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A NEW APPROACH TO DETECTING AND CLASSIFYING MULTIPLE FAULTS IN IEEE 14-BUS SYSTEM

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Faults in the power system generally provide considerable changes in its quantities such as under or over-power, over-current, current or power direction, frequency, impedance, and power factor. Reading data related to both currents and voltages is usually involved for detecting and situating the fault on the transmission network. These days, any outage of power in a power grid leads to heavy financial losses for commercial, industrial, and domestic consumers. Random and irregular faults in transmission grids contribute significantly to events of power outages. A significant contribution of this study is a new technique for simulating a multiple simultaneous faults model. The recommended approach is an effective technique for detection, classification and localization of faults in transmission networks of electric power. To attain this objective, a training procedure and a neural network simulation were carried out using m-file in MATLAB. A virtual bus has been proposed to analyze the fault which happens on the transmission line and bus. This technique has been applied on the IEEE 14 bus and multiple simultaneous faults have been mentioned in this study. The fault situations are simulated in m-files through the two-port network performance method, which is a highly enhanced scheme in comparison to the existing methods. The results have been arrived upon by subjecting different buses to varying types of fault. The results provide comprehensive information regarding fault current, post-fault voltages, and fault MVA on all the buses. The values at the bus for voltage, power consumption, and phase angles were specified. As suggested by the findings of the simulation, the proposed methodology is an effective technique for detection, classification and localization of faults

Keywords: simultaneous faults, artificial neural network, fault detection, classification, two-port network

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1. Introduction

Providing a nonstop and reliable energy source is the main goal of power systems. These days, any outage of power in a power grid leads to heavy financial losses for commercial, industrial, and domestic consumers. Random and irregular faults in transmission grids contribute significantly to events of power outages. Precision in establishing the fault location accelerates functioning of the line and reduces the losses incurred because of power outages. Until now, several methods have been suggested for the localization of faults [1–3]. In [4], there are simultaneous faults when occurring in the power systems. Two techniques were employed to make a comparison of the results. The two-port technique used here is more accurate than the conventional method [4].

Natural incidents can lead to short circuits, that is, faults that are phase to phase or single phase to ground or phase to ground or 3-phase faults. The majority of the faults in a power system taking place in an overhead lines network are single-phase-to-ground type of faults which are caused by lightning-stimulated temporary high voltage as well as from falling trees. In the network of overhead lines, tree contact due to wind is the main reason for faults. The more time it takes to detect and fix a fault, the greater the possibility of damage in the power system, specifically during peak loads, which might cause system collapse, leading to a very long power outage that may extend to a larger portion of the grid. Minimizing the outage period and immediate reinstatement of power supply can be attained if the sort of fault and its location are discovered in an accurate and timely manner.

2. Literature review and problem statement

The effect of the faults is usually regarded as very serious for the proper functioning of the power system as it causes a power system disturbance and destabilizes the entire system. The impact of single faults (not two simultaneous faults) in different system locations on the distance stage has been investigated in [5]. Different faults were assessed along with their effect on the transmission system. The fuzzy neural technique was employed in building the distance phase (ANFIS) in [5]. Quick fault localization can accelerate the restoration process and can therefore make the power system more reliable. Fault localization is a significant problem in the research related to power transmission systems. Correct fault localization is crucial in helping the team to reach the right place directly and repair the line as quickly as possible. This reduces the duration of outage, restores power supply and decreases costs.

Several fault-locating techniques have been suggested based on different methods of power frequency wave assessment as well as travelling wave theory. The researchers in [6] provide an in-depth analysis of the work for determining the location of faults in the system using the Direct Circuit method. While [7] highlights a method for determining the location of faults in the system using the digital fault recorded data (DFRD) method. Furthermore, [8] discusses the strategies for the current frequency method for determining the location of faults in the system using the adaptive neural network (ANN). The authors in [9] have demonstrated Support Vector method for determining the location of faults in the system using the Adaptive Neural Network (ANN). A method for determining the location of faults in the system using the adaptive neural network (ANN) is noted in [10]. The type of fault is determined for a single transmission line and a double transmission line. The authors in [11] raised several concerns about faults location in the system. They suggested the current and voltage signatures for determining the location of faults in the system using the Adaptive Neural Network (ANN). The work [12] presented a method for determining the location of faults in the system using Time Domain Reflectometry (TDR) by obtaining data for voltage and current for grounding cables. A method for determining the location of faults in the system using Discrete Wavelet Transform and neural Back-propagation and hybridization between the two algorithms is considered in [13, 14]. A continuous wavelet transform is proposed for determining the location of faults in the system [15, 16].

Several ANN-based methods have been recommended for the protection of transmission lines in the pasted in numerous works. ANN (Artificial Neural Network) is convenient for applications related to the power system since it can be trained using off-line data [17]. A review of the method for determining faults using the Adaptive Neural Network (ANN) by means of current and voltage signature was proposed in [17]. Furthermore, [18] presented the Adaptive Neural Network (ANN) for determining the type and location of the fault by the signature of the current and voltage. In [19], the Clarke-Concordia method for determining fault types and location of the dual transmission line is suggested. While [20] includes a method for determining the type and location of faults by using artificial neural network. The research [21] includes a method for determining faults and the location of faults by means of voltage and current signature using artificial neural network. In [22], a comprehensive method for determining faults and the location of faults by means of voltage and current signature using the algorithms for continuous wavelet transform and fuzzy neural network is presented. Numerous neural networks applications have been employed formerly to improve the protection strategy in the power transmission system. Since the last couple of decades, ANNs have been employed as fault detection methods for quicker and more efficient localization of faults. Application of ANNs for locating the faults in the power transmission lines has been investigated in detail in which both current and voltage measurements are utilized as inputs as mentioned in [23, 24].

