the earth. This weakening of insulating strength, however, is not threatening till it influences the normal operation of the system. If the insulation strength reduces below a specific value, it will result in the breakdown of the insulator and a sudden rise in current. Such reduction of insulating strength can also lower the impedance between conductors and the earth or between conductors below the normal circuit load impedance.

A power system normally consists of various elements such as Power Transformer, Synchronous generators, switchgear, transmission and distribution networks, and other auxiliary equipment. Although a normal power system is equipped with protection at various levels, the probability of the occurrence of unwanted conditions is always high. Many times such faults occur very frequently, and henceforth it is extremely important to diagnose and remove the unhealthy part from the remaining healthy system. Such probability is very high for an overhead line as they are exposed to ever-changing weather conditions.

There may exist different reasons for their occurrence, like a short circuit between physical contact, trees falling on the overhead lines, physical contact of birds or animals with lines, collisions of vehicles with towers, poles, etc., blowing of heavy winds, etc. Such short circuits can also take place as a result of prolonged usage and wear and tear of the insulator by switching surges or lightning strokes. These faults may exist for a while or may remain until they are diagnosed and cleared. Accordingly, they are termed temporary faults and permanent faults, respectively. The temporary faults may eventually become permanent faults if they are not cleared in time. The permanent fault may occur mainly due to the failure of cable insulation failure, wires falling on the earth, or objects coming into contact with the lines. The percentage of occurrence of these faults due to various reasons along with their frequencies are illustrated in Table I

Similarly, the possibility of the occurrence of these faults in different equipment along with their frequency is illustrated in Table II.

Of all the faults that a power system can undergo, SLGF fault is the most common one. It occurs when the insulation between one of the conductors and the earth breaks down. The second next common fault is the short circuit between two conductors that occurs when the insulation between phase conductor breaks down. The organization of various sections of this paper is as follows
Section 1: Introduction
Section 2: Methodology adopted for fault identification
Section 3: System configuration and modeling
Section 4: Application of Neural network for data classification
Section 5. Online Calculation which includes test results.
Section 6. Conclusion

2. Methodology Adopted For Fault Identification

The methodology adopted for fault identification is mainly split into three major steps i.e System Modelling, Fault data collection artificial neural formulation as shown in figure 1.

Figure 1. Methodology block diagram

A. *System Modelling*

This step includes the collection of data on the proposed system for which analysis is to be carried out which is then followed by defining the input variables and corresponding rated value. The last step would to be make the Simulink model of the system on MATLAB Simulink Interface as shown in figure 2 [14].

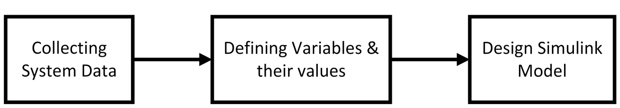


Figure 2. System Modelling

The modelling of the proposed scheme can also be done on other software like ETAP. The Data can be taken from an existing network also or from a standard IEEE 13 or 32 bus system. The data so collected would then be required to be modelled on different platforms. To run the Simulink model it is necessary to define different variables. The Selection of the magnitude of these variables is very important and must be carefully set.

B. *Collection of Fault Data*

The purpose of this step is to collect data corresponding to a different fault and its location via running a short circuit and load flow tests. Figure 3 shows the block diagram of the Fault data collection in detail.

Figure 3. Fault data collection

Under normal conditions, the contribution of different source currents is as per the loading conditions, however, during faulty conditions this relation does not hold good. In the event of a fault, the contribution of different source currents defines a particular fault point. To derive the mathematical relationship between a fault and its corresponding data, neural network training with some part of the collected data needs to be carried out. Therefore corresponding to each fault, a short circuit test is to be carried out which involves all types of faults at all locations. The succeeding step would be the division of the system into different sections/zones that will ensure planning against is-landing conditions, failure of re-closure, etc. would be to identify the type of the fault and its location based on the training of an artificial neural network [14].

Identification of a given fault is attributed on account of the high value of pre and post-current before and after the fault has occurred. The normalization value of current for ten different types of faults can be calculated using equation 1. The equation used for normalizing network inputs also is given by the same equation 1.

$$I_{normal} = (2I - \ I_{max} - I_{min})/(I_{max} - I_{min}) \qquad (1)$$

The minimum and maximum magnitude of current corresponding to different types of fault are denoted as Imin and Imax respectively.

