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Fast and Accurate Load Flow Solution for On-line Applications Using ANN

Wael Abdullah Alsulami

Protection and Testing Div., Asset Maintenance Dept.-Jed - Jeddah, Kingdom of Saudi Arabia

Abstract: This paper aims to develop a fast load flow computation technique without sacrificing accuracy for various on-line applications of large power systems. Both planning and operation of any power system requires the conduct of many load flow analyses corresponding to various operating modes with different system loading conditions and network configurations. Load flow analysis is performed for the determination of steady state operating status of power systems in terms of bus voltage magnitudes and angles, real and reactive powers and the transmission line losses. The load flow analysis involves the solution of non-linear algebraic equations and hence the conventional load flow algorithms are iterative in nature. The state-of-the-art approach for load flow analysis is based on Newton-Raphson algorithm (NRLF) or its derivatives such as fast decoupled load flow. As these methods are capable of providing the steady state solution within the specified accuracy, these techniques are effectively utilized as a planning tool by various utilities throughout the world. However, these are seen to be ineffective for on-line computations of practical large power systems because of the significant computational over-head due to the inherent iterative nature of such algorithms. Even though the non-iterative DC load flow approach, derived out of NRLF is computationally faster than the conventional techniques, solution accuracy is significantly less than that of its iterative counterparts. Hence, this paper proposes to develop a fast and accurate approach for the on-line load flow analysis. It is proposed to apply artificial neural network (ANN) technique as these are seen to be non-algorithmic in nature. The multi-layer feed-forward ANN for the load flow solution used in this study has one hidden layer with 100 neurons in addition to the input and output layers. The real and reactive power demands are given as the inputs to the ANN. The output consists of the bus voltage magnitudes and angles at the load buses. The proposed ANN is trained using the conventional NRLF load flow solution of a practical power grid at various load levels. The investigations revel that the ANN as a potential tool for the on-line load flow solution of practical power systems.

Keywords: Neural network; power flow; load flow; on-line applications; power network.

1. Introduction

Load flow analysis is performed on a power system to determine the steady state of the system in terms of the real and reactive powers along with the magnitude and phase angle of the voltage at each bus of the system for the specific loading conditions. For the past three decades, various numerical analysis methods have been applied in solving the non-linear algebraic equations of the load flow problem. The most commonly used iterative methods are the Gauss-Seidel, the Newton-Raphson and Fast Decoupled method [1]. Newton-Raphson load flow (NRLF) and fast decoupled load flow (FDLF) algorithms are utilized by various electric utilities for off-line studies in the planning stage as it is possible to get accurate solution within a few iterations independent of the system size. This is attributed to the quadratic convergence characteristics of these algorithms [6].

Load flow analysis is also necessary as an on-line tool for the system monitoring and control [3]. The system security is to be established throughout the operation of the power system. This is ensured by performing load-flow analysis at regular short intervals on an on-line basis with the most recent data acquired by the load dispatch center. The conventional NRLF and FDLF are not well-suited for such on-line applications because of the computational overhead due to the iterative approach inherent in these algorithms. The DC load flow approach deduced out of the NRLF is non-iterative and provides solution faster than the other approaches. However, these are very inaccurate because of the assumptions made in the derivation of the DC load flow equations [6]. Hence, in this study, it is intended to develop a fast and accurate load flow technique for on-line applications such as power system security evaluation. It is proposed to investigate artificial neural network (ANN) for this purpose, as it is inherently non-algorithmic in nature.

ANNs have been used in a board range of applications including: pattern classification, pattern recognition, optimization, prediction and automatic control. In spite of different structures and training paradigms, all ANN applications are special cases of vector mapping. The application of ANNs in different power system operation and control strategies has led to acceptable results [7][8].

2. Methodology

A. *Study Design*

The study attempts to apply multilayer feed forward ANN (MLFFNN) for the load flow analysis of power systems. The major tasks proposed to be used in the study as the following:

i. Collect and arrange the practical system data for load flow analysis.
ii. Develop and apply NRLF program on practical power System.
iii. Design a MLFFNN for load flow analysis and train the same using error back-propagation learning algorithm.
iv. Evaluate the effectiveness of the MLFFNN in terms of solution accuracy and computation speed.

B. *Power Flow Methods*

First The numerical analysis involving the solution of algebraic simultaneous equations forms the basis for solution of the performance equations in computer aided electrical power system analyses e.g. for load flow analysis [1]. The first step in performing load flow analysis is to form the Y-bus admittance using the transmission line and transformer input data. The nodal equation for a power system network using Y bus can be written as follows:

$$I = Y_{Bus}V \qquad (1)$$

The nodal equation can be written in a generalized form for an n bus system.

$$I_i = \sum_{j=1}^{n} Y_{ij}V_j \quad \text{for } i = 1, 2, 3, n \qquad (2)$$

The complex power delivered to bus i is

$$P_i + jQ_i = V_i I_i^* \qquad (3)$$

$$I_i = \frac{P_i - jQ_i}{V_i^*} \qquad (4)$$

Substituting for Ii in terms of Pi & Qi, the equation gives

$$\frac{P_i - jQ_i}{V_i^*} = V_i \sum_{j=1}^{n} y_{ij} - \sum_{j=1}^{n} y_{ij}V_j \quad j \neq i \qquad (5)$$

The above equation uses iterative techniques to solve load flow problems. Hence, it is necessary to review the general forms of the various solution methods; Gauss-Seidel, Newton-Raphson and Fast decoupled load flow.

