Fault Location Estimation of Kurdistan Power System using ANN

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Abstract— **This paper deals with one of the most powerful technique which is application of Artificial Neural Networks (ANNs) to detect, locate and specify type of the fault in high voltage transmission lines of Kurdistan power system. The proposed fault detector and locator were trained using various sets of data available from a selected power network model and simulating different fault scenarios (fault type) and different power system data. Different fault locators are proposed and carried out in order to determine which ANN fault locator structure leads to the best performance.**

Keywords: Power System, Different types of faults, Fault location, Artificial Neural Networks.

I. INTRODUCTİON

As knowing the power system of Kurdistan span relatively large distances connected with high voltage overhead lines, these transmission lines are considered the most vital components in power systems connecting both generating and consumer areas with huge interconnected networks. These areas characterized with rough weather, Therefore, possibility of fault always exist, in addition to the increasing of load demand makes these lines more disposed to failure, the most common faults, they may be triggered by lightning strokes, trees may fall across lines, fog and salt spray on dirty insulators may cause the insulator strings to flash over, ice and snow loadings may cause insulator strings to fail mechanically.

The fault cause short to long term power outages for customers and may lead to significant losses, especially for the manufacturing industry. Fast detecting, isolating, locating and repairing of these faults are critical in maintaining a reliable power system operation in addition, the faults that occur in power systems are required to prevent the propagation to other areas in the protective system. The functions of the protective systems are to detect, then classify and finally determine the location of the faulty line of voltage and/or current line magnitudes. Then at last, for isolation of the faulty line the protective relay have to send a signal to the circuit breaker [1]

When a fault occurs on an electrical transmission line, it is very important to detect it and to find its location in order to make necessary actions in order to repairs and restore power as soon as possible. The time needed to determine the fault point along the line will affect the quality of the power delivery. Therefore, it is very important to have a well coordinated protection system that detects any kind of abnormal flow of current in the power system, identifies the type of fault and then accurately locates the position of the fault in the power system [2].

An accurate fault location on the line is an important requirement for a permanent fault. Pointing to a weak spot, it is also helpful for a transient fault, which may result from a marginally contaminated insulator, or a swaying or growing tree under the line [1,2].

Transmission lines experience temporary and permanent faults. Temporary faults, which are the most dominant faults on overhead lines, are self-cleared. In consequence, the power supply continuity is not permanently affected, which is advantageous. In turn, after the permanent fault occurrence, the related protective relaying equipment enables the associated circuit breakers to de-energize the faulted sections. In the case of permanent faults, the restoration of power supply can be done after the maintenance crew finishes the repair of the damage caused by the fault. For this purpose, the fault position has to be known; otherwise the whole line has to be inspected to find the damaged place. Thus, it is important that the location of a fault is either known or can be estimated with reasonably high accuracy. This allows saving money and time for the inspection and repair, as well as to provide a better service due to the possibility of faster restoration of power supply. This also enables the blackouts to be avoided. Temporary faults are self cleared and do not affect permanently the supply continuity, however, the location of such faults is also important. In this case the fault location can help to pinpoint the weak spots on the line. As a result, the plans of maintenance schedules can be fixed for avoiding further problems in the future [3].

After the fault, the related relaying equipment enables the associated circuit breakers to de-energize the faulted sections. Once the fault is cleared and the faulted phases are declared, the fault locator is enabled to detect the fault position. Then, the maintenance teams informed to the location to fix the resultant damage. Later, the line returned back to service [3,4]. Since transmission line networks spread for some hundreds of kilometers in different environmental and geographical circumstances, locating these faults based on the human experience and the available information about the status of all breakers in the faulted area is not efficient and time consuming [4].