C. *Formulation of Artificial Neural Network:*

Once the data corresponding to different faults and their location gets recorded, the next step would be to design the artificial neural network which will first be required to be trained by the stored data. Once the training part is done it is then validated and tested on arbitrary data for checking its accuracy as shown in figure 4. To open the correct unhealthy section, verification of the direction of the input current via breaker is obligatory. After the successful identification of fault type and location, the circuit breaker finally isolates the unhealthy section from the remaining healthy part.

TABLE I. **CODING FOR VARIOUS FAULTS**

S. No	Fault Reasons	%out of total
I	Switching operations	20%
II	Failure of the equipment's	20%
III	Mechanical failure, wind	20%
IV	Lightning discharge	12%
V	Others (tree falling, etc.)	8%

TABLE II. **RATE OF FAULT OCCURRENCE IN DIFFERENT EQUIPMENT**

S. No	Equipment's	%out of total
I	Overhead Transmission and distribution lines	50%
II	Switch gear	15%
III	Power and distribution Transformers	10%
IV	Underground Cables	10%
V	Instrument Transformer (CTs and PTs))	2%
VI	Control Equipment (CTs and PTs))	3%
VII	Miscellaneous	10%

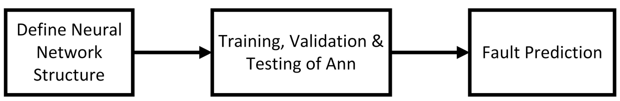


Figure 4. Formulation of Artificial Neural Network

To open the correct unhealthy section, verification of the direction of the input current via breaker is obligatory.

3. SYSTEM CONFIGURATION AND MODELLING

In this proposed scheme, a distributed generation system has been considered and the above-mentioned procedure is being followed which includes the development of a single line diagram, development of MATLAB Simulink model, performing simulation for different short circuit faults, data collection, training of the neural network, and validation and testing. The system considered here is a distribution network incorporated with two DGs which are interconnected with the grid. The entire 100-kilometer distribution network existing between DG's and the grid is divided into different zones of 2 km each. For data collection purpose 10 basic short circuit faults are being carried out at 2 km, 4 km, 6 km, 8km, and so on within a set simulation time and sample interval simulations has been carried out. Each simulation gives out a set of 18 input values (9 current values and 9 voltage values) 3 each for DG1, DG2, and grid. This way data corresponding to different faulty cases has been collected which will then be utilized to train of neural network. Figure 5 shows a single-line diagram of the considered network.

Figure 6 Shows the equivalent model of an existing Distribution network in the MATLAB Simulink platform. From the single-line diagram, it can be seen that there are two distributed generators connected to the grid in star to ground arrangement. Both these generators are interconnected with the grid through a delta-star transformer. The grid is rated at the voltage level of 132 kV at the power frequency of 50 Hz. The SC MVA level of the grid is taken at 100 MVA with a reactance-to-resistance ratio of 7. Since the distribution network operates at a lower voltage level, hence it is reduced from 132 to 66 kV at the rated MVA of 100 kV.