C. Newton-Raphson Method

The Newton-Raphson Method is an iterative method which approximates a set of non-linear simultaneous equations to a set of linear simultaneous equations using Taylor's series expansion and the terms are limited to the first approximation. It is the most iterative method used for the load flow because its convergence characteristics are relatively more powerful compared to other alternative processes and the reliability of Newton-Raphson approach is comparatively good since it can solve cases that lead to divergence with other popular processes [6]. If the assumed value is near the solution, then the result is obtained very quickly, but if the assumed value is farther away from the solution then the method may take longer to converge [3]. This is another iterative load flow method which is widely used for solving nonlinear equation.

The admittance matrix is used to write equations for currents entering a power system. The real and imaginary parts are separated:

$$P_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) \qquad (6)$$

$$Q_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}|\sin(\theta_{ij} - \delta_i + \delta_j) \qquad (7)$$

The above Equation (6) and (7) constitute a set of non-linear algebraic equations in terms of $|V|$ in per unit and δ in radians. Equation (6) and (7) are expanded in Taylor's series about the initial estimate and neglecting all higher order terms, the following set of linear equations are obtained.

The element of the Jacobian matrix is obtained after partial derivatives of Equations (6) and (7) are expressed which gives linearized relationship between small changes in voltage magnitude and voltage angle. The equation can be written in matrix form as:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_3 \\ J_2 & J_4 \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta |V| \end{bmatrix} \qquad (8)$$

$J1$, $J2$, $J3$, $J4$ are the elements of the Jacobian matrix.

The difference between the schedule and calculated values known as power residuals for the terms $\Delta P_i^{(k)}$ and $\Delta Q_i^{(k)}$ is represented as:

$$\Delta P_i^{(k)} = P_i^{sch} - P_i^{(k)} \qquad (9)$$

$$\Delta Q_i^{(k)} = Q_i^{sch} - Q_i^{(k)} \qquad (10)$$

The new estimates for bus voltage are

$$\delta^{(k+1)} = \delta_i^{(k)} + \Delta \delta_i^{(k)} \qquad (11)$$

$$|V^{(k+1)}| = |V_i^{(k)}| + \Delta |V_i^{(k)}| \qquad (12)$$

D. Artificial Neural Network

Artificial neural networks (ANNs) can be viewed as massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections. Neural network models attempt to use some organizational principles (such as learning, generalization, and computation) in a network of weighted graphs in which the nodes are artificial neurons and directed edges (with weights) are connections between neuron outputs and inputs [9]. The main characteristics of neural networks are that they have ability to learn complex nonlinear input – output relationships, use sequential training procedures, and adapt themselves to the data.

The intelligence of ANN and its capability to solve hard problems emerges from the high degree of connectivity that gives neurons its high computational power through its massive parallel distributed structure. The current resurgent of interest in ANN is largely because ANN algorithms and architectures can be implemented in VLSI technology for real time applications [9]. The development of ANN involves two phases: training or learning phase and testing phase. Training of ANN is done by presenting the network with examples called training patterns. During training, the synaptic weights get modified to model the given problem. Soon as the network has learnt the problem it may be tested with new unknown patterns and its efficiency can be checked (testing phase). Depending upon the training important, ANN can be classified as supervised ANN or unsupervised ANN.

The complexity of real neurons is highly abstracted when modeling artificial neurons. These basically consist of inputs, which are multiplied by weights and then, computed by a mathematical function which determines the activation of the neuron. Another function computes the output of the artificial neuron. ANNs combine artificial neurons in order to process information.

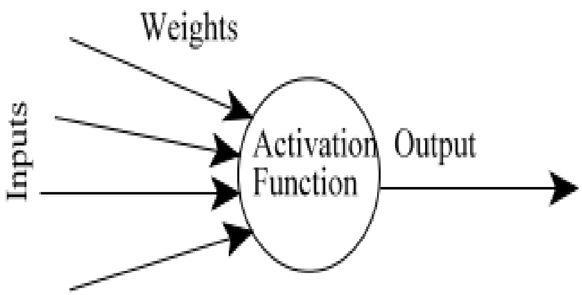

Fig. 1. An Artificial Neuron.

The behavior of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. The most common used function is sigmoid function.

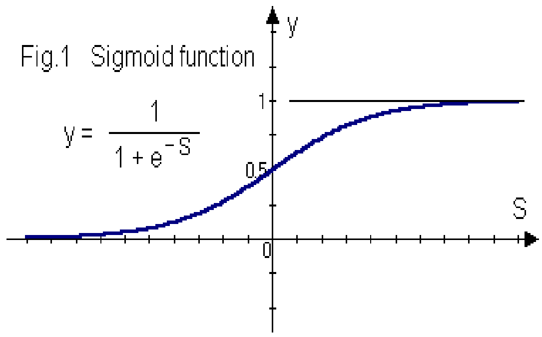

Fig. 2. Sigmoid Function.

For sigmoid units, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but must be considered rough approximations.

To make a neural network that performs some specific task, we must choose how the units are connected to one another, and we must set the weights on the connections appropriately. The connections determine whether it is possible for one unit to influence another. The weights specify the strength of the influence [7].