The applications of neural network can be summarized into two categories. The first is to use neural network to differentiate various fault patterns from normal operating condition, according to different measured process output data. The training of neural network can be offline or online. In the second category, neural networks are used as classifiers to isolate faults represented by process model generated residuals. The process model can be a mathematical model based on which the fault diagnosis structure utilizes some process mechanism provided by the quantitative model, and therefore facilitates the implementation and training of the neural classifier. In cases when mathematical process models are not available, a neural process model can be employed to generate residuals another network which is then used to isolate faults [5,6].

II. LİTERATURE REVİEW

The subject of fault location has been of considerable interest to electric power utility engineers for a long time. During the last decade a number of fault location algorithms have been developed, including the steady-state phasor approach, the differential equation approach and the traveling-wave approach (Lian and Salama, 1994), as well as two-end (Sheng and Elangovan Elangovan, 1998) and one-end (Zhang et al., 1999) algorithms. In the last category, synchronized (Kezunovic and Mrkic, 1994) and non-synchronized (Novosel et al., 1996) sampling techniques are used. However, two-terminal data are not widely available. From a practical viewpoint, it is desirable for equipment to use only one-terminal data. The one-end algorithms, in turn, utilize different assumptions to replace the remote end measurements. Most of fault locators are only based on local measurements. Currently, the most widely used method of overhead line fault location is to determine the apparent reactance of the line during the time that the fault current is flowing and to convert the ohmic result into a distance based on the parameters of the line. It is widely recognized that this method is subject to errors when the fault resistance is high and the line is fed from both ends, and when parallel circuits exist over only parts of the length of the faulty line [6,7].

Recent applications in protection have covered fault diagnosis for electric power systems (Mohamed and Rao,1995), transformer protection (Zaman and Rahman, 1998) and generator protection (Megahed and Malik, 1999), (Oleskovicz et al., 2001; Purushothama et al., 2001; Osowski and Salat, 2002). However, almost all of these applications in protection merely use the ANN ability of classification, that is, ANNs only output 1 or 0 [7,8].

A feed-forward neural network based on the supervised back-propagation learning algorithm was used to implement the fault detector and locators. The neural fault detector and locators were trained and tested with a number of simulation cases by considering various fault conditions (fault types, fault locations, fault resistances and fault inception angles) and various power system data (source capacities, source voltages, source angles, time constants of the sources) in a selected network model [1,6]

Traditional power system fault location techniques involve the use of different protection or recording devices, such as Digital Fault Recorders, Digital Relays, Sequence of Events Recorders, and Phasor Measurement Units [9].

III. FAULT CLASSİFİCATİON USING ANN

Fault classification is integrated in two basic steps. The first step is preparation of the fault data for different faults the second step is diagnosis fault using a proper artificial neural network.

Artificial Neural Networks are a parallel distributed processing system made up of highly interconnected neural computing elements. These networks have the ability to learn and thereby acquire knowledge. This acquired knowledge makes neural network to solve problems. Neural networks architectures have been classified into various types based on their learning mechanism. These neurons are connected to form a network and are organized in the form of layers. These are connected by highly synaptic weights. The Artificial Neural Networks (ANNs) have a learning ability as synaptic weights can be strengthened or weakened during the learning process, and in this way, information can be stored in the neural network. Each neuron has activation function, as a function of inputs it has received. A neuron sends its activation as a signal to several other neurons. It is important to note that a neuron can send only one signal at a time, although signals are broadcasted to several other neurons [10,11]

The artificial neural network used in the proposed methodology is a multilayer back propagation neural network. This type of neural network is used in pattern recognition, classification, function approximation etc. The artificial neural network model with multiple inputs and one output for the fault diagnosis in analog circuit is shown in "Fig. 1". Here $X=[X_1,X_2,X_3,\ldots\ldots.X_n]$ is the input vector and n is the number of neurons in the input layer. Y_k is the output of the neural network. Where k represents the different components presented in the analog circuit [11].