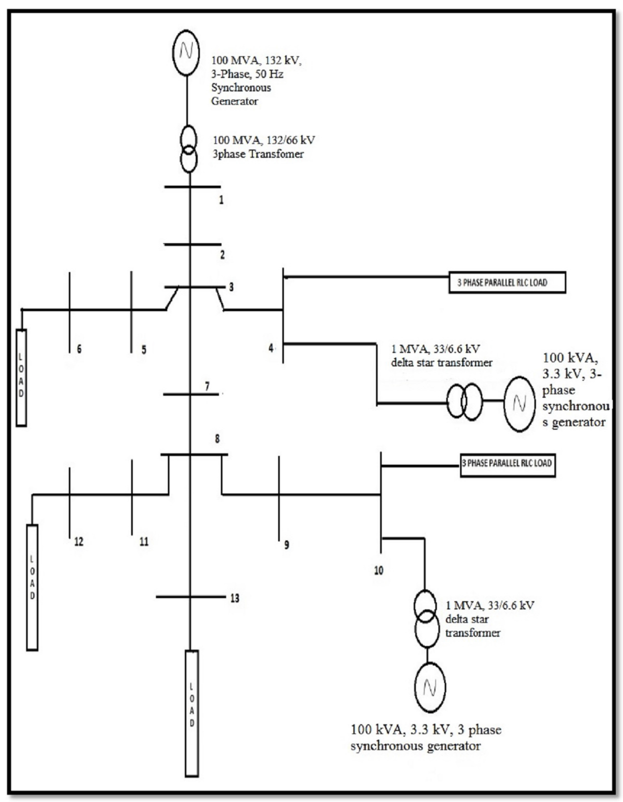


Figure 5. Single-line diagram of the proposed scheme

The VI measurement Box connected across each of the transformers can be used to record the current and voltage magnitude of the grid, DG 1, and DG2 for the R, Y, and B phases.Both the distributed generating sources are operating at a voltage level of 3.3 kV which is possible by two step-down distribution transformers each rating 66/3.3 kV.

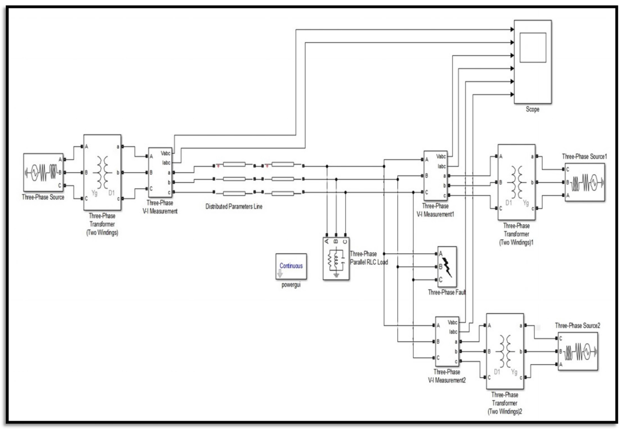


Figure 6. Simulink Model of the test system

These distributed generators are then connected to the grid through a long 3-phase distribution network of 100 kilometers that is further split into 50 sections of 2 km each.// To record the data corresponding to different faults, scopes are connected against each generator. This can be achieved by connecting a single common scope with all three sources. The scope will measure the magnitude of the current and voltage of each of the three sources across the R, Y, and B phases. This way, a total of 18 values are being recorded at a time, with 9 voltages and 9 currents. Although MATLAB interface has been used for simulation, however, it can also be carried out through an electrical transient analyzer program (ETAP4.04). The two distributed generators then feed this power to a small community of approximated three-phase load of 10 Kilowatt. To improve the system's security and protection, a real-time network must be ready for all contingency conditions like faults. This is possible when the switchgear and security systems are trained to operate very quickly so that even if a fault occurs, it can only cause minimal damage. Therefore, a strong protective scheme becomes obligatory which requires modeling of the real-time system to be action ready for all the exigency conditions. And therefore, the Simulink model and load flow analysis is an important step before designing the protection scheme. For this purpose, MATLAB Simulink is being employed here for modeling the system. The tool used for carrying out online calculations, load flow, short circuits, and training of neural networks is MATLAB software.

A. *Collection of Fault Data*

To differentiate between the values corresponding to healthy conditions and faulty conditions, it is important to conduct load flows and fault analysis on various locations with one of the sources kept as the reference. In literature, many authors have tried to explain various methods of carrying out the short circuit and steady-state analysis [16]. The data corresponding to steady state and various faults can be recorded through steady state and fault analysis at different locations for each fault case. This entire procedure is to be followed on MATLAB Simulink with the help of 3 phase fault boxes. The data corresponding to the steady state can be obtained by deselecting all the elements in the fault between columns, as shown in figure 7. This will facilitate the collection of the magnitude of current and voltage corresponding to R, Y, and B phases under a normal steady state from the workspace.
The number of values for current and voltage for each such case can be altered by appropriately selecting the simulation time and sample time. In this case, it is kept at 0.2 seconds and 0.00002 seconds, respectively.