In This paper, multilayer feed forward ANN (MLFFNN) is applied for the load flow analysis of power systems. The ANN architecture for load flow analysis is shown in fig.3. Active and reactive powers for the load buses are to be given as inputs. The voltage magnitudes and angles at various load buses are the outputs.

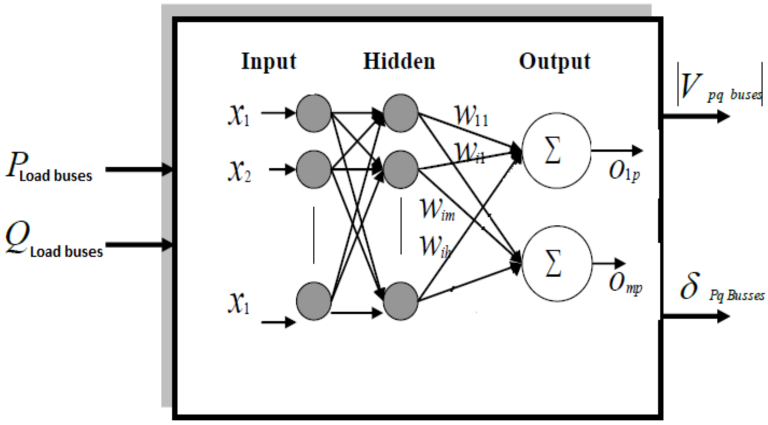

Fig. 3. Schematic Diagram of the ANN for Load Flow Analysis.

The back-propagation algorithm is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back-propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal [7].

In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the EW.

The flow chart of the error back-propagation learning algorithm is shown in fig.4.

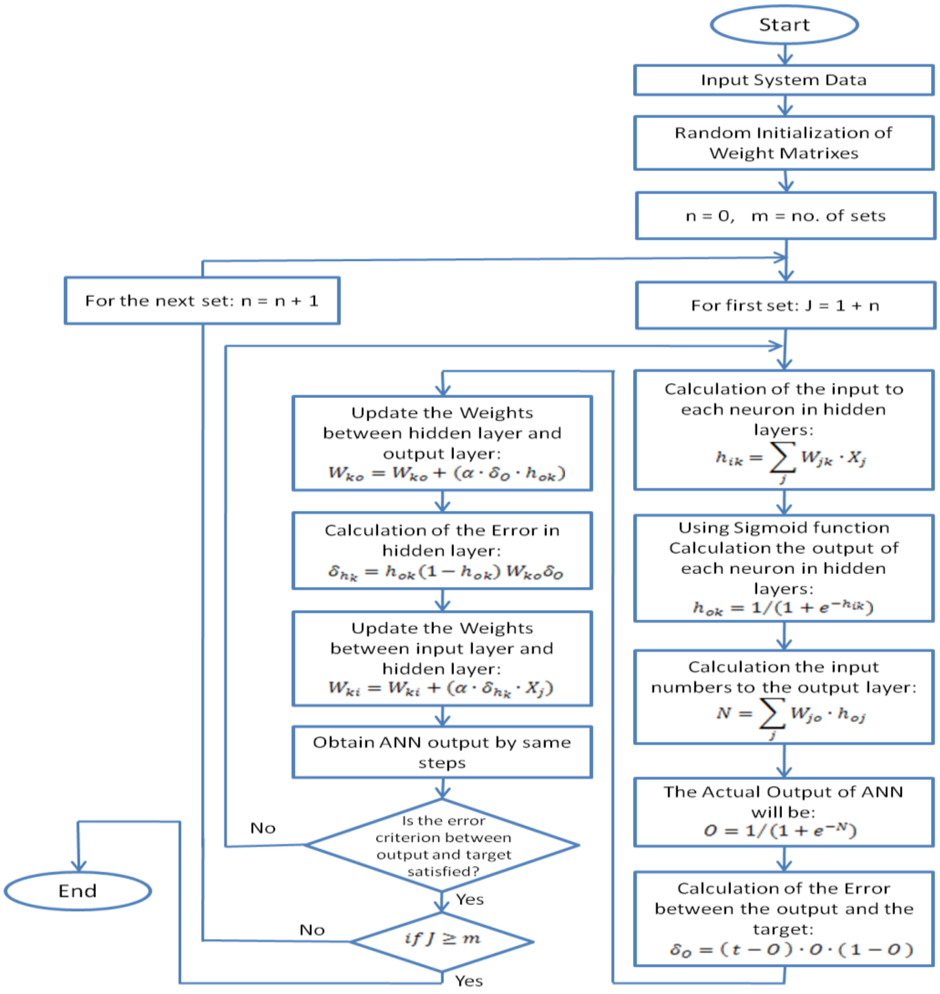

Fig. 4. Flow chart of the error back-propagation learning algorithm.

Ann for Practical power grid

A practical power grid is composed of 18 substations. Three substations are connected to the generation side. The single line diagram of the network is shown in fig. 5.