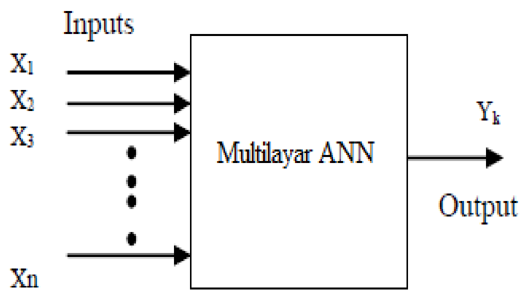

FIGURE 1. MODEL OF NETWORK USED IN DIAGNOSIS FAULT

X1.......Xn represents the coefficients of the polynomial fitted to the output frequency response of the analog circuit. Y_k is the output of the neural network. Fault classifiers use of multilayer perceptron neural network and employed the back-propagation learning strategy. Although back propagation learning strategy is inherently slow in learning and poses difficulty in choosing the optimal size of the network, it is undoubtedly the ideal strategy to be employed when there is a large training set available because back-propagation algorithm can provide a very compact distributed representation of complex data sets [12].

IV. NEURAL NETWORK DESİGN FOR FAULT LOCATİON

To prepare the input data for neural network, the best way is to collect the real data from the faults or practical tests.

In the real world, many factors are effective in the fault current and voltage and affect the accuracy of fault location. But due to lack of information and impossibility of performing practical tests, modeling is the only alternative. Input patterns of neural networks contain of the train and test vectors. The numbers of test vectors are a ratio of train vectors and are completely independent. The training input pattern data in neural networks are the only source of information.

Input patterns contain the rms. values of three-phase voltages and currents in the instance of fault before enough for detection and location of the fault. After the neural net is trained offline using this data with unsupervised and supervised learning procedures; the network is able to perform the untrained mapping. If these patterns were quite exact and real, the operation of the network would be more accurate. So, it is required to obtain the fault currents and voltages corresponding to different faults for different locations along the feeder [12, 13].

Fault location prediction for the other types of faults

The fault detection program defines which of these networks to initiate. So, the structure of fault detector based on neural networks concepts can be considered as shown in "Fig. 2".

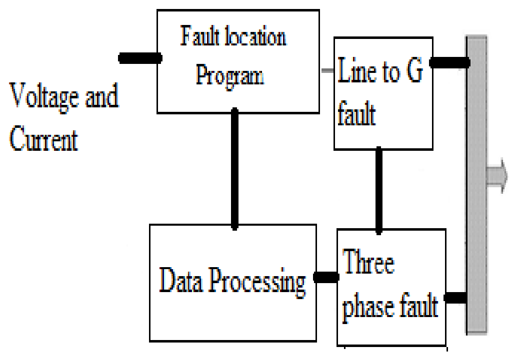

FIGURE 2. BLOCK DIAGRAM OF NEURAL NETWORKS AS A FAULT LOCATOR

The simulation presented in this paper is based on four different A, B, C and G outputs were considered to determine whether each of the three phases A,B, C and/or ground G are present in the fault loop.

The networks' architectures were decided empirically, which involved training and testing different number of networks.

Three layer networks were found to be appropriate for the fault selector application.

V. NEURAL NETWORK DESİGN FOR FAULT TYPES

There are three phases (A, B, C) and neutral or ground G. Their combinations are subjected to faults. The data required to differentiate between these types of faults are the three phase voltages and currents.

The data generates four output statuses associated with the four fault types. The outputs contain variables whose values are given as either 0 or 1 as shown in table (I) corresponding to the existence of that class of fault.

TABLE I NETWORK TRUTH TABLE

	Network Outputs			
Type of Fault	***Phase A***	***Phase B***	***Phase C***	***Ground***
A-G fault	1	0	0	1
B-G fault	0	1	0	1
C-G fault	0	0	1	1
A-B-C Fault	1	1	1	0

The proposed neural network should classify if the specific phases involved in the fault scenario or not.