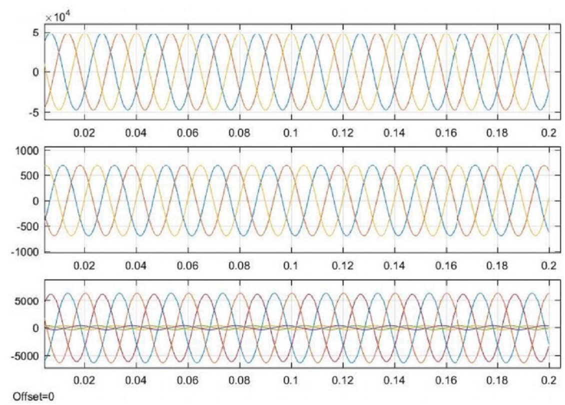


Figure 7. Load flow balance condition

Thereby, each such simulation brings 1000 values each for DG1, DG2, and Grid current and voltage for all the three phases.' The instantaneous value of all these quantities can be checked from the scope results, which indicate all the quantities are equally displaced from each other by 120 degrees. The steady-state values of voltage & current of all three sources are already stored in the workspace and can eventually be used for training purposes. A similar approach would be adopted to carry out the short circuit tests, and likewise, the already saved data can be extracted from the workspace. Figure 8 shows the scope results corresponding to an LG fault. The short circuit test for other marked locations, such as 2, 4, 6, and so on, can be executed.

The data corresponding to all such locations for all types of faults can then be recorded and transformed into a matrix form for training purposes. The neural network training gives the best results when the number of variables for both input-output is neither too large nor too small. Any deviation from the mentioned criteria may alter the neuron structure.

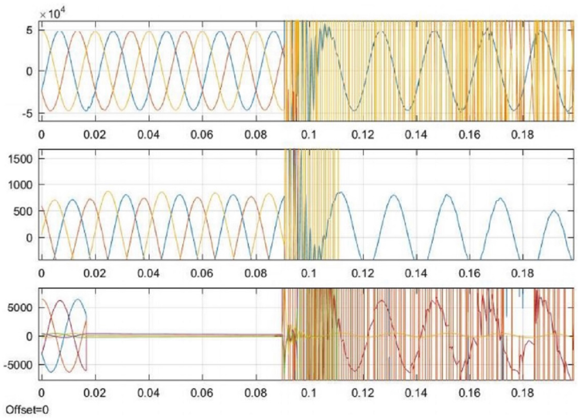


Figure 8. Scope results for a typical line-to-ground fault

4. ARTIFICIAL NEURAL NETWORK FOR DATA CLASSIFICATION

Once the data gets stored and transformed into the required matrix form, the next step would be to conduct the online calculation. This calculation will be performed by an artificial neural network program. To identify the type and location, it becomes necessary to successfully train the neural network through collected data and once the training is completed, testing and validation are to be carried out.

A. *Artificial Neural Network (ANN)*

It may be defined as the information processing epitome, which works the same way as our biological nervous systems [17]. It includes millions of neurons that are complicatedly interconnected and operate in coalition with one another to solve specific problems. The major area where the artificial neural network is primarily used is in the field of pattern classification. Figure 9 shows an elementary artificial neuron [18].

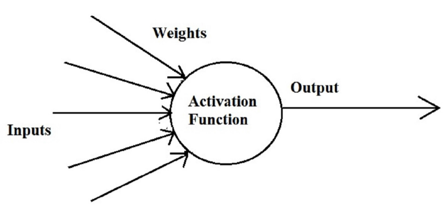


Figure 9. An artificial neuron

As learning in organic systems includes alterations in the synaptic network that can be realized among different neurons, these include synapses like input, which upon multiplication by signal strength or weight derives a mathematical relationship that further causes neurons to activate. The other identity functions determined the output of the ANN which many times depends upon a particular threshold.

One of the most important internal functions of an ANN network is the activation function which is defined as a weighted sum i.e. Equation 2 represents the sum of the inputs x multiplied by their corresponding weights Wji. 2:

$$A_j\ (\overline{x,}\overline{w}) = \sum_{i=o}^{n} x_i w_{ji} \tag{2}$$

The output of the system is a sigmoidal function as shown in equation 3

$$O_j(\overline{x},\ \overline{w}) = \frac{1}{1 + e^{A_{j(\overline{x},\ \overline{w})}}} \tag{3}$$

Figure 10 shows the sigmoid function.