ANNs (Artificial neural networks) concept has been recommended for this aim in [25]. Using Wavelet-Based Algorithms, voltage and current signature are proposed for determining the location and type of faults [26]. While the Initial Current Traveling Wave algorithms in [27] are suggested for determining faults and the type of faults by current signature and voltage signature [28]. Nonetheless, techniques based on ANNs require a large amount of training data and the outcome accuracy is greatly dependent on the process used to get the training samples. Several techniques have been proposed for the classification of transmission line faults [29, 30]. There have been several studies in the literature reporting numerous methods to detect fault types and locations. However, it is clear from the above literature that numerous issues have not been addressed. It can be summarized that most of the previous research above did not address the occurrence of simultaneous faults as well as open faults. Furthermore, some of these works on faults were made on buses only. While another work takes a single line to ground (SLG) fault on the buses only.

The objective of this work is to identify and classify faults in the transmission lines of the power system. To deal with the issue of an extremely huge data set with various fault conditions, a multistep optimized neural network method has been suggested. The fault situations are simulated in m-files through the two-port network performance method, which is a highly enhanced scheme in comparison to the existing methods. Table 1 gives a summary of key points from the literature. This technique has been analyzed using the IEEE 14 bus and the resultant multiple simultaneous faults have been registered in this thesis. As suggested by the results of the simulation, the proposed method is an effective one for the localization, classification and detection of faults in a power transmission system.

It appears from Table 1 that most of the previous works did not address two simultaneous faults at the same time, except for research number 5. Nevertheless, the analysis of the location, type of faults, and open fault was not addressed in this work.

Table 1

Summary of key points from the literature

Ref	Type of algorithm	Single fault	Multiple simultaneous faults	Localization of fault	Classification of fault	Detection of fault	Fault on the bus	Fault on the T.L	Open fault
[31]	Anfis	✓	×	×	×	✓	✓	×	✓
[4]	Two port network	✓	✓	×	×	✓	✓	×	×
[5]	Anfis	✓	×	×	×	✓	✓	×	×
[7]	Digital fault recorded data	✓	✓	✓	×	✓	×	✓	×
[8]	ANN	✓	×	✓	✓	✓	✓	✓	✓
[6]	Direct Circuit Analysis	✓	×	✓	×	✓	×	✓	×
[12]	Time Domain Reflectometry	✓	×	✓	×	✓	×	✓	✓

In this work, faults concurrent with fault detection using the two-port network algorithm were used, as well as the localization and classification of faults with the type of fault using ANN, making faults on the bus and the transmission line as well, simultaneous parallel faults and series faults, i. e. open faults.

3. The aim and objectives of the study

The main aim of this study is detection, classification and localization of faults. Faults location is crucial information, particularly for high-voltage power systems. The information about the fault location enables swift fault resolution and better transient stability.

To achieve this aim, the following objectives are accomplished:

– simulate various types of faults in MATLAB simulation m-file code;

– two-port network method has been used to test and validate the IEEE 14-bus system. Furthermore, identify and classify any fault type through the novel (voltages and currents) signatures technique;

– use (ANN) to classify the faults and detect their locations.

4. Materials and methods

In this part, the method and material used in this work were presented. However, before using this method, the power system model under study (14-bus IEEE) in the first section has been explained. The IEEE 14-bus test case represents a simple approximation of the American Electric Power system. It has 14 buses, 5 generators, and 11 loads. While the second part is going in a deep explanation of simultaneous fault by two-port network theory. Furthermore, the third section of the method highlighted the fault detection mechanism in the power system have been a desecration. The system comprises 11 loads and 17 transmission lines. An Artificial Neural Network (ANN) is a useful tool for pattern recognition, generalization, and classification, which has motivated several ANN-based fault detection and classification techniques in the recent past [10].

Several researchers have utilized artificial neural networks to detect fault location. The ANN-based fault detector and classifier consist of the following design steps:

– creation of an appropriate training set that contains all probable scenarios that the ANN is required to learn;

– choosing an appropriate ANN structure for a specific application;

– training the ANN;

– assessment/validation of the trained neural network by feeding test data to determine its accuracy in generalization.

4. 1. Power system model under study

A single-line representation of the 14-bus IEEE standard system obtained from [1] is presented in Fig. 1. Five synchronous machines with IEEE type-1 exciters are used to create the system. Three of such machines are of synchronous compensators utilized specifically for reactive power support. Eleven loads with a total of 259 MW and 81.3 MVAR are present in the system. Dynamic data used for generator exciters were obtained from [32].

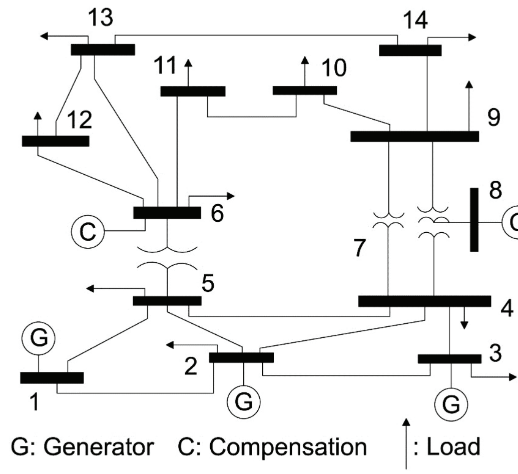

Fig. 1. IEEE 14 bus standard system

A Scaled Conjugate Gradient neural network comprises three layers: the first being the input layer having three neurons, the second being a two-neuron hidden layer, and the final output layer having two neurons. It is clear from the figure that the output from one neuron feeds all the neurons of the subsequent layer, where every neuron has its specific weight. When starting the algorithm, all the inputs weights are set to 1. Obtaining an output from a Scaled Conjugate Gradient neural network requires the input values to be fed to the input layer, which subsequently passes through the middle layer and output layer. The number of inputs determines the required number of neurons in the input layer. Similarly, the number of neurons in the output layer is determined by the number of outputs required. The hidden layer count and the number of neurons in the hidden layers may not be well-defined. Instead, it could be modified depending on data type and network configuration. The proposed technique can precisely estimate the fault distance during ground faults like line-to-LG (LLG) and line-to-ground (LG). Nevertheless, the system lacks the necessary accuracy in locating faults such as LL-to-line (LLL), line-to-line (LL), and faults specific to an open conductor. This paper provides a technique for fault detection, classification and localization in transmission lines of the power grids, to identify and determine fault location throughout the electrical network precisely.

