Designing ANN For Load Flow In Electrical Power Systems Using EBP Algorithm

Dhari Y. Al-Samaraee,* May R. Victor*

Received on: 9/3/2005
Accepted on: 19/12/2005

Abstract

Load flow studies are important in power system planning, control and operating strategies when applied in real time mode. Comparative study between different load flow solution methods [the (Newton Raphson (NR), Fast De-coupled (FD)) conventional methods and Artificial Neural Network (ANN) method] is carried out. Feed Forward model of the neural network based on Error Back propagation (EBP) algorithm has been used for load flow problem and, a method tested using one of the Iraqi National Grid Systems.

A computer program was performed using MATLAB software program in order to design the system that is used to enter the sample values of the power system units.

The result of the study shows an efficient technique to be used for getting the difference in time rate of the final processing reveal that ANN showed good efficiency in the process of deriving results from the two conventional methods to the same input data. The simulations of the proposed approach are presented.

Keywords: Load Flow, ANN, Power System.

دراسة سريان الحمل في منظومة القدرة الكهربائية باستخدام الشبكات العصبية الاصطناعية

الخلاصة

تشكل دراسة سريان الحمل الأهمية البالغة في التخطيط والسيطرة والإستراتيجيات التشغيلية لنظام القدرة في الزمن الحقيقي.في البحث الحالي تمت المقارنة بين مختلف طرق حلول مشكلة سريان الحمل (طريقة نيوتن رافسن (Newton Raphson) و(طريقة خفض الاقتران السريعة (Fast De-coupled)) التقليديتين وطريقة الشبكات العصبية الاصطناعية (Artificial Neural Network). فضلا عن استخدام أنموذج التغذية الأمامية للشبكات العصبية الاصطناعية المعتمدة على خوارزمية الانتشار الرجعي للخطأ (Error Back propagation) لحل مشكلة سريان الحمل في أحد أنظمة الشبكة الوطنية العراقية،واستحدث برنامج حاسوبي باستخدام الوحدة البرمجية MATLAB لتصميم منظومة لإدخال قيم مدخلات مكونات منظومة القدرة.أثبتت الدراسة كفاءة الأسلوب المقترح وأمكانية استخدامه في أيجاد الفرق في معدل الزمن لغرض المعالجة النهائية للطرق الثلاث كما وأظهرت كفاءة جيدة في معالجة النتائج في طريقة الشبكات العصبية الاصطناعية عن الطريقتين التقليديتين . وأن النتائج المستحصلة من الطريقة المقترحة قد مثلت وعرضت في هذا البحث .

* Dept. of Technical Education, UOT., Baghdad-IRAQ.

https://doi.org/10.30684/etj.24.10A.6
2412-0758/University of Technology-Iraq, Baghdad, Iraq

List of symbols

ε	Tolerance
η	Learning rate
α	Momentum
δ_k	Voltage phase angle at bus k
θ_{km}	Mutual admittance angle between bus k and m
ANN	Artificial Neural Network
EBP	Error Back propagation
FD	Fast Decoupled
GS	Gauss Seidel
NR	Newton Raphson
PG	Generated active power
P_L	Loaded Active power
QG	Generated Reactive power
Q_L	Loaded reactive power
SSE	Single square error

1. Introduction

In power systems, load flow calculation is basic and necessary. In most cases load flow is the solution for static operating conditions of an electric power system and is required for power system planning, operation and control. Much has been written in the past on the subject of load flow problem analysis.

Georgios, L., in [1] presents and develops an approximate linear solution for the load flow equations and then a fast linear load flow solution method was deduced. The approximate linear solution of load flow equations that is developed and proved mathematically is used as the initial value for the Gauss-Siedel (GS) and fast de-coupled (FD) load flow numerical methods. Since the approximate linear solution is very close to the actual one, this helps the above mentioned methods to converge faster than giving another initial value. Typically, their iteration number is halved.