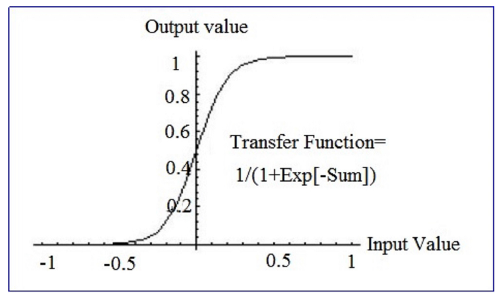


Figure 10. Sigmoid function

A simple Neural network depicting different layers is shown in figure 11.

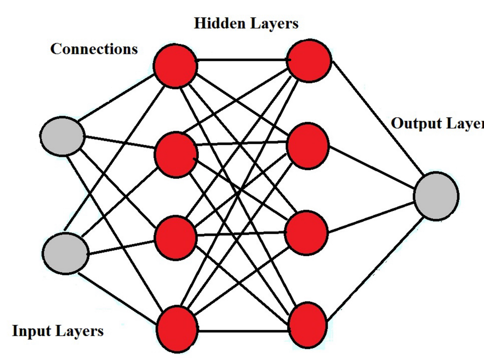


Figure 11. A Typical Artificial Neural network

The algorithm used here is backpropagation. There is one hidden layer used, as more numbers of layers were decreasing the accuracy. As many as 18 neurons are used in input layers, while in hidden layers, this number is limited to 12. The number of neurons in hidden layers is chosen based on the minimum convergence error between training, validation, and testing.

The parameters that affect the overall accuracy of an ANN are the inter-relation among different neurons, activation functions, and methods via which weights can be determined. The network accepts inputs through input-layer neurons, whereas the network's output is delineated through output layer neurons. Some intermediate hidden layers are also present within the structure. Since this algorithmic program uses the concept of supervised learning, input-output samples are required to be analyzed one after another.

5. Designing Of Neural Network For Classification

After completing the load flow and short circuit tests, the next step would be to design the neural network structure for fault classification. Data collection, as mentioned above, is to conduct various faults at different locations and record the corresponding data in matrix form. The same data in the ANN formulation would be used to train and validate an artificial neural network.

The first step involved in ANN formulation is to complete the artificial neural network training through the data collected earlier. Followed by its validation and testing once the training is completed.

The last step is fault classification and localization through the validation process.

After successful identification of the type and location of the fault, the unhealthy part can be removed from the remaining healthy system.

A. *Training of Neural Networks*

Successful training of the neural network required an input matrix in the correct format, including all possible outcomes. The identification of a given type of fault can be done through simple coding, where each of the phases A, B, C, and ground can be assigned 1 if they are involved in the fault; otherwise, they will be assigned 0. For example, the coding for a double line to ground fault (AB to ground) will have the code 1101. Similarly, the coding for phase B to C line-to-line faults will have the code 0110.

The coding for the location can be marked in the same manner. For example, if the fault is at the grid, then near the grid it will be at 1, for all other locations it will be marked as zero. Thus, the total no. of input and output are 18 & 12, respectively. Therefore, the dimensions of the input & target matrix are 531x18 and 531x12, respectively. The neural network structure consisting of input, Output, and hidden layer along with the number of neurons are shown in figure 12. The toolbox itself splits the recorded data for validation, training, and testing. By default, around 70% (567 samples) have been used for training purposes.

Around 15% which are 105 samples of the total 531, have been kept reserved for deriving generalized values. Once the generalization does not improve anymore, the training would stop. As it does not have any impact on training, the result obtained would have independent characteristics. Here, around 15% (105 samples) have been taken for this purpose. It may be noted that the allocation for training, validation, and testing can be altered as per need.

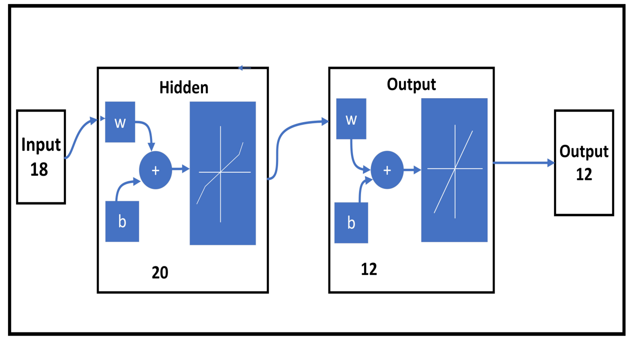


Figure 12. Neural network structure

B. *Test Results*

The outcomes of the proposed methodology on the test system involving two DGs and a grid together forming a distribution network can be studied through figure 13. It shows the best validation occurs at 28 epoch. The R-value for all stages, including training of the neural network, validation, and testing, is all coming out to be around unity, which can be verified through straight-line linear regression characteristics.