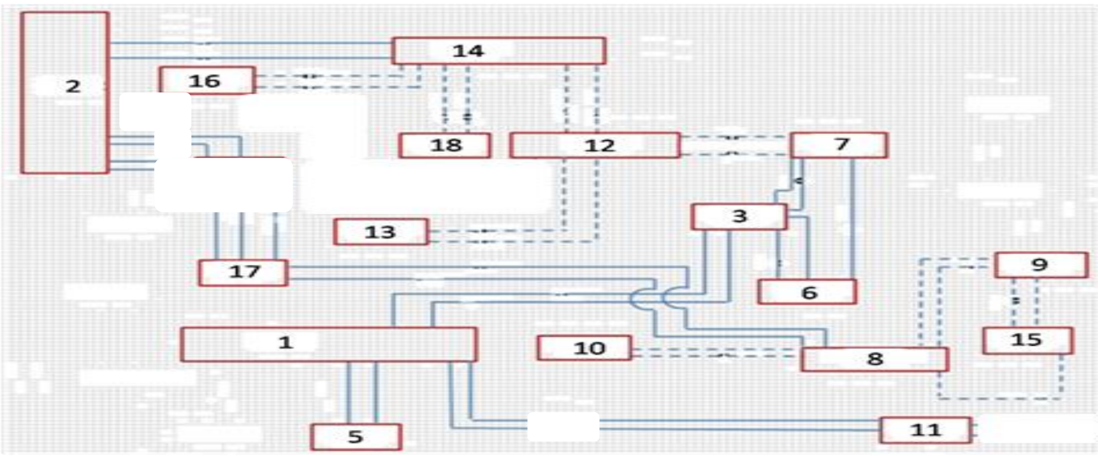

Fig. 5. Single Line Diagram of a Practical Power Grid

E. Study System

The study system given in fig. 5. is analyzed by Newton-Raphson power flow analysis method. A program developed by MATLAP platform used for analysis.

The line data, resistance, reactance and one-half the total capacitive susceptance in per unit on a 100-MVA base are tabulated in Table.1 .

Table 1. Line Data.

Bus No.	Bus No.	R (pu)	X (pu)	1/2 B (pu)
1	3	0.00002	0.00033	0.00899
1	3	0.00002	0.00033	0.00899
2	14	0.00124	0.02357	0.63693
2	14	0.00124	0.02357	0.63693
2	4	0.00045	0.00853	0.23055
2	4	0.00045	0.00853	0.23055
2	4	0.00045	0.00853	0.23055
2	4	0.00045	0.00853	0.23055
4	17	0.00109	0.0207	0.55924
4	17	0.00109	0.0207	0.55924
4	17	0.00109	0.0207	0.55924
3	6	0.00067	0.01284	0.34698
3	6	0.00067	0.01284	0.34698
3	7	0.00122	0.02314	0.62527
3	7	0.00122	0.02314	0.62527
1	5	0.00085	0.01609	0.43475
1	5	0.00085	0.01609	0.43475
6	7	0.00054	0.01023	0.27638
7	12	0.00005	0.00092	0.92896
7	12	0.00005	0.00092	0.92896
8	9	0.00009	0.00163	0.04411
8	9	0.00009	0.00163	0.04411
8	17	0.0008	0.02404	13.58297
8	17	0.0008	0.02404	13.58297
8	10	0.00013	0.00223	2.26464
8	10	0.00013	0.00223	2.26464
8	15	0.00013	0.00383	2.16485
9	15	0.00008	0.00235	1.32822

9	15	0.00008	0.00235	1.32822
1	11	0.00013	0.00383	2.16485
1	11	0.00013	0.00383	2.16485
12	14	0.00006	0.00191	1.07918
12	14	0.00006	0.00191	1.07918
12	13	0.00013	0.00225	2.27884
12	13	0.00013	0.00225	2.27884
14	18	0.00009	0.00266	1.50387
14	18	0.00009	0.00266	1.50387
14	16	0.00006	0.00181	1.02263
14	16	0.00006	0.00181	1.02263

F. ANN Training

ANN is designed for variable busbar loading values. All other parameters are kept constant. The ANN is consisting of one input layer, one hidden layer and one output layer. 16 sets of Bus data are generated to do load flow analysis to each set to get the output to train the ANN model.

The best result has been obtained by using trainbr as learning algorithm. 288 active power values and 288 reactive power values are used to train the developed ANN. The output values of training are voltage magnitudes and angles which obtained from developed analytical algorithm. Training process ended after 303 iterations. Fig. 6 shows training process.

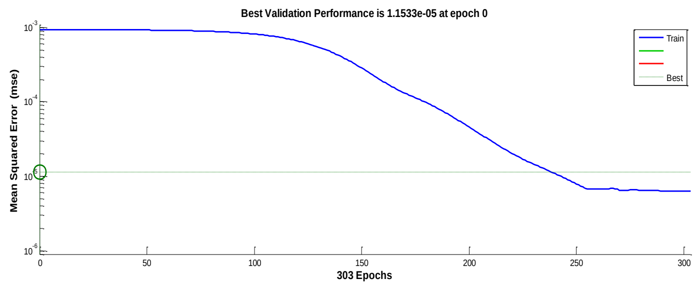

Fig. 6. ANN Training Process.