Monticelli, A., et.al in [2] they present a new framework that allows systematic studies on the hypothesis and derivations concerning a variety of versions of the fast de-coupled load flow method. De-coupled is not seen as merely zeroing coupling sub matrices of a full Newton Jacobian matrix. Instead, it is treated as an intelligent two-step procedure that solves the full Newton iteration equations without extra approximation, a completely new derivation of the standard fast de-coupled method is presented.

Taiyou, Y., et.al, in [3] suggest a very efficient way to formulate power system problem, and further to calculate the Jacobian and Hessian matrix of power flow and line flow equations. By analyzing the structure of related matrices, based on the developed model, optimal power flow problem is solved by Newton-Raphson method. Sparse techniques are applied in the formulation and calculation. The results from tested cases show the efficiency formulation and make large power system calculation easier.

Izudin, D., et.al in [4] have modified the standard NR method for the solution of load flows ill-condition power systems and presents a new approach for constructing and solving quadratically convergent algorithms. This approach covers the case of regular solutions. So it can be viewed as a natural generalization of NR method.

This work depends upon two conventional methods (NR and FD) load flow methods in addition to using ANN algorithm, which is EBP algorithm. Then a comparison among them all was executed. The program mentioned in this work is capable of dealing with one of the Iraqi National Grid System, which is composed of (19) busbars in Figure (3).

2. Research Problem

The problem of this work is solved through design and implementation of computer software programs on load flow analysis in electrical power system using conventional methods and intelligent method (ANN) , and then study load flow under load variation in one day period.

The utilizer of the computer software program should have some degree of expertise in: -

1. Elements of the electrical power system and the measured parameters of these elements.
2. Types of busbars.

3. Artificial Neural Network

ANN is an information-processing system that has certain performance characteristics in common with biological neural networks. One of the main advantages of the ANNs is that they infer solutions from data without prior knowledge of the regularities in the data, they extract the regularities empirically [5]. ANNs are essentially a computational model, attempting to achieve good performance via large interconnections of simple computations elements The models of ANNs were inspired by the capability of the brain to "learn" patterns via recognition and "respond" to patterns hither to unknown based on what it has already learnt through exposure [6].

A variety of ANN confirmations have been developed for different applications, one of the most popular ANN configurations is the feedforward Error Back propagation (EBP) network. The EBP is gradient descent error correcting algorithm. The algorithm updates the network weights in such a way that the network output error is minimized. This work consists of one input layer, two hidden layers and one output layer as shown in Figure (1).

A typical operation of this ANN can be classified into two stages: a) training stage and b) testing stage. The training stage is conducted by using various training data sets that include the respective inputs and the corresponding desired outputs. The initial network connection weights are set to equal small random numbers. After the network is properly trained, the testing stage will start. In this stage, a set of test data is applied to the network. Afterward, the performance of the network is analyzed [7].

4. Application of neural network system for load flow calculation:

4.1 Learning algorithm:

In this study, we construct multi-input and multi-output in each layer and the connections from the output layer to the input layer do not exist in the neural network system. This neural network system is learned by: ***Error Back propagation algorithm***_(EBP) learning consists of two passes through the different layers of the network: forward pass and backward pass as show in figure (2a, 2b). During the forward pass the synaptic weights of the network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with an error – correction rule[8,9].

4.2 Power system to be learned:

The potential of the neural network based model to solve the ac load flows was tested on a sample of 19-busbar system. The 19 busbars system as shown in Figure (3) has one generator bus considered as slack busbar with voltage fixed at 1<0 and 13 load (P-Q) busbars and 5 generator (P-V) busbars . The bus admittance value is shown in table (1) for the system at 400MVA base.

The neural network model developed for 19 busbars system was trained to provide the values of voltage magnitude and angles as output at 13 load busbar for the input values of active and reactive power, voltage angles and reactive power as output at 5 generator busbars for the input values for real power and voltage magnitude . The model has (36-90-80-36). For this system model we consider the convergence conditions when the activation function is tangent sigmoid function and the number of units in the hidden layers is changed in the two layers system shown in Figure (4). The learning rate (η) used in this work = 0.00010409 and the momentum (α)= 0.9 .