The R values for different stages are shown in Table III.

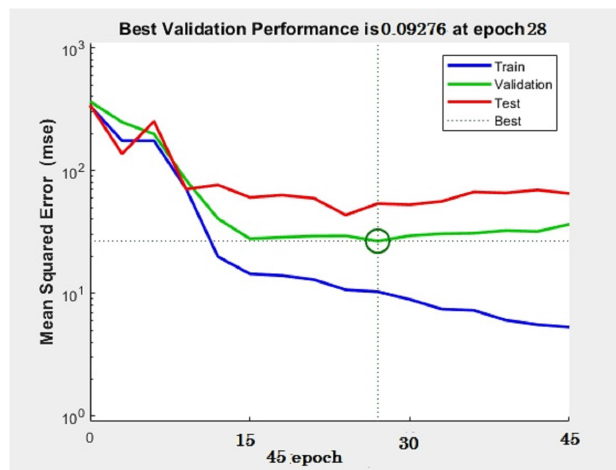


Figure 13. Performance plot

The performance plot showing the relation between mean square error and epoch individually for training, validation, and testing indicates that validation is most effective at 0.09276 at 28 epochs.

Figure 14 shows the neural network training regression characteristics of the proposed scheme, which validates successful pattern recognition through strain linear regression characteristics. The main parameter that depicts the effectiveness of pattern recognition is the mean square, which is shown in figure 15.

TABLE III. **R Values for Training, validation, and testing**

S.NO	Stage	R value
1	Training	0.96813
2	Validation	0.91437
3	Testing	0.92759
4	Overall	0.95308

TABLE IV. **VALIDATION RESULTS**

S.NO	Grid Voltage	Grid Current	Actual fault	Identified fault and Location
1	25387.20	311.9391	L-G at grid	L-G at grid
2	30794.7987	3269.251493	L-G at 20 km	L-G at 20 km
3	33612.73656	290.9789679	L-G at 40 km	L-G at 40 km
4	27477.67753	361.1462966	3-phase fault at 60 km	L-G at 3-phase fault at 60 km
5	27410.4671734	354.00263984	3-phase fault near grid	3-phase fault near grid

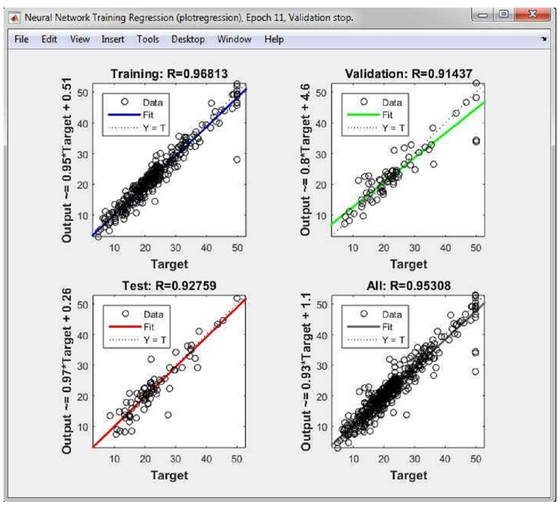


Figure 14. Neural Network Training Regression curve

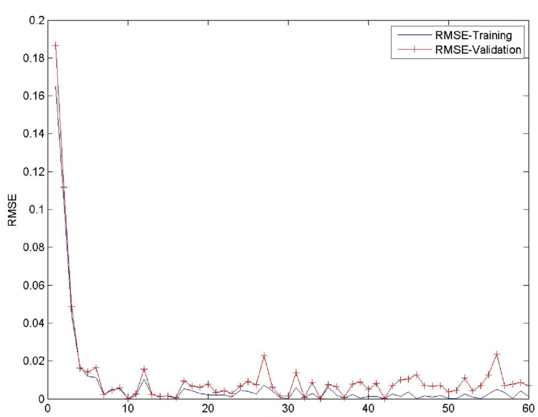


Figure 15. Mean Square Error

In this case, it comes out to be less than 1% indicating the successful training, validation & testing of the network. Likewise, figure 16 represents a confusion matrix that indicates less than 5 % error in pattern classification across the different classes. On the basis of neural network training from the earlier recorded data, the proposed scheme finds the following set of values as mentioned in Table IV.