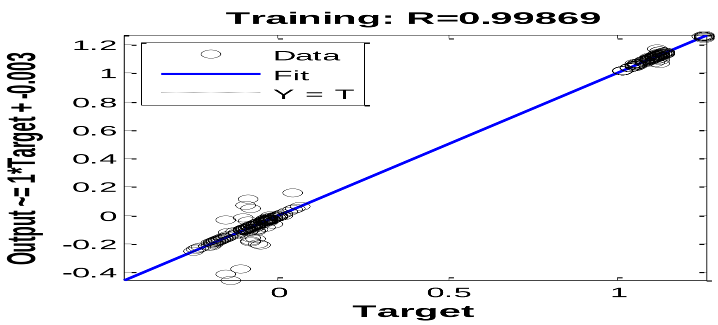

Fig. 7. The Relationship between the Targets and the Outputs of the Network.

Both analytical and ANN analysis results for 4 sets of them are shown in Table 2 . Table 2 also shows the convergence of analytical and ANN solution methods.

Table 2. Results of Training Sets.

Bus No.	Set No.: 1		Analytical Results		ANN Results		Convergence	
	P (pu)	Q (pu)	V (pu)	Angle (rad)	V (pu)	Angle (rad)	V (pu)	Angle (rad)
4	0.18	0.066667	1.110176	-0.00437	1.1084	-0.00451	0.001727	0.00014
5	0.113333	0.056667	1.015611	-0.00297	1.0178	-0.00913	-0.00219	0.006163
6	0.616667	0.25	1.056883	-0.04691	1.0555	-0.04251	0.001376	-0.0044
7	1.77	0.723333	1.116426	-0.09716	1.1156	-0.09707	0.000859	-8.1E-05
8	1.92	0.553333	1.096394	-0.15849	1.099	-0.15973	-0.00282	0.00123
9	2.336667	0.88	1.097397	-0.16646	1.1012	-0.16224	-0.00377	-0.00422
10	2.05	1.133333	1.04	-0.14976	1.04	-0.14685	0	-0.00291
11	2.653333	1.02	1.062767	-0.02553	1.0635	-0.02361	-0.00075	-0.00192
12	2.703333	0.89	1.120916	-0.10088	1.1188	-0.10083	0.002123	-4.6E-05
13	1.546667	0.686667	1.124341	-0.10521	1.1233	-0.10514	0.001091	-6.4E-05
14	2.89	1.013333	1.12573	-0.10144	1.1282	-0.10133	-0.00251	-0.00011
15	2.846667	1.2	1.098712	-0.17101	1.1029	-0.16827	-0.00416	-0.00275
16	1.986667	0.656667	1.126972	-0.10612	1.1243	-0.10601	0.002689	-0.00011
17	0.5	0.203333	1.257999	-0.07129	1.2558	-0.06961	0.002163	-0.00168
18	1.62	0.476667	1.128349	-0.10661	1.1257	-0.10622	0.002669	-0.00039
Bus No.	Set No.: 2		Analytical Results		ANN Results		Convergence	
	P (pu)	Q (pu)	V (pu)	Angle (rad)	V (pu)	Angle (rad)	V (pu)	Angle (rad)
4	0.186667	0.07	1.109714	-0.01667	1.1122	-0.01719	-0.00247	0.000518
5	0.146667	0.043333	1.015886	-0.00377	1.0183	-0.00985	-0.00242	0.006083
6	0.696667	0.286667	1.05341	-0.04723	1.0523	-0.04759	0.001072	0.000354
7	1.773333	0.813333	1.108616	-0.09622	1.1097	-0.09602	-0.0011	-0.00021
8	1.8	0.61333	1.095568	-0.18801	1.098	-0.19014	-0.00234	0.00213
9	2.73	0.84	1.096346	-0.19676	1.0968	-0.19625	-0.00049	-0.00051
10	2.143333	1.073333	1.04	-0.17958	1.04	-0.18216	0	0.002574
11	3.53	1.38	1.060023	-0.03057	1.0656	-0.0278	-0.00555	-0.00277
12	2.293333	0.84	1.112933	-0.09993	1.1135	-0.0994	-0.00058	-0.00053
13	1.546667	0.76	1.116076	-0.10431	1.1177	-0.10421	-0.0016	-0.0001
14	2.806667	1.03	1.117299	-0.10116	1.1159	-0.10139	0.00138	0.000232