5.Simulation study:

An important term should be defined before finding out the results, it is going to help in specifying the results and this term is the Recognition Rate (R.R). The Recognition Rate is the percentage of the number of patterns, which are classified properly into a number of complete patterns.

After training the neural network on the patterns models and the network acquires the main properties of these patterns, then the neural network should be tested by using the unknown patterns which have not been included in the neural network training as in table (2). Then these patterns are prepared for training procedures in order to specify the ability of network to check or analyze the trained patterns as in table (3) and table (4).

The increase in the number of epoch of training the neural network impacts directly the increasing in the percentage of specifying the network to test patterns. Whenever the training time is large, that means the epoch number is high, then the specifying average increases. But training time increase is not of great benefit in the first stages of epoch where time consuming is of no use. And this impact can be seen in the Figure (5). Here in table (5) shows the change in the Recognition Rate when the period of training time of learning the general patterns is increased.

6. Conclusions:

1. The proposed approach requires much less computation time compared with that for an optimization process as in Figure (5). Therefore, it is suitable to be used for on-line implementation of load flow calculations even for a large distribution system.
2. The possibility of detecting the load variation error with high percentage after training the neural network on most of the error properties in comparison with old

methods which couldn't detect and analyze errors.

3. The properties of an activity based on the efficiency of the training methods which are used to derive these properties by the training method of EBP are good because the two properties (recognition and distinguishing) are maintained.
4. The applied trial and error method that is used to specify the standard features of the neural network lead to achieve a good recognition rate after implementing the designing procedure of the network in the final stage as in figure (6).

References

1. Georgios, L., "Fast Linear Method and Convergence Improvement of Load Flow Numerical Solution Methods", Electric Power System research, pp (23-31), 1989.
2. Monticelli, A., Garcia, A., Saavedra, O. R., "Fast Decoupeld Load Flow : Hypothesis, Derivations, and Testing", IEEE Transactions on Power Systems , Vol.5, No.4, pp (1425-1431), November 1990.
3. Taiyou, Y., Robert, L., "Solving Optimal Flow Problem with Sparse Techniques", 1998.
4. Izudin, D., Mevludin, G., Sendin, K. , Naser, P., "Modification to Newton -Raphson LoadFlow for Regular Singularity Case",1999.
5. Eskandarian A., Omar T., Bedewi, N., "Vehicle Crash Modeling using Recurrent Neural Networks", Mathl Comput. Modeling, Vol.28, No.9, (pp.31-42),1998.
6. Kalra, P. K., Srivastava, S.C., Joshi, S.K.,"Artificial Neural Network Based Load Flow Models", Alershot, UK,1993.
7. Shin, T. Ch. , David, C. Y, and Moghaddamjo, A. R., " Weather Sensitive Short- Term Load Forecasting Using Nonfully Connected Artificial Neural Network", University of Wisconsin-Milwaukee, Transaction on Power Systems , Vol. 7, No. 3, August 1992.
8. Haykin, S., "Neural Network A Comprehensive Foundation", Prentice Hill, 1999.
9. Reddy D., Chosh K., Vardhan, V., "Identification and Interpretation of Manufacturing Process Patterns Through Neural Networks", Math. compt. Moduling , Vol.27, No.5, pp (15-36), 1998.