A large number of three layers networks were extensively simulated and studied. The input and output layers has fixed six (three phase voltages and currents) and four neurons, respectively. The hidden layer is tried with different neurons numbers. The most suitable network size for the classification task was found to be hidden layer with five hidden neurons as shown in "Fig. 3".

The selected network was able to recognize correctly the type of the fault category.

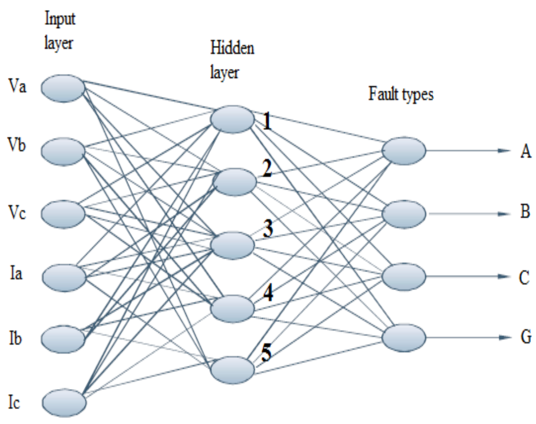

FIGURE 3. BACK PROPAGATION NEURAL NETWORK FOR FAULT TYPE

VI. SİMULATİON STUDY

The model of power system used for the algorithm is 132 kV Kurdistan power system simulated with aid of program PSAT as shown in "Fig. 4". The implementation includes two types of faults (single phase-to-ground fault, a type of fault that occupies about 90% of all of the transmission line faults, and three phase fault which considered a most sever fault) simulation has been conducted at different locations of the transmission line, for each of these locations there are data sets, and each set contains the instantaneous phase voltages and currents corresponding to each fault type. The normal operating case is taken as a reference for the faulted cases.

Hence the training set consisted of about 500 input output sets (100 for each of the four faults and 50 for the no fault case) with a set of six inputs and one output in each input-output pair. Back-propagation networks with a variety of combinations of hidden layers and the number of neurons per hidden layer have been studied.

A. Training the neural network for single line – ground Fault location

There is no exact method for determining the number of hidden layer neurons, but it can be said that the number of hidden layer neurons is a function of the order of nonlinearity between the input and output space; so the number of neuron based on the proposed problem is obtained by trial and error.

Feed forward back – propagation neural networks have been surveyed for the purpose of single line – ground fault location, mainly because of the availability of sufficient relevant data for training. In order to train the neural network, several single phase faults have been simulated on the transmission line model. For each of the three phases, faults have been simulated at every 1 km on a 100 km (chose the longest transmission line).

Along with the fault distance, the fault resistance has been varied. About 90% of the transmission line faults are single phase to ground fault which one of the conductors is short circuited to the earth without or via a fault resistance. Majority of the fault location algorithms are affected by the fault resistance, therefore it is essential to take the effect of fault resistance on the accuracy of the proposed algorithm. Hence, a total of 2400 cases have been simulated (100 case for each of the three phases' voltages and currents with each of the four different fault resistances as 0.25, 0.5, 0.75, and 1 ohm respectively). In each of these cases, the voltage and current samples for all three phases are given as inputs to the neural network as shown in table (II). The output of the neural network is the distance to the fault from selected bus. Firstly, a few of the various neural networks (with varying combination of hidden layers and number of neurons per hidden layer) that performed reasonably well are presented along with their respective error performances. Then the training performance of the neural network was 6-15-4 (6 neurons in the input layer, 1 hidden layer with 15 neurons in it and four neurons in the output layer) as a best performance.

B. Training the neural network for three phase fault location

Feed forward back – propagation algorithm was once again used for the purpose of three phase fault location on transmission lines, since these networks perform very efficiently when there is enough training data set. For the purpose of training the neural network, several three phase faults have been simulated on the modeled transmission line. The various factors that were varied were the fault distance (incremented by 1 km each time). About 2400 fault cases were simulated with each of the four different resistances as 0.25, 0.5, 0.75 and 1 ohm respectively. In each of these cases, the voltage and current samples on all three phases are fed as inputs to the neural network. The neural network's output is the distance to the fault from terminal A (which is the line between bus number 4 & 5 selected as a study case since it has the longest line in the power system). Thus each input output pair fed into the neural network has a set of six inputs represent current and voltage and one output.