4. 2. Simultaneous fault by two-port network theory

Among the most significant challenges facing massive power systems, there are circumstances where several malfunctions occur concurrently. These malfunctions could be caused by a lightning strike, weather storms, and multiple reasons on different components of the power system caused in different places but at the same time. Concurrent faults cause more harm than single, localized faults. Such faults that occur at different places of the system at the same time are called Simultaneous Faults. Therefore, a need arises to simulate such faults in the power system to facilitate protection relay control operations so that the system may be protected from massive damage to the components and power systems equipment. In this study, we covered the simulation with two simultaneous faults. Four cases arise when two faults co-occur, in two different regions i and j, which are specified below:

– A parallel (Shunt) fault at *i* and *a* parallel (Shunt) fault at *j*.

– a parallel (Shunt) fault at i and a series (Open) fault at *j*.

– a series (Open) fault at i and a parallel (Shunt) fault at *j*.

– a series (Open) fault at i and a series (Open) fault at *j*.

The two-port network method is among the essential methods used to designate two simultaneous faults. The method is quite accurate, and it incorporates the representation of a parallel fault (Shunt) and also the series fault (open). Two-port analysis method consists of several models (*z*, *y*, *h*). The analysis is done according to the type of fault occurring.

Two-port network technique can be divided into 3 modelling types as per the correlation of current and voltage, as displayed in Table 2.

Table 2

Voltages and currents relationships of *z*, *y* and *h* parameters [3]

Impedance Parameters *Z*	$\begin{bmatrix} V1 \\ V2 \end{bmatrix} = \begin{bmatrix} Z11 & Z12 \\ Z21 & Z22 \end{bmatrix} \begin{bmatrix} I1 \\ I2 \end{bmatrix}$
Admittance Parameters *Y*	$\begin{bmatrix} I1 \\ I2 \end{bmatrix} = \begin{bmatrix} Y11 & Y12 \\ Y21 & Y22 \end{bmatrix} \begin{bmatrix} V1 \\ V2 \end{bmatrix}$
Hybrid parameters *H*	$\begin{bmatrix} V1 \\ I2 \end{bmatrix} = \begin{bmatrix} H11 & H12 \\ H21 & H22 \end{bmatrix} \begin{bmatrix} I1 \\ V2 \end{bmatrix}$

Table 3 displays the correlation of two-port network components with the kind of faults, where port (*i*) denotes the fault location occurring on the bus-bar while port (*j*) is the faults that occur on the second bus-bar, and both faults occur at the same time but in different locations of the power system.

Table 3

Relationships of *Z*, *Y* and *H* parameters with the type faults in two bus-bars in power system

	Fault location (port *j*)						
	Fault type	SLG	2LG	L-L	3LG	1LOpen	2Lopen
Fault location (port *i*)	SL-G	Z Type	H Type	H Type	Z Type	Z Type	H Type
	2L-G	Y Type	Y Type	Y Type	Y Type	Y Type	H Type
	L-L	Y Type	Y Type	Y Type	Y Type	Y Type	H Type
	3L-G	Z Type	Y Type	Y Type	Z Type	Y Type	H Type

The breakdown in the power system transmission line is denoted by a virtual bus-bar configuration (VPC) on the line where the system comprises (*n*) generalities and turns into (*n*+1). Fig. 2 displays a system comprising generic 1 and 2, and generation impedances as every impedance comprises 3 phases (*Zabc*), 3-phase transmission line impedance (*ZLabc*) as well as a length (*L*).

$$Y \text{ bus before fault} = \begin{bmatrix} Y11 & Y12 \\ Y21 & Y22 \end{bmatrix}. \tag{1}$$

In (1), every element is represented by a matrix of dimension (2*2). As displayed in Fig. 2, the fault spot is regarded as a third bus. At this point, the new matrix for bus impedance will have dimension (9*9). Furthermore, Fig. 3 illustrates the transmission line with a fault.

We deem the third bus as faulty. The bus voltages change on all the 3 buses because the fault can be derived using the following equation.

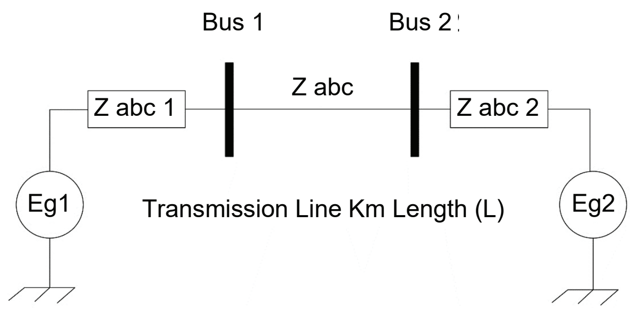

Fig. 2. Transmission line considered for analysis

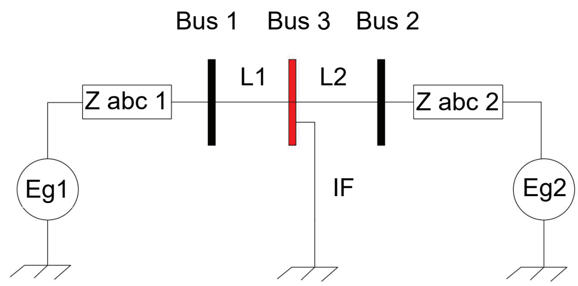

Fig. 3. Transmission line with a fault

Where:

– [0]: null matrix of dimension 3*1.

– IF: three-phase fault current at the faulted bus 3 with direction as shown in Fig. 3. – Dimension of I Fault is 3*1.

– ΔVi: Change in the three-phase voltages at the bus due to the fault at bus three. Dimension is 3*1.

– *yabc*: Inverse of the three-phase line impedance matrix per unit length, i. e. $yLabc=(zLabc)^{-1}$;

– *Z* Bus fault: Three-phase bus impedance matrix with the fault considered at bus three. The dimension of this matrix is (9*9).

– *L*: Total length of the transmission line.

– *L*1, *L*2: Lengths from each bus to the fault point.

– $\Delta V1$, $\Delta V2$: Measured at both buses one and two.