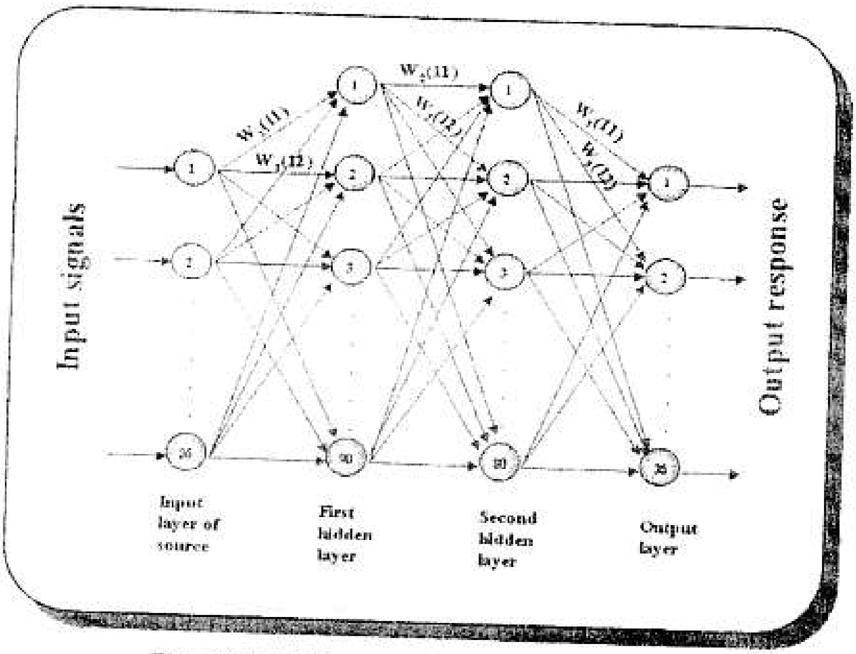

Fig. (1) MLFF network of the 19 busbar

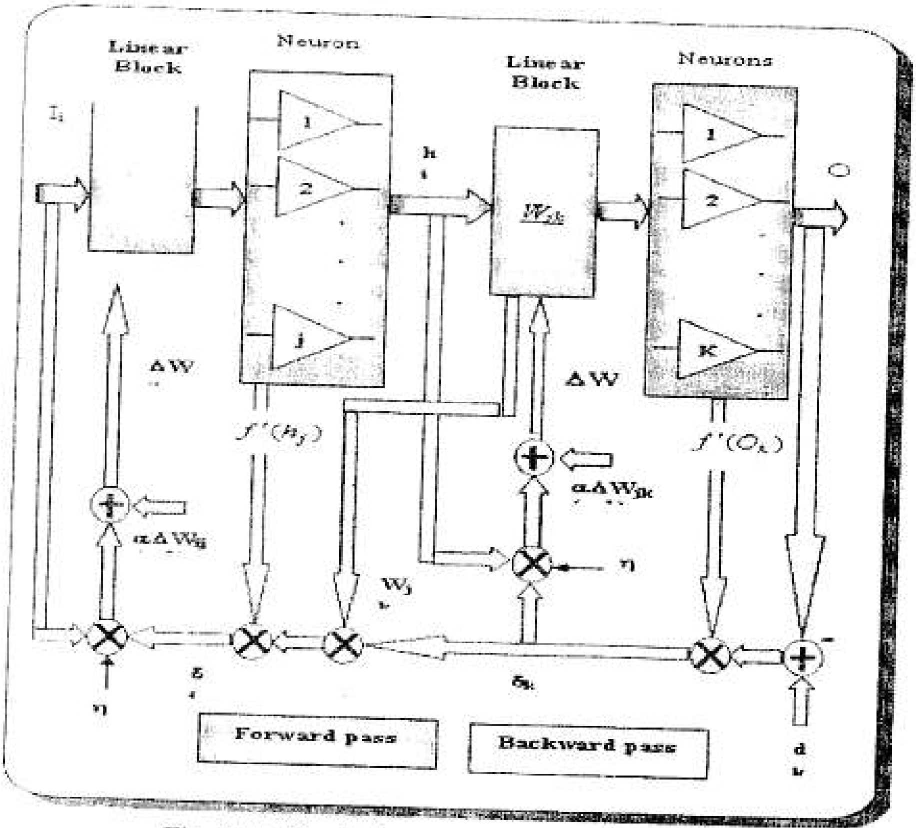