15	2.92	1.363333	1.097293	-0.2013	1.0967	-0.19628	0.000627	-0.00502
16	2.116667	0.96	1.117986	-0.10598	1.118	-0.10529	-3.2E-05	-0.00069
17	0.42	0.176667	1.256777	-0.08905	1.2567	-0.08809	8.26E-05	-0.00097
18	1.586667	0.68	1.119146	-0.10628	1.1193	-0.10627	-0.00011	-9.7E-06
Bus No.	Set No.: 3		Analytical Results		ANN Results		Convergence	
	P (pu)	Q (pu)	V (pu)	Angle (rad)	V (pu)	Angle (rad)	V (pu)	Angle (rad)
4	0.14	0.076667	1.109585	-0.01779	1.1118	-0.02471	-0.00218	0.006924
5	0.14	0.053333	1.015655	-0.0036	1.0171	-0.00847	-0.00142	0.004868
6	0.696667	0.293333	1.057213	-0.04622	1.0648	-0.04947	-0.00754	0.003248
7	1.863333	0.64	1.118452	-0.09348	1.1149	-0.11122	0.003502	0.017738
8	1.576667	0.61333	1.096523	-0.1928	1.095	-0.20046	0.00141	0.00766
9	2.58	0.89	1.097747	-0.20113	1.1107	-0.21825	-0.01292	0.017129
10	2.68	1.076667	1.04	-0.18591	1.04	-0.18135	0	-0.00456
11	3.5	1.376667	1.060499	-0.03045	1.0591	-0.03236	0.00142	0.001912
12	2.346667	0.843333	1.122954	-0.09701	1.1248	-0.09604	-0.00189	-0.00097
13	2.036667	0.663333	1.126372	-0.10264	1.1226	-0.10003	0.003771	-0.00261
14	2.656667	1.21	1.127465	-0.09719	1.1396	-0.107	-0.01217	0.009804
15	2.796667	1.023333	1.099453	-0.2055	1.1017	-0.21367	-0.00221	0.008173
16	1.903333	0.673333	1.128799	-0.10158	1.1269	-0.09431	0.001933	-0.00728
17	0.553333	0.19	1.256623	-0.0928	1.2555	-0.11016	0.001153	0.017352
18	1.326667	0.48	1.130123	-0.10143	1.1367	-0.09998	-0.00658	-0.00145
Bus No.	Set No.: 4		Analytical Results		ANN Results		Convergence	
	P (pu)	Q (pu)	V (pu)	Angle (rad)	V (pu)	Angle (rad)	V (pu)	Angle (rad)
4	0.17	0.073333	1.110754	0.060371	1.1111	0.060128	-0.00031	0.000243
5	0.133333	0.04	1.015983	-0.00346	1.0155	-0.00791	0.000476	0.004455
6	0.603333	0.32	1.05535	-0.02968	1.0477	-0.03083	0.007633	0.001156
7	1.586667	0.653333	1.112522	-0.05689	1.1151	-0.05705	-0.00256	0.000167
8	1.74	0.60333	1.096298	-0.07038	1.092	-0.07393	0.00410	0.00355
9	2.086667	1	1.09713	-0.0774	1.1023	-0.07211	-0.00514	-0.00529
10	2.293333	1.026667	1.04	-0.06236	1.04	-0.06201	0	-0.00035
11	3.24	1.45	1.059544	-0.02778	1.0625	-0.02623	-0.00301	-0.00156
12	2.126667	1.126667	1.116762	-0.05952	1.1161	-0.05928	0.000679	-0.00025
13	1.653333	0.773333	1.119873	-0.06416	1.1188	-0.06495	0.001026	0.000785

14	2.13	0.826667	1.121584	-0.05758	1.1247	-0.05847	-0.00309	0.000894
15	2.476667	1.203333	1.098513	-0.08135	1.0966	-0.07593	0.0019	-0.00542
16	2.046667	0.886667	1.122265	-0.06262	1.1225	-0.0623	-0.00021	-0.00032
17	0.49	0.193333	1.259611	0.002013	1.2537	0.005109	0.005868	-0.0031
18	1.7	0.466667	1.124204	-0.06304	1.124	-0.06254	0.000218	-0.0005

4. ANN Testing and Validation

72 active power values and 72 reactive power values (4 sets of data) are used to test and validate the developed ANN model of a practical power network. The output values of training are voltage magnitudes and angles which obtained from developed analytical algorithm. Fig. 8 shows testing and validation process.

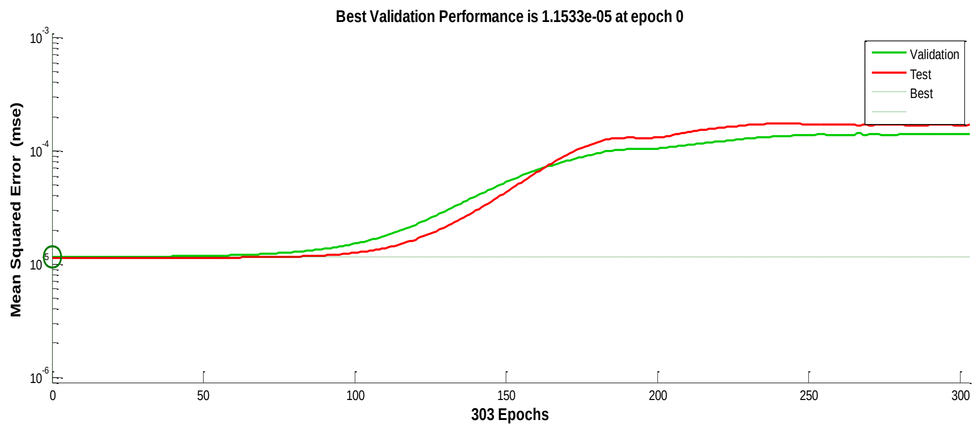

Fig. 8. Testing and Validation Process.