– $\Delta V3$: 3×1 matrixes of the voltages at the faulty point.

$$\begin{bmatrix} \Delta V1 \\ \Delta V2 \\ \Delta V3 \end{bmatrix} = Z \text{ bus fault} \begin{bmatrix} 0 \\ 0 \\ IF \end{bmatrix}, \tag{2}$$

$$\begin{bmatrix} 0 \\ 0 \\ IF \end{bmatrix} = Y \text{ bus fault} \begin{bmatrix} \Delta V1 \\ \Delta V2 \\ \Delta V3 \end{bmatrix}. \tag{3}$$

In (3), bus fault *Y* is the 3-phase matrix of bus admittance having dimension (9*9) and is equal to the inverse of symbolically, it can be denoted by (4). Each component is a matrix with dimension (3*3). Matrices of bus admittance are associated with the real configuration of the related power system. Components of the bus admittance matrix of the *Y* bus (before fault occurrence) are already known to us. By using the system connections shown in Fig. 2, the *Y* bus fault components can be associated with the *Y* bus components as displayed in (5)–(9).

$$Z \text{ bus fault} = \begin{bmatrix} Y11' & Y12' & Y13' \\ Y21' & Y22' & Y23' \\ Y31' & Y32' & Y33' \end{bmatrix}; \tag{4}$$

$$Y11' = Y11 + \frac{yLabc}{L1} - \frac{yLabc}{L}; \tag{5}$$

$$Y12' = Y21' = [0]_{3*3}; \tag{6}$$

$$Y13' = Y31' = -\frac{yLabc}{L1}; \tag{7}$$

$$Y23' = Y32' = -\frac{yLabc}{L2}; \tag{8}$$

$$Y22' = Y22 + \frac{yLabc}{L2} - \frac{yLabc}{L}; \tag{9}$$

$$Y33' = Y33 + \frac{yLabc}{L1} + \frac{yLabc}{L2}. \tag{10}$$

The following equations can be formed:

$$[0]_{3*3} = \left(Y11 - \frac{yLabc}{L}\right)\Delta V1 + \\ + \frac{yLabc}{L1}\Delta V1 - \frac{yLabc}{L1}\Delta V3; \tag{11}$$

$$[0]_{3*3} = \left(Y22 - \frac{yLabc}{L}\right)\Delta V2 + \\ + \frac{yLabc}{L2}\Delta V2 - \frac{yLabc}{L2}\Delta V3. \tag{12}$$

Variables $L1$ and $L2$ are related as:

$$L1 + L2 = L. \tag{13}$$

Equations (11) and (12) denote 6 complex equations. Voltages at the buses 1 and 2 are measured constantly. Thus, $\Delta V1$ and $\Delta V2$ are established. The unknowns in (11), (12) represent the failure voltage $\Delta V3$, $L1$ and $L2$. The above-mentioned equations are solved for $L1$ to obtain the equation:

$$L1 = \frac{|\Delta V1 - \Delta V2 + LQ(1)|}{|P(1) + Q(1)|}. \tag{14}$$

This algorithm suggests a fault localization method which is based on coordinated voltage measurements for 2 terminal power transmission lines. This technique was used to signify the occurrence of faults on the power system transmission lines.

4. 3. Fault detection mechanism in the power system

Multiple fault analysis using a two-port network is highlighted in the flowchart in Fig. 4. The diagram shows how the two-port network operates and how to enter the number of buses and transmission lines. It also shows the values of the parameters of the transmission lines, the values of the voltage of generators, and the measurement of voltages and currents of the system before the faults. The required model is chosen for the two-port network methods in order to simulate the required fault through special models, which is the method (*Z, Y, H*). Through these models, the faults are detected in the system and the faults are analyzed through the values of currents and voltages after the faults.

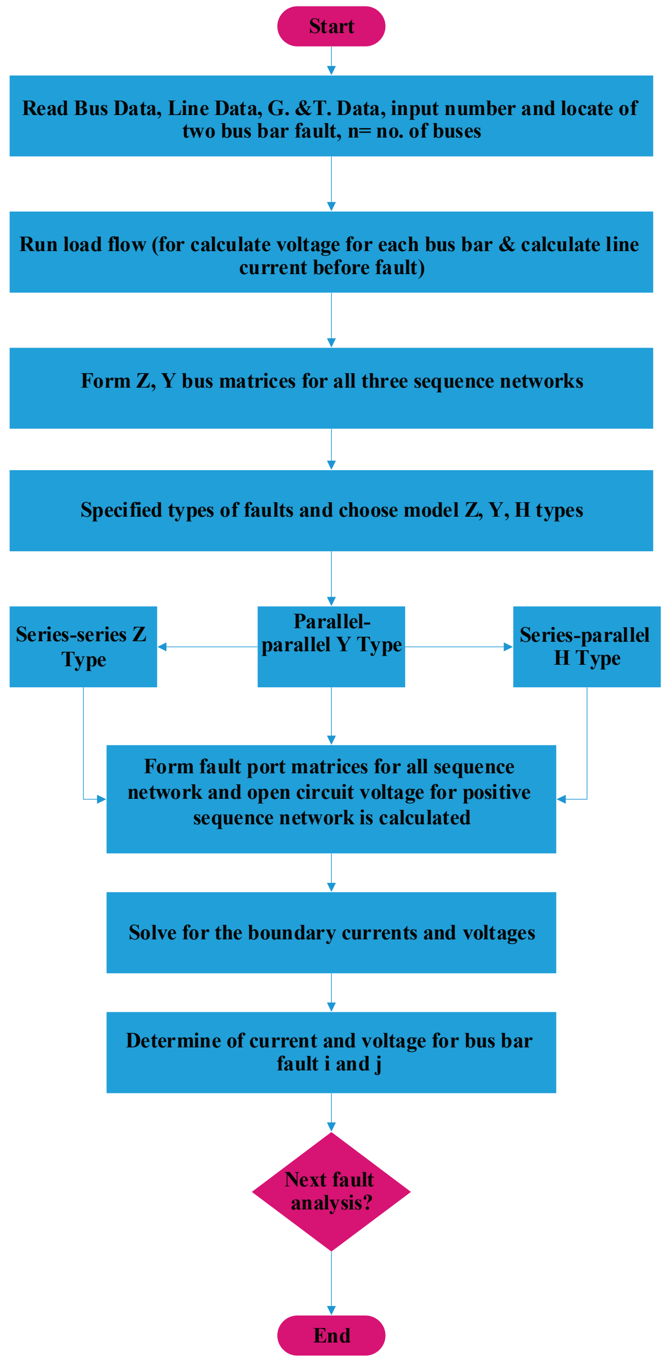

Fig. 4. Flowchart by two-port network analysis

5. Results

In this section, the results have been classified into three categories. The first category is related to the simulation of various types of faults in MATLAB, while the second group of results concerns the IEEE 14 bus system analysis. The third category regards the classification and detection of faults by using ANN.