Fig. (2a) Block diagram of EBP algorithm

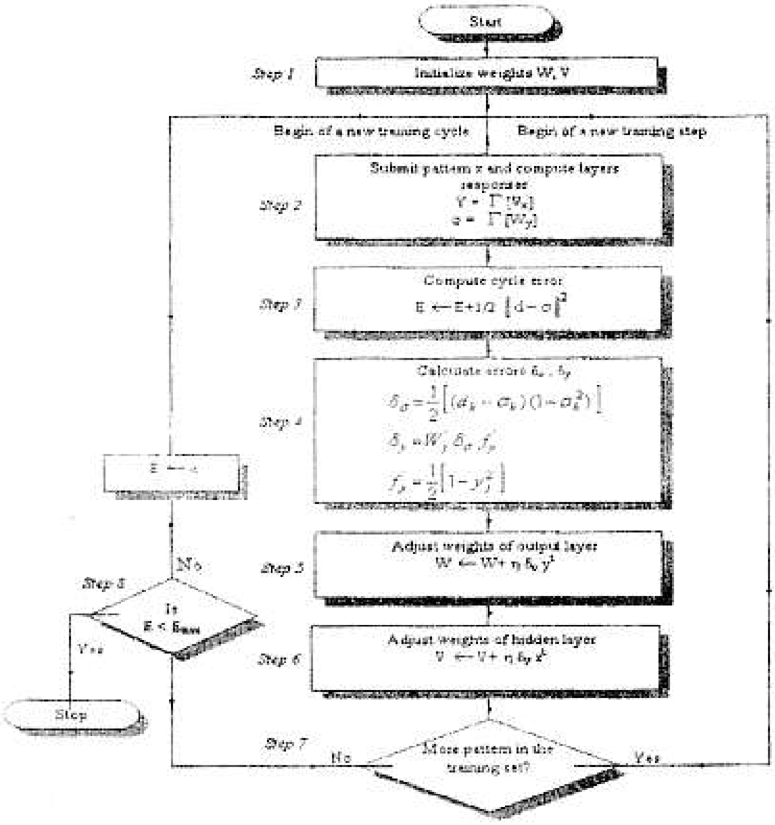

Fig. (2b) Flow chart for Error Back-Propagation Training (EBPT algorithm)