It seen from table (III), that the maximum error is about ±0.7 km, which is fairly acceptable, However neural networks that can perform better are more desirable, the neural network with 6 neurons in the input layer, 3 hidden layers with 6, 21 and 16 neurons in them respectively and 1 neuron in the output layer (6 – 6 – 21 – 16 – 1).

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VII. CONCLUSİON

Detection of fault location has to be done as quickly as possible, for the purpose of isolating the faulty section of the system in order to maintain system stable using neural network designed for such case.

The neural network performance of the proposed scheme is evaluated using various fault types. It was shown that the network was able to perform fast and correctly for different combinations of fault conditions, e.g. fault type and fault location.

A large number of back propagation neural network with different structures were studied and analyzed, it is found that through trial and error that a back propagation network with two hidden layers provides the best training performance.

To increase processing speed, the size of the neural network reduces by measuring voltage and current at one end and if less number of inputs is used however, sufficient input data to characterize the problem must be ensured.

Three lines			Line to ground	
Length	Voltage		Voltage	
km	kv	degree	kv	degree
1	6.22	-13.52	6.89	-12.6
2	6.17	-12.67	6.82	-11.66
3	6.11	-11.84	6.75	-10.76
4	6.06	-11.04	6.68	-9.89
5	6	-10.27	6.61	-9.05
6	5.9	-8.82	6.54	-8.24
7	5.79	-7.46	6.48	-7.46
8	5.75	-6.82	6.41	-6.72
9	5.7	-6.2	6.35	-6
10	5.65	-5.61	6.29	-5.31
11	5.6	-5.04	6.23	-4.65
12	5.56	-4.48	6.17	-4.01
13	5.52	-3.95	6.11	-3.29
14	5.47	-3.44	6.06	-2.8
15	5.43	-2.95	6	-2.24
16	5.39	-2.47	5.95	-1.69
17	5.35	-2.02	5.9	-1.17
18	5.31	-1.58	5.85	-0.67
19	5.28	-1.16	5.8	-0.19
20	5.24	-0.75	5.75	0.28
21	5.21	-0.036	5.71	0.72
22	5.17	0.01	5.67	1.15
23	5.14	0.37	5.62	1.56
24	5.11	0.72	5.58	1.95
25	5.08	1.05	5.54	2.32
26	5.05	1.36	5.51	2.69
27	5.02	1.67	5.47	3.03
28	5	1.96	5.43	3.36
29	4.97	2.24	5.4	3.68
30	4.95	2.5	5.37	3.98
31	4.92	2.76	5.34	4.27
32	4.9	3	5.31	4.54
33	4.88	3.23	5.28	4.81
34	4.86	3.45	5.25	5.06
35	4.83	3.66	5.22	5.3
36	4.82	3.86	5.2	5.52
37	4.8	4.05	5.17	5.74
38	4.78	4.22	5.15	5.94
39	4.76	4.39	5.13	6.14
40	4.75	4.55	5.11	6.32
41	4.73	4.7	5.09	6.49
42	4.72	4.84	5.07	6.66
43	4.71	4.97	5.05	6.81
44	4.69	5.09	5.04	6.95
45	4.68	5.2	5.02	7.08
46	4.67	5.3	5.01	7.21
47	4.66	5.39	4.99	7.32
48	4.65	5.48	4.98	7.43
49	4.64	5.62	4.97	7.52
50	4.63	5.68	4.96	7.61