5. 1. Simulation of various types of faults in MATLAB

Initially, the Newton-Raphson method was used to determine load flow so that the bus voltage, the power generated, and power consumed by the system before fault occurrence are ascertained, as specified in Table 4. Furthermore, 10 iterations and have a maximum power mismatch of 1.39758e-08.

Table 4

Power flow analysis for IEEE-14 Bus bar; Newton-Raphson method

Bus No.	Volt Mag.	Angle Degree	Load MW	Load Mvar	Generation MW	Generation Mvar	Injected Mvar
1	1.060	0	0	0	221.265	–285.910	0
2	1.065	–0.572	21.700	12.700	40.000	–46.325	0
3	1.060	–1.242	94.200	19.000	0.000	–74.373	0
4	1.065	–1.091	47.800	–3.900	0	0	0
5	1.064	–0.950	7.600	1.600	0	0	0
6	1.120	–1.597	11.200	7.500	0	–1.096	0
7	1.094	–1.289	0	0	0	0	0
8	1.090	–1.289	0	0	0	–22.378	0
9	1.098	–1.393	29.500	16.600	0	0	0
10	1.102	–1.445	9.000	5.800	0	0	0
11	1.110	–1.522	3.500	1.800	0	0	0
12	1.117	–1.666	6.100	1.600	0	0	0
13	1.115	–1.636	13.500	5.800	0	0	0
14	1.104	–1.585	14.900	5.000	0	0	0
Total			259.000	73.500	261.265	–430.083	0

5. 2. IEEE 14 bus system analysis

The results of this study have been presented using the two-port network technique where faults happen simultaneously in a standard system comprising 17 lines using the IEEE 14 bus, which is depicted in Fig. 5. The fault on the transmission line is represented by using the virtual bus (bus 15).

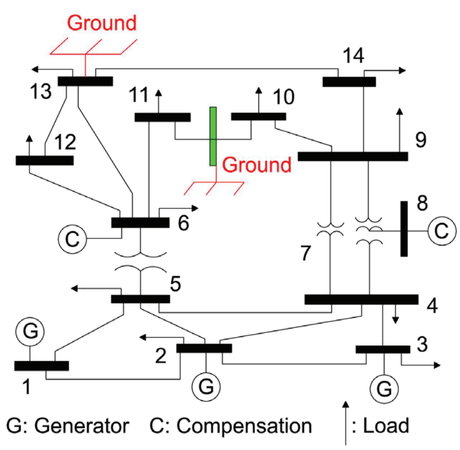

Fig. 5. IEEE-14 bus simultaneous dual fault

Table 5 shows the voltages from the 14-bus IEEE system before the fault. The voltages are equal and have phase angles at a difference of 120-degrees. The first case was the occurrence of two faults at the same time on bus 13 and the type of fault was phase A to the ground and double line-line faults BC (phase – phase) faults on the transmission line between bus (10) and bus (11) after a distance of (Df=30 %) from bus 10 as presented in this table. Furthermore, the values of current before and after the fault are specified in Table 6.

Fig. 6 illustrates the results of this study that have been presented using the two-port network technique where faults happen simultaneously in a standard system comprising 17 lines using the IEEE 14 bus. Table 7 specifies the 14-bus IEEE system voltages, which are equal before the failure, and the phases are at a 120-degree difference. When bus 11 faces a double simultaneous fault having a double line to ground type (AC-G) and a two-line open (AB) fault between bus line 4 and 5, at a distance of (Df=50 %) from bus 4, the voltages are specified in Table 7, while the values of current flowing through before and after the fault are specified in Table 8.

Table 5

Magnitudes and angles of bus voltages before and after the faults

No. of buses	Voltage Mag. before fault	Voltage Angle Degree before fault	Voltage Mag. after fault for each phase	Voltage Angle Degree after fault for each phase
BUS 1	1.060	0	1.057	–0.039
			1.057	–120.051
			1.057	120.034
BUS 2	1.065	0.5722	1.056	0.466
			1.056	–119.580
			1.057	120.711
BUS 3	1.060	1.2419	1.035	0.828
			1.032	–119.357
			1.034	121.7542
BUS 4	1.064	1.0905	0.975	0.525
			0.985	–120.599
			1.001	124.042
BUS 5	1.063	0.9504	0.966	0.406
			0.995	–120.559
			1.005	123.274
BUS 6	1.120	1.5967	0.773	–5.522
			0.981	–123.582
			0.959	124.647
BUS 7	1.093	1.2891	0.946	–1.225
			0.931	–124.692
			0.938	127.738
BUS 8	1.090	1.2891	1.045	0.602
			1.026	–120.306
			1.032	122.988
BUS 9	1.098	1.3926	0.859	–3.692
			0.838	–130.669
			0.842	133.791
BUS 10	1.101	1.4448	0.843	–4.0347
			0.686	–136.138
			0.770	144.466
BUS 11	1.110	1.5216	0.809	–4.790
			0.730	–131.584
			0.808	140.055
BUS 12	1.117	1.6662	0.481	–9.867
			1.015	–127.376
			0.989	128.855
BUS 13	1.115	1.6355	0.185	7.369
			1.029	–131.866
			1.051	131.707
BUS 14	1.104	1.5849	0.562	–2.2570
			0.919	–131.127
			0.931	132.938
BUS 15	1.000	0	0.733	–7.062
			0.500	–148.466
			0.642	155.858