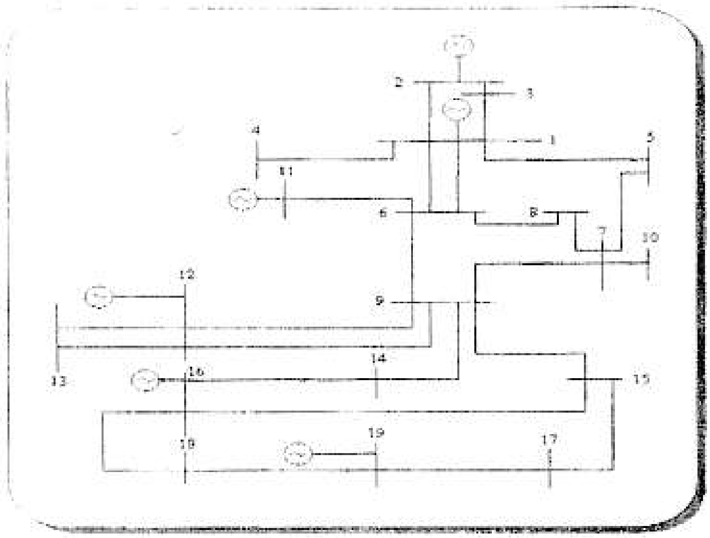

Fig. (3) Iraqi National Grid System

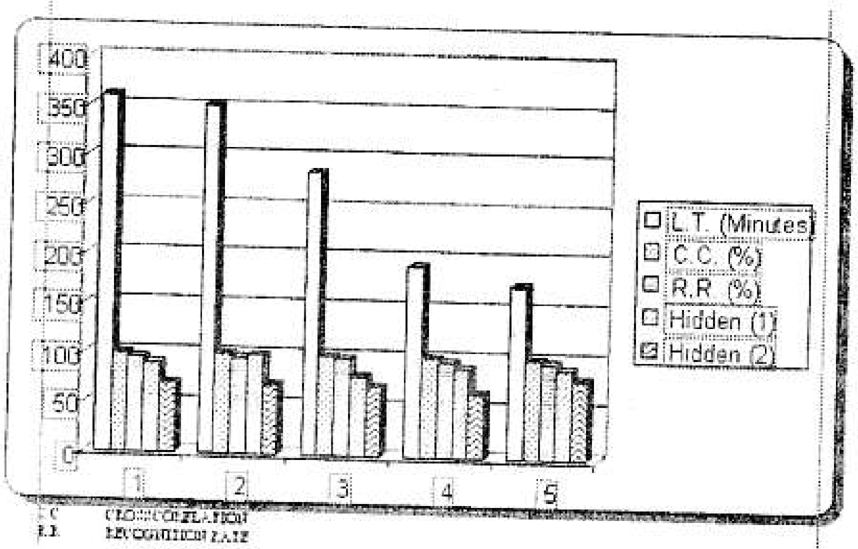

Fig. (4) The number of epoch with respect to the first and second layers.

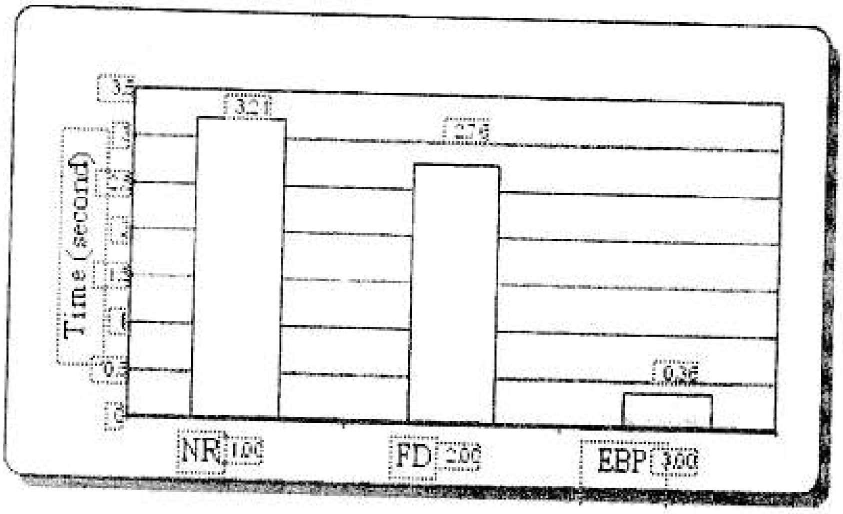

Fig. (5) The average time of data process for, (a) NR method, (b) FD method, (c) EBP algorithm

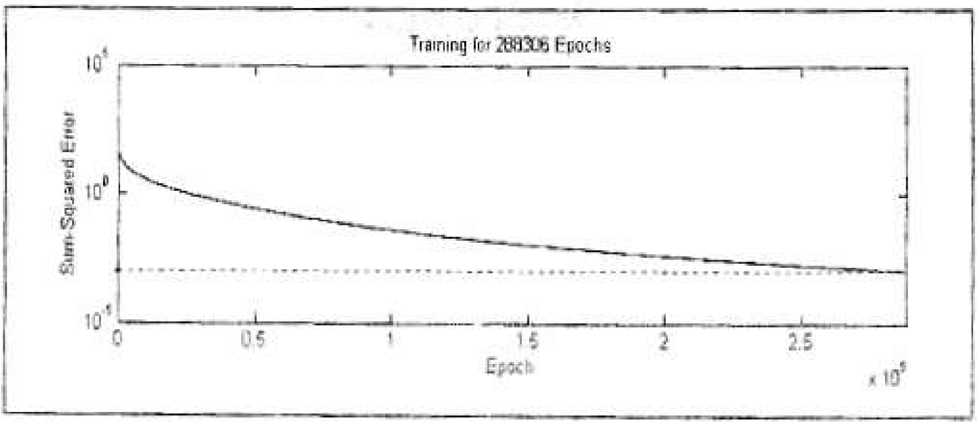

Fig. (6) Training SSE with epoch for EBP algorithm

Table (1): Input data for the test at 19 busbars.