TABLE II INPUT DATA FOR FAULT

Length	Three Lines S.C.			Line to Ground		
km	Ia	Ib	Ic	Ia	Ib	Ic
1	82	33.34	47.2	90.79	43.53	61.6
2	80.19	33.13	46.88	88.67	43.14	61.03
3	78.48	32.92	46.57	86.67	42.75	60.48
4	76.88	32.71	46.27	84.78	42.37	59.93
5	75.36	32.5	45.97	83	42	59.4
6	72.57	32.1	45.39	81.31	41.63	58.87
7	70.08	31.7	44.84	79.72	41.26	58.36
8	69.93	31.51	44.56	78.22	40.91	57.85
9	67.85	31.32	44.3	76.79	40.56	57.36
10	66.81	31.14	44.04	75.45	40.22	56.88
11	65.84	30.96	43.78	74.17	39.88	56.4
12	64.91	30.78	43.53	72.96	39.56	55.94
13	64.03	30.61	43.29	71.81	39.24	55.49
14	63.19	30.44	43.05	70.72	38.92	55.05
15	62.39	30.27	42.81	69.68	38.62	54.62
16	61.63	30.11	42.58	68.7	38.33	54.2
17	60.91	29.95	42.36	67.76	38.04	53.79
18	60.22	29.8	42.14	66.87	37.76	53.4
19	59.57	29.65	41.93	66.02	37.49	53.01
20	58.95	29.5	41.73	65.22	37.22	52.64
21	58.35	29.36	41.53	64.45	36.97	52.28
22	57.79	29.23	41.33	63.72	36.72	51.93
23	57.25	29.09	41.14	63.03	36.48	51.59
24	56.74	28.96	40.96	62.37	36.24	51.26
25	56.25	28.84	70.78	61.74	36.02	50.94
26	55.78	28.72	40.61	61.13	35.8	50.63
27	55.34	28.6	40.45	60.56	35.59	50.33
28	54.92	28.49	40.29	60.02	35.39	50
29	54.52	28.38	40.13	59.5	35.19	49.77
30	54.14	28.27	39.98	59	35	49.5
31	53.77	28.17	39.84	58.54	34.82	49.24
32	53.43	28.07	39.7	58.09	34.65	49
33	53.1	27.98	39.57	57.67	34.48	48.76
34	52.79	27.89	39.44	57.26	34.32	48.53
35	52.5	27.8	39.32	56.88	34.16	48.31
36	52.22	27.72	39.2	56.52	34.01	48.1
37	51.95	27.64	39.09	56.17	33.87	47.9
38	51.71	27.57	38.99	55.85	33.74	47.71
39	51.47	27.5	38.89	55.54	33.61	47.53
40	51.25	27.43	38.79	55.25	33.49	47.36
41	51.05	27.37	38.7	54.98	33.37	47.19
42	50.85	27.31	38.62	54.72	33.26	47.04
43	50.67	27.25	38.54	54.48	33.16	46.98
44	50.51	27.2	38.46	54.25	33.06	46.75
45	50.35	27.15	38.39	54.04	32.97	46.62
46	50.21	27.1	38.33	53.85	32.88	46.50
47	50.08	27.06	38.27	53.67	32.8	46.39
48	49.96	27.02	38.22	90.79	32.65	46.24
49	49.76	26.96	38.12	88.67	32.5	46.14
50	49.68	26.93	38.08	53.5	32.3	45.98
51	49.61	26.9	38.05	53.14	32.1	45.78
52	49.54	26.88	38.02	53.08	31.8	45.57
53	49.49	26.87	38	52.97	31.74	45.38
54	49.46	26.85	37.98	52.91	31.36	45.18
55	49.43	26.84	37.96	52.87	30.84	44.96
56	49.41	26.85	37.95	52.78	31.43	44.75
57	49.43	26.87	37.95	52.74	31.12	44.60
58	49.49	26.88	37.98	52.71	30.87	44.43
59	49.6	26.99	38.02	52.68	30.43	44.30
60	49.96	27.06	38.17	52.65	29.83	44.18
61	50.21	27.15	38.27	52.64	29.45	44.08
62	50.5	27.25	38.4	52.61	28.64	43.92
63	50.85	27.35	38.54	52.59	28.14	43.87
64	51.25	27.37	38.7	52.57	27.97	43.81
65	51.71	27.5	38.89	52.55	27.34	43.77
66	52.22	27.64	39.09	52.53	26.47	43.67
67	52.8	27.8	39.32	52.51	25.88	43.63
68	53.45	27.98	39.57	52.49	24.63	43.59
69	54.16	28.17	39.84	52.47	24.03	43.55
70	54.96	28.38	40.13	52.43	23.83	43.53
71	55.84	28.6	40.45	52.41	22.73	43.52
72	56.8	28.84	40.78	52.40	21.98	43.50
73	57.87	29.09	41.14	52.39	21.13	43.48
74	59.05	29.36	41.52	52.38	20.76	43.47
75	60.35	29.64	41.92	52.37	20.23	43.46