Table 6

Magnitudes and angle currents of buses before and after faults

No. of buses	Current Mag. before fault for each phase	Current Angle Degree before fault for each phase	Current Mag. after fault for each phase	Current Angle Degree after fault for each phase
BUS 13	0.0091	98.130	4.5678	–70.538
	0.0091	–21.868	0	0
	0.0091	–141.86	0	0
Line 10–11	0.0423	124.263	0	0
	0.0423	4.2638	3.102	–172.866
	0.0423	–115.73	3.102	7.133

Table 7

Magnitudes and angles of bus voltages before and after the faults

No. of buses	Voltage Mag. before fault	VoltageAngle Degree before fault	Voltage Mag. after fault for each phase	Voltage Angle Degree after fault for each phase
BUS 1	1.060	0	1.0552	0.1441
			1.0604	–120.1432
			1.0222	119.5137
BUS 2	1.065	0.5722	1.0528	0.9242
			1.0666	–119.7318
			0.9535	119.1896
BUS 3	1.060	1.2419	1.0357	1.8347
			1.0656	–118.8049
			0.7082	113.7357
BUS 4	1.064	1.0905	1.1241	–8.7660
			1.2485	–109.3506
			0.3045	–46.0772
BUS 5	1.063	0.9504	1.1326	–8.7286
			1.2397	–109.1595
			0.3032	–42.9742
BUS 6	1.120	1.5967	0.8592	5.1931
			1.2188	–119.7053
			0.4243	95.0377
BUS 7	1.093	1.2891	0.9660	–4.4141
			1.2673	–114.7592
			0.1654	95.3289
BUS 8	1.090	1.2891	1.0270	1.9730
			1.1188	–119.0627
			0.8071	119.0441
BUS 9	1.098	1.3926	0.8383	–6.3066
			1.3622	–115.1196
			0.1086	9.5472
BUS 10	1.101	1.4448	0.6881	–4.7486
			1.4558	–116.8554
			0.2237	–37.6867
BUS 11	1.110	1.5216	0.3519	6.3050
			1.6744	–120.4660
			0.5950	–57.1596
BUS 12	1.117	1.6662	0.8571	4.4986
			1.2262	–119.1861
			0.3939	93.4131
BUS 13	1.115	1.6355	0.8513	3.6644
			1.2383	–118.9669
			0.3615	93.0664
BUS 14	1.104	1.5849	0.8385	–1.8266
			1.3063	–116.6556
			0.172	73.0555
BUS 15	1.000	0	1.1201	–13.4294
			1.2318	–106.8166
			0.6855	–52.1744

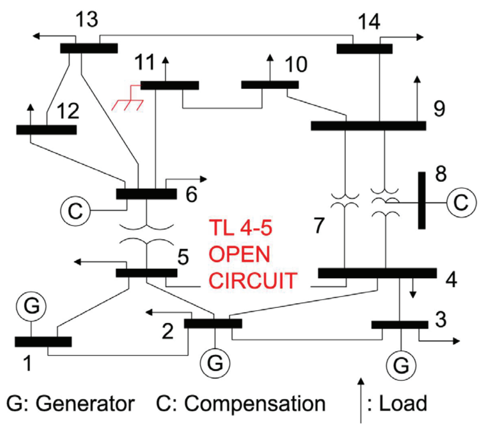

Fig. 6. IEEE-14 bus simultaneous dual fault

Table 8

Magnitudes of currents of buses before and after faults

No. of buses	Current Mag. before fault for each phase	Current Angle Degree before fault for each phase	Current Mag. after fault for each phase	Current Angle Degree after fault for each phase
BUS 11	0.0026	147.52	3.674	–91.492
	0.0026	27.52	0	0
	0.0026	–92.48	5.443	57.248
Line 4–5	0.0643	–5.0269	0	0
	0.0643	–125.02	0	0
	0.0643	114.97	22	46.411

5. 3. Training and a simulated neural network (ANN)

The behavior of the selected ANN depends on numerous parameters, such as the number of hidden layers, the number of hidden neurons, transfer functions, initial weights and biases, training rule and training parameters. In some cases, choosing one of these parameters wrongly may lead to overfitting or other kinds of problems. Fig. 7 highlights the flow for multiple fault classification using the neural network.

In order to prove the effectiveness of the fault classification technique by using the suggested fault classification based on ANN, a number of fault cases were tested under different parameter variations. The magnitudes of three phases current (|Ia|, |Ib|, |Ib|, $|I_0|$) were used as input of the neural network. It should be mentioned that the input variables have to be normalized in order fit into the ANN input range (±1). Furthermore, the output of the ANN fault locator is the estimation of fault location (in Km) in the transmission lines. After the process of training the neural networks is completed, all the networks of the fault locator are evaluated using varying fault scenarios, which were not part of the training data. Table 9 shows the parameters of the neural network to classify the type of faults in the system.

Fig. 8 shows the representation model for classifying faults in the system using a neural network and parameters of the neural network to classify the type of faults in the system. While Fig. 9 shows the results of ANN training in analyzing the type of fault as well as the fault location.

Table 9

Elements of the neural network to classify the type of faults in the system

ANN Parameters	Characteristics
Training Algorithm	Scaled Conjugate Gradient
No. of Epochs	9
Training Goal (MSE)	1.5462 e^{-17}
No. of Inputs	10
No. of Output Neurons	5 Neurons
No. of Hidden Layer	300 Layer
Bias (W_0)	1