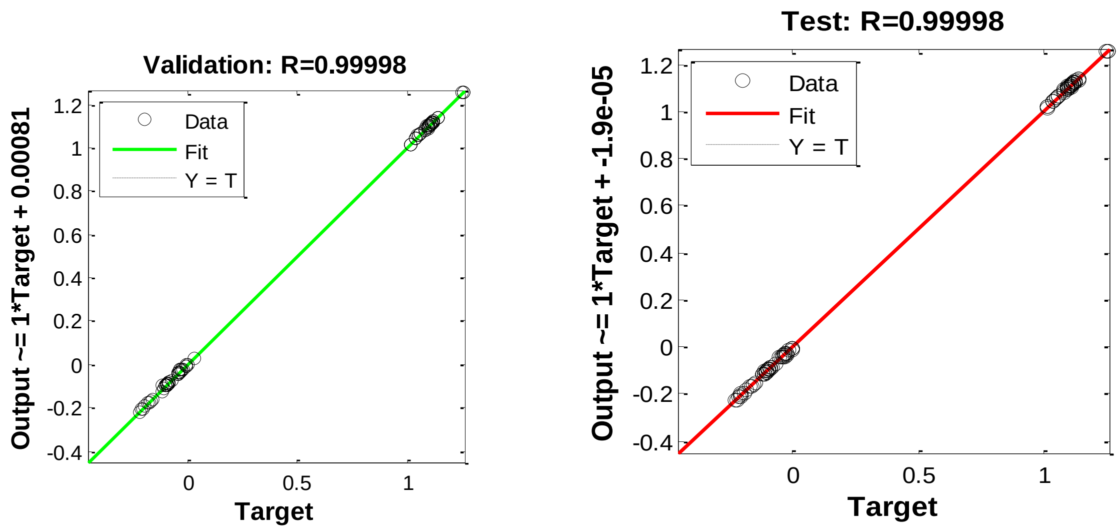

Fig. 9. The Relationship between the Targets and the Outputs of the Network.

Both analytical and ANN analysis results are shown in Table 3 below. Table 3 also shows the convergence of analytical and ANN solution methods.

Table 3. Results of Testing and Validation Sets.

Bus No.	Set No.: 1		Analytical Results		ANN Results		Convergence	
	P (pu)	Q (pu)	V (pu)	Angle (rad)	V (pu)	Angle (rad)	V (pu)	Angle (rad)
4	0.176667	0.073333	1.109909	-0.00312	1.1112	-0.00325	-0.0013	0.000123
5	0.163333	0.06	1.015464	-0.00414	1.016	-0.00812	-0.00057	0.003983
6	0.79	0.31	1.055609	-0.04797	1.0537	-0.04611	0.001927	-0.00185
7	1.643333	0.676667	1.115075	-0.09536	1.1173	-0.09572	-0.00219	0.000359
8	1.443333	0.703333	1.095761	-0.15972	1.0992	-0.16007	-0.00345	0.000349
9	2.426667	1.026667	1.096592	-0.16762	1.1024	-0.16566	-0.00581	-0.00196
10	2.66	1.05	1.04	-0.15281	1.04	-0.15152	0	-0.00129
11	3.546667	1.33	1.060633	-0.0305	1.0631	-0.0319	-0.00242	0.001402
12	2.6	0.803333	1.119501	-0.09906	1.1171	-0.0991	0.002435	4.06E-05
13	2.056667	0.643333	1.12295	-0.10478	1.1211	-0.10586	0.001821	0.001088
14	2.613333	1.07	1.123989	-0.09838	1.1265	-0.0981	-0.00254	-0.00027
15	2.68	1.126667	1.09814	-0.17183	1.1007	-0.1704	-0.00257	-0.00143
16	1.886667	0.7	1.125152	-0.10323	1.123	-0.10343	0.002147	0.000197
17	0.503333	0.23	1.257093	-0.07095	1.253	-0.06981	0.004126	-0.00114
18	1.223333	0.593333	1.126237	-0.1023	1.1266	-0.1024	-0.0004	9.19E-05
Bus No.	Set No.: 2		Analytical Results		ANN Results		Convergence	
	P (pu)	Q (pu)	V (pu)	Angle (rad)	V (pu)	Angle (rad)	V (pu)	Angle (rad)
4	0.186667	0.06	1.109203	-0.01641	1.1115	-0.01672	-0.0023	0.000309
5	0.136667	0.046667	1.015819	-0.00353	1.0178	-0.01228	-0.00195	0.008755
6	0.583333	0.236667	1.05651	-0.04223	1.0551	-0.04121	0.001413	-0.00102
7	1.92	0.723333	1.114425	-0.08699	1.1129	-0.08638	0.001526	-0.00061
8	1.566667	0.723333	1.095153	-0.19622	1.0958	-0.19706	-0.00065	0.000845
9	2.98	1.106667	1.095845	-0.20577	1.1037	-0.20108	-0.00787	-0.00469
10	2.013333	0.943333	1.04	-0.18743	1.04	-0.18548	0	-0.00195
11	3.386667	1.176667	1.061864	-0.02861	1.0656	-0.02851	-0.00374	-0.00011
12	2.056667	0.94	1.118825	-0.09034	1.1194	-0.0905	-0.00058	0.000165
13	1.81	0.583333	1.122498	-0.09541	1.1228	-0.09546	-0.00032	5.57E-05
14	2.066667	1.06	1.123466	-0.09064	1.1222	-0.09049	0.00123	-0.00015
15	3.183333	1.033333	1.097598	-0.21074	1.0975	-0.20798	5.28E-05	-0.00276
16	2.306667	0.846667	1.124234	-0.09578	1.1224	-0.09523	0.001843	-0.00055