Case	Bus1	NAME1	Bus2	NAME2	R	X	B	Limit
1	2	K200	3	K300	0.00143	0.01252	0.36439	100
1	3	K300	1	K100	0.00398	0.03624	1.074	100
1	2	K200	1	K100	0.00541	0.04876	1.43839	100
1	1	K100	5	K500	0.0019	0.01669	0.4858	100
1	1	K100	6	K600	0.00483	0.04393	1.30163	100
1	1	K100	6	K600	0.00541	0.04905	1.4926	100
1	1	K100	4	K400	0.00639	0.05682	0.94487	100
1	6	K600	11	K111	0.00483	0.04393	1.30165	100
1	5	K500	7	K700	0.00481	0.04373	1.29581	100
1	7	K700	8	K800	0.00028	0.00256	0.07588	100
1	8	K800	6	K600	0.00093	0.00847	0.25099	100
1	6	K600	9	K900	0.00143	0.013	0.38524	100
1	7	K700	9	K900	0.00104	0.00945	0.28017	100
1	7	K700	10	K101	0.00075	0.00689	0.20429	100
1	9	K900	14	K141	0.00292	0.02659	0.78799	100
1	9	K900	15	K151	0.00244	0.02226	0.65958	100
1	9	K900	12	K121	0.0012	0.01005	0.31598	100
1	9	K900	12	K121	0.0012	0.01005	0.31598	100
1	12	K121	13	K131	0.00077	0.00644	0.2027	100
1	12	K121	13	K131	0.00077	0.00644	0.2027	100
1	14	K141	16	K161	0.00383	0.03486	1.03314	100
1	15	K151	16	K161	0.00433	0.0394	1.1674	100
1	15	K151	17	K171	0.0052	0.04728	1.40088	100
1	16	K161	18	K181	0.00437	0.03979	1.17907	100
1	18	K181	19	K191	0.00119	0.01083	0.32103	100
1	19	K191	17	K171	0.0013	0.011182	0.35022	100
-1	-1	-1	-1	-1	-1	-1	-1	-1

Table (2): Input data for the test at 19 busbars

US	NAME	TYPE	V	PG	QG	PL	QL	BASE
1.	K100	401	2	0	0	144	74	400
2.	K200	400	1	404	0	0	0	400
3.	K300	0	0	0	0	260	90	400
4.	K400	0	0	0	0	54	11	400
5.	K500	0	0	0	0	140	25	400
6.	K600	0	0	0	0	320	160	400
7.	K700	0	0	0	0	315	168	400
8.	K800	0	0	0	0	135	11	400
9.	K900	0	0	0	0	96	54	400
10.	K101	0	0	0	0	78	33	400
11	K111	401	1	125	0	74	16	400
12	K121	398	1	321	0	48	20	400
13.	K131	0	0	0	0	66	14	400
14	K141	0	0	0	0	54	20	400
15	K151	0	0	0	0	60	32	400
16	K161	402	1	363	0	64	30	400
17	K171	0	0	0	0	74	20	400
18	K181	0	0	0	0	138	46	400
19.	K191	390	1	380	0	0	0	400

Table (3): Output data for the test.

	Newton Raphson		Fast De-coupled		Error Back propagation	
NO.	NR(v)	NR(d)	FD(v)	FD (d)	EBP(v)	EBP(d)
1	1.0025	0	1.0025	0	1.0030	0
2	1.0000	0.0009	1.0000	0.0009	1.0000	0.0009
3	0.9956	0.0003	0.9956	0.0003	0.9900	0.0002
4	1.0198	-0.0006	1.0198	-0.0006	1.0090	-0.0006
5	1.0048	-0.0007	1.0048	-0.0007	1.0000	-0.0007
6	0.9984	-0.0011	0.9983	-0.0011	0.9900	-0.0011
7	0.9920	-0.0013	0.9920	-0.0013	0.9800	-0.0013
8	0.9932	-0.0013	0.9932	-0.0013	0.9800	-0.0013
9	0.9987	-0.0007	0.9987	-0.0007	0.9890	-0.0007
10	0.9898	-0.0013	0.9898	-0.0013	0.9800	-0.0013
11	1.0025	-0.0007	1.0025	-0.0007	1.0030	-0.0007
12	0.9950	-0.0005	0.9950	-0.0005	0.9950	-0.0005
13	0.9949	-0.0006	0.9949	-0.0006	0.9810	-0.0006
14	1.0101	-0.0001	1.0101	-0.0001	1.0000	-0.0001
15	1.0097	0.0001	1.0097	0.0001	1.0000	0.0001
16	1.0050	0.0010	1.0050	0.0010	1.0050	0.0011
17	0.9861	0.0012	0.9861	0.0012	0.9800	0.0012
18	0.9822	0.0013	0.9822	0.0013	0.9700	0.0013
19	0.9750	0.0017	0.9750	0.0017	0.9750	0.0017
Time (s)	4		3.41		0.93	
C.C.*	-------		0.99998		0.99708	