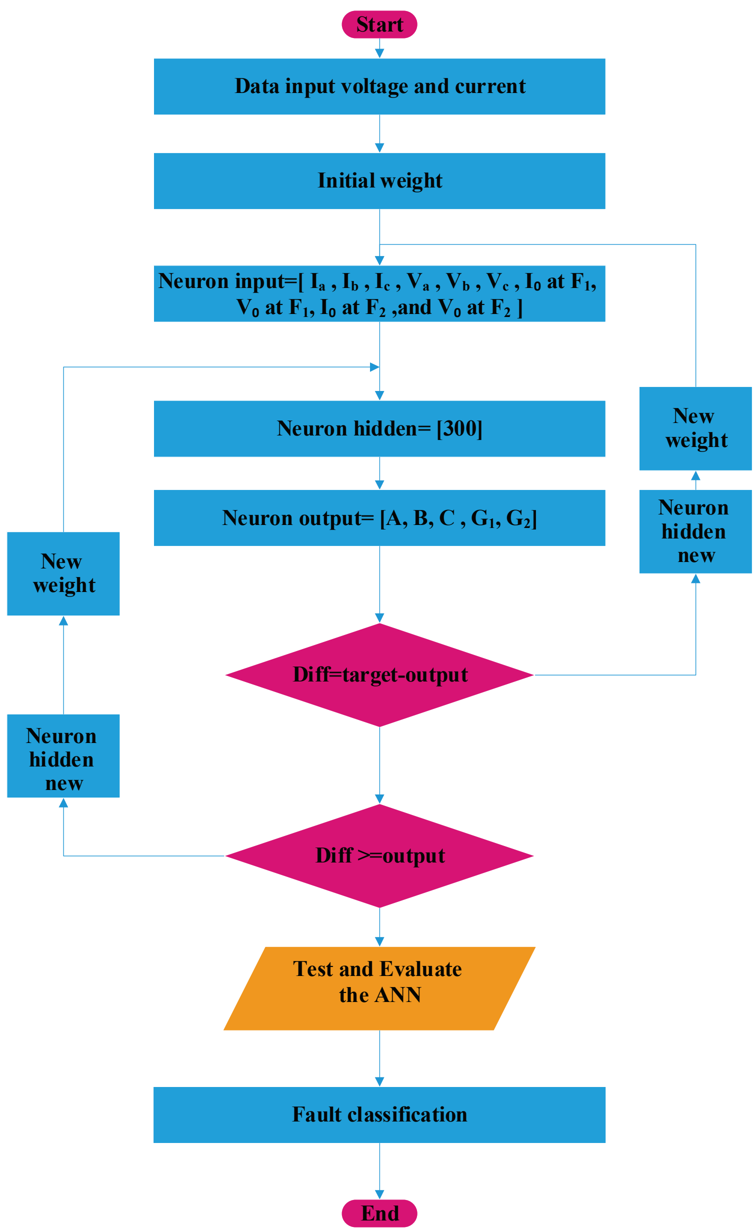

Fig. 7. Flowchart of the process of identifying types of faults in the system using the neural network

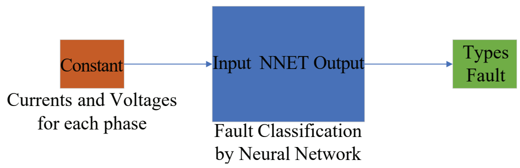

Fig. 8. Representation model for classifying faults in the system using a neural network

The entirety of faulty types and locations in the transmission system is simulated to assess the performance of the proposed fault location technique. Table 10 shows the parameters of the neural network to localize the fault in the system. In addition, Fig. 9 displays fault location by the neural network model using MATLAB. Equation No. 15 represents the calculation of the absolute error ratio in the transmission line. The location of the fault in the transmission line is revealed by an adaptive neural network. Performance evaluation of the neural fault locator is based on the criterion specified in the equation below:

$$\text{Absolute Error}(\%)= =\left(\frac{|\text{Estimated distance} - \text{Actual disance}|}{\text{Length of line}}\right)* *100\,\%. \qquad (15)$$

Estimated distance: fault location computed by the adaptive neural network.

Actual distance: the location of the actual or real fault on the transmission line.

Length of line: REPRESENTS the length of the transmission line obtained by the fault.

Absolute Error: represents the percentage of error for the fault location computed and detected by the adaptive neural network.

The flow chart in Fig. 10 illustrates the mechanism of the adaptive neural network in determining the locations of faults in the system through the three-phase currents in addition to the zero current components. The adaptive neural network for locating faults consist of four inputs, three-phase currents, compound zero current, and one output, which represents the location of the estimated fault by the neural network.

Table 10

Parameters of the neural network to locate the fault in the system

ANN Parameters	Characteristics
Training Algorithm	Scaled Conjugate Gradient
No. of Epochs	50
Training Goal (MSE)	6.1051 e^{-13}
No. of Inputs	4
No. of Output Neurons	1 Neurons
No. of Hidden Layer	200 Layer
Bias (W_0)	1

The neural network contains 200 hidden layers in its structure, and the search and training method was used, which is Scaled Conjugate Gradient, and Fig. 11 represents the circuit modeling of the neural network to determine the location of the malfunction in the Matlab program.