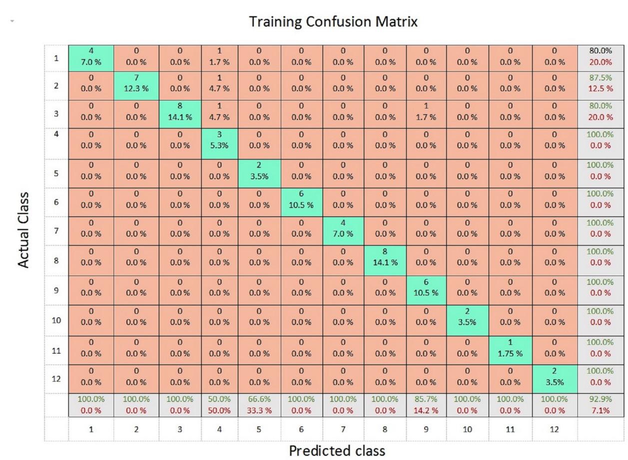


Figure 16. Confusion matrix

6. CONCLUSION

The proposed work helps in mitigating the protection challenges encountered in distributed generation systems when incorporated with a distribution network. Such a system is difficult to protect in the event of a fault as the conventional relaying cannot be easily adapted for a distributed generation system in a distribution network. In this paper, the system used is a distributed generation system that consists of two distributed generators which are located at the load end, and a utility grid. The work aims here to locate and determine the fault type in such a network and can help in mitigating protection-related challenges.

MATLAB Simulink is used to represent the system in an equivalent manner. Load flow and short circuit tests for various locations were conducted and corresponding data was recorded and transformed into an input and output matrix. These matrices were then used to train and validate a neural network. The number of neurons kept inside the hidden layer is 20 while in the output layer, this figure is 12.

From the total 531 data samples, 70 % percent were utilized for training while the remaining 30 % is equally kept for training and validation. The indicator for successful testing and validation is MSE (Mean Square Error). For a successful result, its value must be very close to zero. In this case, it is nearly zero which indicates the successful training, validation, and testing. The overall accuracy of the proposed scheme comes out to be more than 90% based on mean square error (less than 1 %) and R-value for different stages.

Once this process gets completed, the proposed scheme would be in a position to identify any abnormal conditions on account of the successful training of the neural network. The mean square error indicates a minor deviation between the actual and expected results and thereby leaves scope for improvement through other algorithms. The accuracy of the suggested method can be verified and compared using the one used by Kun Yu et al [19] where they proposed a method which is based on the traveling wave concept for locating various faults and identifying their location which leaves an area of research in this field. The work aims to mitigate the protection challenges for small-size distributed generation systems. It can be implemented for large-sized distributed generation systems in future work.

References

[1] G. Putrus and E. Bentley, "Integration of distributed renewable energy systems into the smart grid," *Electric Renewable Energy Systems*, pp. 487–518, 2016.

[2] A. Shrestha, R. Bishwokarma, A. Chapagain, S. Banjara, S. Aryal, B. Mali, R. Thapa, D. Bista, B. P. Hayes, A. Papadakis *et al.*, "Peer-to-peer energy trading in micro/mini-grids for local energy communities: A review and case study of nepal," *IEEE access*, vol. 7, pp. 131 911–131 928, 2019.

[3] F. Bastiao, P. Cruz, and R. Fiteiro, "Impact of distributed generation on distribution networks," in *2008 5th International Conference on the European Electricity Market*. IEEE, 2008, pp. 1–6.

[4] R. Agrawal and D. Thukaram, "Identification of fault location in power distribution system with distributed generation using support vector machines," in *2013 IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*. IEEE, 2013, pp. 1–6.

[5] S. M. Brahma and A. A. Girgis, "Development of adaptive protection scheme for distribution systems with high penetration of distributed generation," *IEEE Transactions on power delivery*, vol. 19, no. 1, pp. 56–63, 2004.