C.C. Cross correlation

Table (4): Output losses for the test

Bus1	Name1	Bus2	Name2	NR		FD		ANN	
				Ploss (MW)	Qloss (MVAR)	Ploss (MW)	Qloss (MVAR)	Ploss (MW)	Qloss (MVAR)
2	k200	3	k300	1.27675	-25.098	1.276755	-25.099	1.334157	-24.3956
3	k300	1	k100	0.077379	-106.488	0.077379	-106.488	0.10987	-105.654
2	k200	1	k100	0.61027	-138.699	0.610267	-138.699	0.599311	-138.87
1	k100	5	k500	0.953703	-40.5566	0.953747	-40.5561	0.970295	-40.2027
1	k100	6	k600	0.92657	-121.849	0.926758	-121.847	0.982587	-120.324
1	k100	6	k600	0.825748	-141.861	0.825916	-141.859	0.87567	-140.242
1	k100	4	k400	0.268525	-94.2289	0.268509	-94.229	0.214637	-93.7148
6	k600	11	k111	0.125944	-129.131	0.125945	-129.131	0.172178	-127.695
5	k500	7	k700	0.334933	-126.121	0.339054	-126.119	0.391505	-123.456
7	k700	8	k800	0.006977	-7.41251	0.006977	-7.41244	0.001274	-7.27586
8	k800	6	k600	0.187421	-23.1819	0.18746	-23.1813	0.280452	-21.7981
6	k600	9	k900	0.29296	-35.7484	0.292879	-35.7488	0.317282	-34.8349
7	k700	9	k900	1.050204	-18.2148	1.050141	-18.2151	1.108518	-17.0832
7	k700	10	k101	0.050619	-19.5928	0.050626	-19.5925	0.031184	-19.3335
9	k900	14	k141	0.555889	-74.4392	0.555748	-74.4397	0.556797	-72.8667
9	k900	15	k151	1.101366	-56.4707	1.101084	-56.4725	1.114152	-55.0721
9	k900	12	k121	0.158546	-30.0725	0.158497	-30.0728	0.18214	-29.5693
9	k900	12	k121	0.158546	-30.0725	0.158497	-30.0728	0.18214	-29.5693
12	k121	13	k131	0.008542	-19.9951	0.008542	-19.9951	0.370679	-16.6872
12	k121	13	k131	0.008542	-19.9951	0.008542	-19.9951	0.370679	-16.6872
14	k141	16	k161	1.421222	-91.948	1.421026	-91.9491	1.430397	-90.8126
15	k151	16	k161	0.874192	-110.511	0.874076	-110.511	0.877159	-109.344
15	k151	17	k171	1.139604	-129.155	1.139445	-129.155	1.078518	-127.508
16	k161	18	k181	0.211615	-114.491	0.211616	-114.491	0.401981	-111.354
18	k181	19	k191	0.453627	-26.6157	0.453625	-26.6158	0.440891	-26.3493
19	k191	17	k171	0.7821	-26.9453	0.782035	-26.9458	0.729071	-27.1928

Table (5): Present no of the epoch with the recognition rate.

Recognition Rate (%)	96.8	96.3	97.4	96.9
No. of epoch	288306	288830	299801	330575
No of the test pattern is 53				