17	0.55	0.233333	1.254983	-0.09307	1.2528	-0.09115	0.002141	-0.00192
18	1.473333	0.48	1.126081	-0.09537	1.1273	-0.09491	-0.00117	-0.00047
Bus No.	Set No.: 3		Analytical Results		ANN Results		Convergence	
	P (pu)	Q (pu)	V (pu)	Angle (rad)	V (pu)	Angle (rad)	V (pu)	Angle (rad)
4	0.15	0.08	1.110514	0.04775	1.1141	0.047211	-0.00358	0.000539
5	0.16	0.04	1.015947	-0.00409	1.017	-0.00515	-0.00105	0.001063
6	0.64	0.273333	1.056514	-0.03183	1.0543	-0.02969	0.002216	-0.00214
7	1.46	0.61	1.11438	-0.06097	1.1154	-0.06078	-0.00101	-0.00019
8	1.626667	0.65	1.096013	-0.09497	1.0937	-0.09565	0.002298	0.000674
9	2.333333	1.16	1.096737	-0.10265	1.1081	-0.09782	-0.01132	-0.00483
10	2.3	0.883333	1.04	-0.08699	1.04	-0.08275	0	-0.00424
11	2.473333	1.176667	1.061678	-0.02492	1.0551	-0.02805	0.006557	0.003123
12	2.27	1.17	1.118641	-0.06378	1.1178	-0.06414	0.000809	0.000356
13	1.926667	0.66	1.122058	-0.06916	1.124	-0.06891	-0.00191	-0.00025
14	2.15	1.046667	1.123169	-0.06185	1.1225	-0.0614	0.00062	-0.00046
15	2.646667	1.036667	1.098537	-0.10684	1.0978	-0.10699	0.000758	0.000142
16	2.273333	0.783333	1.124176	-0.0672	1.1248	-0.06721	-0.00063	1.63E-05
17	0.43	0.17	1.259092	-0.01438	1.2567	-0.01232	0.00238	-0.00205
18	1.316667	0.506667	1.125709	-0.06609	1.1243	-0.06573	0.001408	-0.00036
Bus No.	Set No.: 4		Analytical Results		ANN Results		Convergence	
	P (pu)	Q (pu)	V (pu)	Angle (rad)	V (pu)	Angle (rad)	V (pu)	Angle (rad)
4	0.2	0.066667	1.110647	0.04333	1.1111	0.042949	-0.00042	0.000381
5	0.143333	0.06	1.015491	-0.00367	1.0164	-0.00761	-0.00087	0.003943
6	0.7	0.25	1.055283	-0.03589	1.0551	-0.0434	0.000221	0.007504
7	1.963333	0.566667	1.110966	-0.0691	1.1053	-0.06979	0.005712	0.000692
8	1.716667	0.593333	1.096852	-0.09422	1.0997	-0.09427	-0.00281	4.43E-05
9	2.47	0.983333	1.097991	-0.10203	1.1005	-0.09635	-0.0025	-0.00568
10	2.046667	1.15	1.04	-0.08546	1.04	-0.07983	0	-0.00563
11	2.596667	1.276667	1.061623	-0.02494	1.067	-0.03127	-0.00533	0.006328
12	2.176667	1.173333	1.115125	-0.07187	1.1179	-0.0719	-0.00278	2.64E-05
13	1.483333	0.66	1.1186	-0.07608	1.1181	-0.07522	0.000453	-0.00086
14	2.633333	1.18	1.119558	-0.06995	1.1181	-0.06964	0.001485	-0.00031
15	2.56	0.986667	1.099834	-0.10599	1.1043	-0.10589	-0.00443	-0.0001

16	1.656667	0.656667	1.120751	-0.0746	1.1272	-0.07527	-0.00641	0.000667
17	0.396667	0.216667	1.259243	-0.01661	1.2585	-0.01455	0.000698	-0.00206
18	1.273333	0.553333	1.121916	-0.07407	1.1262	-0.07258	-0.00424	-0.00149

5. Discussion

Both analytical and ANN results are shown in Table 2. Table also shows the convergence of analytical and ANN solution methods. In the second testing and validation set as an example, the biggest value of the error between the voltage magnitude that obtained by NRLF and ANN is 0.00787 and the biggest value of the error between the voltage angle that obtained by the two ways is 0.008755.

The Root Mean Squared Error (RMSE) values for the voltage magnitude for the sets are 0.0027, 0.0025, 0.0035 and 0.0036 respectively. The RMSE values for the voltage angle for the sets are 0.0023, 0.0032, 0.0019 and 0.0043 respectively. From tables and figures, it can be see that ANN results practically matches with NRLF results and ANN can be used in power flow analysis problems.

6. Conclusion

Growing demand of the power and complexity of the power system network, power system study is a significant tool for a power system operator in order to take corrective actions in time. The advent of digital computers, load-flow solutions were obtained using network analyzers.

Artificial neural network (ANN) technique is used to make the load flow analysis. A practical power network is used as a practical power system to check our technique.

The most widely used numerical method in solving the load flow problem is the Newton-Raphson method. Using MATLAB program, load flow analysis is done for a practical power network. Multilayer feed-forward ANN (MLFFNN) is applied for the load flow analysis of the power network. After that, ANN is trained using error back-propagation learning algorithm.

Testing and validation for the developed ANN are done using four randomly sets and it worked successfully comparing by the results of load flow analysis by Newton-Raphson method for the same sets. Finally, it can be seen that proposed method satisfies the convergence limits. The compared results show that the ANN works properly and can be used in power flow analysis problems.

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