[6] P. P. Barker and R. W. De Mello, "Determining the impact of distributed generation on power systems. i. radial distribution systems," in *2000 Power Engineering Society Summer Meeting (Cat. No. 00CH37134)*, vol. 3. IEEE, 2000, pp. 1645–1656.

[7] R. C. Dugan and T. E. Mcdermott, "Distributed generation," *IEEE industry applications magazine*, vol. 8, no. 2, pp. 19–25, 2002.

[8] V. Calderaro, C. N. Hadjicostis, A. Piccolo, and P. Siano, "Failure identification in smart grids based on petri net modeling," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 10, pp. 4613–4623, 2011.

[9] S. Javadian, M.-R. Haghifam, S. Bathaee, and M. F. Firoozabad, "Adaptive centralized protection scheme for distribution systems with dg using risk analysis for protective devices placement," *International Journal of Electrical Power & Energy Systems*, vol. 44, no. 1, pp. 337–345, 2013.

[10] H. Yang, X. Liu, Y. Guo, and P. Zhang, "Fault location of active distribution networks based on the golden section method," *Mathematical Problems in Engineering*, vol. 2020, 2020.

[11] M. Dashtdar, R. Dashti, and H. R. Shaker, "Distribution network fault section identification and fault location using artificial neural network," in *2018 5th International conference on electrical and electronic engineering (ICEEE)*. IEEE, 2018, pp. 273–278.

[12] A. C. Adewole, R. Tzoneva, and S. Behardien, "Distribution network fault section identification and fault location using wavelet entropy and neural networks," *Applied soft computing*, vol. 46, pp. 296–306, 2016.

[13] J. J. Mora-Flórez, R. A. Herrera-Orozco, and A. F. Bedoya-Cadena, "Fault location considering load uncertainty and distributed generation in power distribution systems," *IET Generation, Transmission & Distribution*, vol. 9, no. 3, pp. 287–295, 2015.

[14] N. Rezaei and M.-R. Haghifam, "Protection scheme for a distribution system with distributed generation using neural networks," *International Journal of Electrical Power & Energy Systems*, vol. 30, no. 4, pp. 235–241, 2008.

[15] R. Pérez and C. Vásquez, "Fault location in distribution systems with distributed generation using support vector machines and smart meters," in *2016 IEEE Ecuador Technical Chapters Meeting (ETCM)*. IEEE, 2016, pp. 1–6.

[16] J. Olamaei, M. A. Ghasemabadi, and M. H. Kapourchali, "An efficient method for load flow analysis of distribution networks including pv nodes," in *2011 2nd International Conference on Electric Power and Energy Conversion Systems (EPECS)*. IEEE, 2011, pp. 1–6.

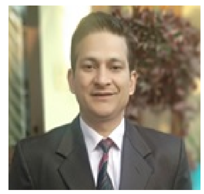
[17] C. Gershenson, "Artificial neural networks for beginners," *arXiv preprint cs/0308031*, 2003.

[18] J. Mao and A. K. Jain, "Artificial neural networks for feature extraction and multivariate data projection," *IEEE transactions on neural networks*, vol. 6, no. 2, pp. 296–317, 1995.

[19] K. Yu, J. Zeng, X. Zeng, F. Liu, Y. Zu, Q. Yu, and C. Zhuo, "A novel traveling wave fault location method for transmission network based on time linear dependence," *International Journal of Electrical Power & Energy Systems*, vol. 126, p. 106608, 2021.

Mr. Saurabh Awasthi obtained Bachelor of Technology in the Specialization of Electrical Engineering from BIET Jhansi, India in the Year 2011. He completed Masters from IIT Roorkee in the field of Renewable energy in 2014.

Prof. Gagan Singh completed B.tech and M.tech in EE from the Dayalbagh Education Institute in Agra, India. In 2002, he received his PhD from UTU Dehradun, India. He is Presently working as Professor in the dept. EECE, DITU Dehrdaun



Dr. Nafees Ahamad earned his bachelor's degree in engineering from MMM Engineering College in Gorakhpur, Uttar Pradesh. He completed his Masters in Digital Communication. He is currently working as an Assistant Professor in the Dept. of EECE, DITU Dehrdaun