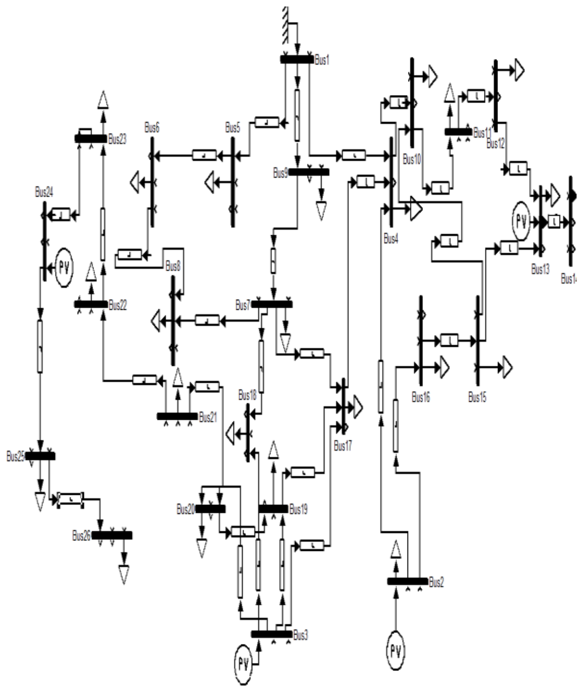

FIGURE 4. KURDISTAN POWER SYSTEM (26 BUS) SIMULATED BY USING PSAT

Actual Length km	**Predicted**	**Error=(actual-predict)**
1	0.5173	0.4827
2	1.563	0.437
3	2.615	0.385
4	3.67	0.33
5	4.72	0.28
6	5.779	0.221
7	6.8	0.2
8	7.854	0.146
9	8.871	0.129
10	9.881	0.119
11	10.92	0.08
12	11.909	0.091
13	12.918	0.082
14	13.876	0.124
15	14.883	0.117
16	15.839	0.161
17	16.8	0.2
18	17.755	0.245
19	18.718	0.282
20	19.683	0.317
21	20.6	0.4
22	21.519	0.481
23	22.503	0.497
24	23.46	0.54
25	24.417	0.583
26	25.338	0.662
27	26.329	0.671
28	27.371	0.629
29	28.315	0.685
30	29.313	0.687
31	30.342	0.658
32	31.369	0.631
33	32.445	0.555
34	33.253	0.747
35	34.657	0.343
36	35.694	0.306
37	36.842	0.158
38	37.893	0.107
39	38.963	0.037
40	40.024	-0.024
41	41.091	-0.091
42	42.131	-0.131
43	43.032	-0.032
44	44.074	-0.074
45	45.712	-0.712
46	46.722	-0.722
47	47.764	-0.764
48	48.632	-0.632
49	49.087	-0.087
50	50.416	-0.416

TABLE III THE FAULT LOCATION RESULTS UNDER VARIOUS FAULT LOCATIONS ON THE LINE FOR 50 KM.

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