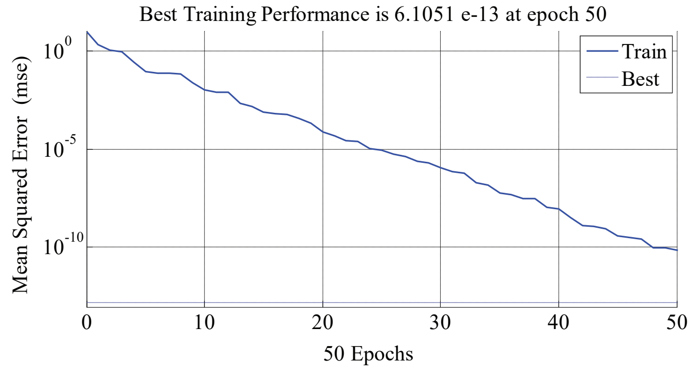

Fig. 9. Explanation of ANN training for fault location

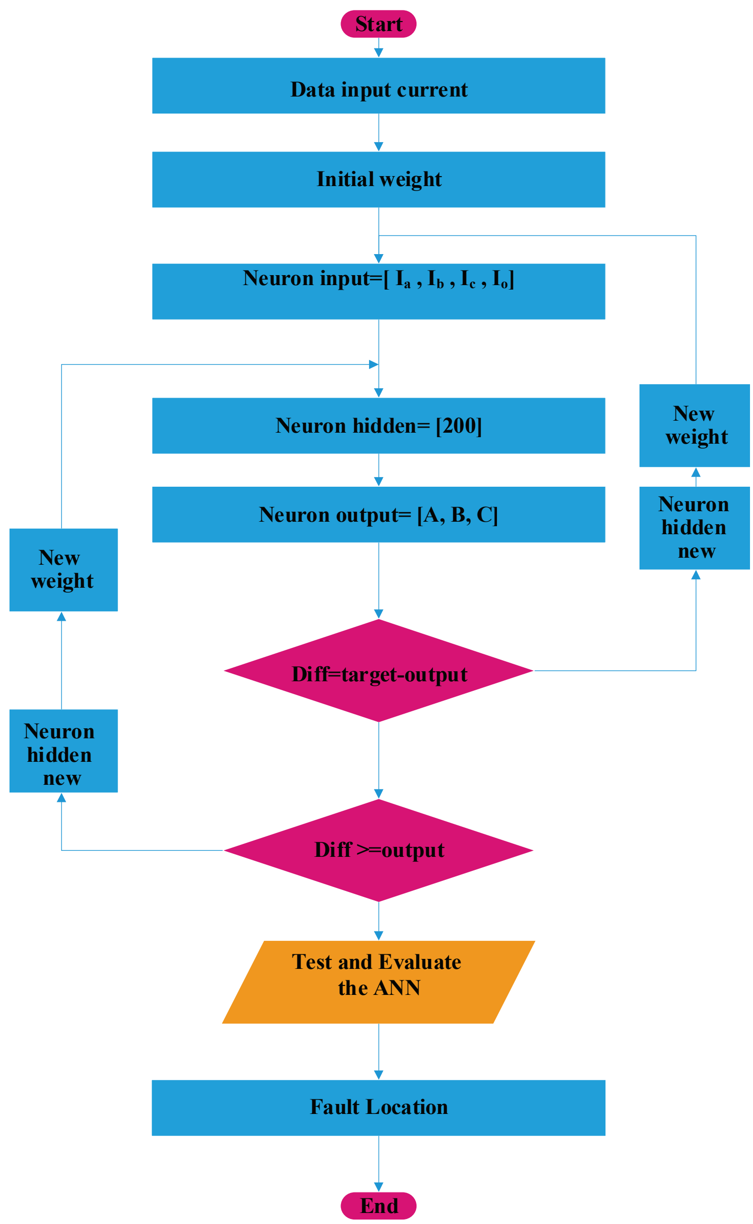

Fig. 10. Flow chart of multiple fault location by neural network

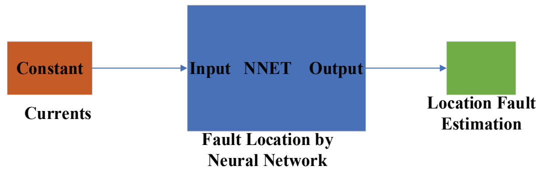

Fig. 11. Fault location by neural network model using MATLAB

6. Discussion of results

The Matlab-m file code was used to create electrical power flow into the system using the Newton-Raphson method. This is in order to find the values and angles of the bus voltages of the system before the occurrence of faults, as well as to find the power generated and the capacity consumed on the buses in the system. In addition, data are obtained from the system analysis using the two-port network method and the representation of faults on the IEEE-14 power system.

The first case was the occurrence of two faults at the same time on bus 13 and the type of fault was phase A to the ground and the other fault was on the transmission line ten and eleven (10)–(11). In addition, the BC (phase – phase) faults are 30 % from bus 10. Table 7 shows that the voltage of bus 13 before the fault was 1.115 P.U, and the voltage of phase A after the fault was 0.185 P.U. Table 8 shows the current of bus 13 before the fault 0.0091 P.U and after the fault 4.56 P.U. In the second case, two faults occurred at the same time on bus 11 and the type of fault was AC-G phase to ground, and the other fault was on the transmission line (5–4). The type of fault, AB open fault, 50 % from bus 4, as according to Table 7, the voltage of bus 11 before the fault was 1.11 P.U. The phase voltage A after the fault was 0.35 P.U and from Table 8 the current of bus 11 before the fault was 0.0026 P.U and after the fault was 5.44 P.U.

The adaptive neural algorithm was used to classify faults and localize faults in the IEEE-14 power system. Where two neural networks were specially trained to find the type of faults occurring in the system by relying on the voltage and current signatures of the three phases of the system and the current and zero voltage components as inputs to the neural network. This network consists of three layers, the Input Layer and Medium Layer, and contains 300 nodes and an Output Layer. After the training process, the type of faults occurring in the system will be discovered. The error rate in the training was very low and the performance of the neural network in detecting the type of defect was effective. The error rate in the training was MSE=1.5e–17 and the number of trials was no. of epochs=9.

The second neural network is to find the locations of faults occurring in the system and by relying on the current signature of the three phases of the system as well as the zero current components as inputs to the neural network. This network consists of three layers, the input layer, and the middle layer, and contains 200 nodes and the output layer. After training, the sites of faults occurring in the transmission line as well as faults occurring on buses will be identified through them. The error rate in this training was very low and the performance of the neural network in detecting the site of the fault was effective. The error rate in training MSE=6.1e–13 and the number of trials was no. of epochs=50.

The advantages of this work can be summarized as:

1. Implementation of double faults that occur at the same moment in the power system.

2. Simulation and implementation of open faults that have not been addressed in the literature.

3. Using the Matlab/Simulink program to represent the IEEE-14 bus power system and cause faults in the system.

While the future work can be classification of fault types and work site detection using fuzzy logic controllers. Also classification of faults types and detection of fault location can be made using a genetic algorithm. Furthermore, the effect of earth resistance in the case of parallel faults with the ground can be studied.

The limitation of this work is the disability to implement triple faults at the same time, because the two-port network method allows simulation of double faults only.

7. Conclusions

1. The system representation was successful by simulating various types of faults.

2. The IEEE 14-bus system was tested to validate this method by using the two-port network. In addition, the present study was designed to determine and detect the differences in the values of voltages and currents on the bus when the fault account.

3. A comparison has been conducted by training and a simulated neural network (ANN), created in MATLAB, trained to classify and detect the location of faults.

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