Radial Basis ANN-Based Static Load Flow Analysis in Iraqi National Super Grid (400 KV)

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Abstract:-

This paper presents the application of Artificial Neural Networks for Load-flow analysis of Iraqi National super grid (400 KV network) using radial basis neural network (RBNN) to handle the slow computational process of Error Backpropagation Neural Network (EBPNN). The proposed method is fast and has acceptable accuracy. Active and reactive powers of system buses excluding slack bus, as well as the magnitudes and phase angle of slack bus are chosen as inputs to the ANN. Phase angle and voltage magnitude of all buses excluding slack bus are chosen as the outputs. Training data are obtained by performed a load flow program using an iterative numerical method namely Decoupled load flow method (DLF), same input and output parameters of RBNN are feed to the EBPNN. Load flow analyses results achieve from two neural methods are compared with the result of DLF method to illustrate the accuracy of result and the results are compiled to form the training set. The proposed algorithm is applied and the numerical results are presented in this paper in order to demonstrate the effectiveness of this proposed algorithm in terms of accuracy and speed. It is concluded that the trained ANN can be utilized for both off-line and on-line simulation studies. The simulation programs implemented using 7.5-Matlab programming language to obtain the satisfactory results.

البحث الحالي يقدم تطبيقا للشبكات العصبية الأصطناعية(ANN) في تحليل تدفق الحمل في منظومة الشبكة الوطنية العراقية ذات الضغط الفائق (400 KV) بأستخدام (Radial basis NN) لمعالجةالبطأ في استحصال النتائج بطريقة (Error Backprpagation NN) . الطريقة المقترحة تمتاز بالسرعة والدقة المقبولة ، تم اختيار القدرة الفعالة والمتفاعلة لعموميات التوصيل عدا العمومي العائم اضافة الى فولتية وزاوية عمومي التوصيل العائم كبيانات دخل لكل منRBNN و EBPNN المقترحة في حين تشكل زاوية ومقدار فولتية عموميات التوصيل في المنظومة عدا العمومي العائم بيانات الخرج للشبكتين. بيانات تدريب الشبكة العصبية يتم الحصول عليها بتطبيق أحد الطرق التكرارية المستخدمة في تحليل تدفق الحمل والمسماة طريقة خفض الأقتران(Decoupled Load-Flow Method) . نتائج تدفق الحمل للمنظومة الكهربائية بأستخدام الطريقة التكرارية (DLF) والشبكتين العصبيتين(RBNN) و(EBPNN) قورنت

لبيان فعالية الطريقة المقترحة من حيث الدقة وسرعة استحصال النتائج، حيث أظهرت هذه النتائج فعالية الطريقة المقترحة وأمكانية تطبيقها عندما تكون الشبكة في الخدمة أو خارجها. برامج المحاكاة المقترحة بنيت بأستخدام لغة البرمجة MATLAB-7.5.

Introduction:-

Load-Flow is very important and fundamental tool for analysis any power system and is used in the operational as well as planning stage. Certain applications, particularly in system automation and optimization of power system, require repeated Load-flow solution. In these applications it is very important to solve the load flow problem as efficiency as possible [1]. Almost all the known methods of numerical analysis for solving a set of non-linear algebraic equations have been applied in developing load flow algorithms. One or more desirable features to compare the different load flow methods can be the speed of solution, memory storage requirements, accuracy of solution and the reliability of convergence depending on a given solution. Though, robustness or reliability of convergence of the method is required for all types of applications, the speed of solution are more important for on-line applications compared to the off-line studies [2].

Many researches on using Artificial Neural network in power systems had been studied; Masanori, S. and et..al in [3] use artificial neural network to calculate various load flow state in power system since the achievement results shown that ANN network is a fast tool to perform the large scale power system calculations. Nguyen, T. T. in [4] presents the development of a ANN networks architecture which implements the Newton-Raphson algorithm for solving of power network load flow equations. Jayendra Krishna and Laxmi Srivastava in [5] develop counterpropagation neural network to solve Load-Flow problem under different loading contingency condition for computing bus voltage magnitudes and angle of the power system, the composition of the inputs variable of the proposed method has been selected to emulate the solution process of a conventional load flow program. Hung-Cheng Chen and et al in [6], proposed partial discharge classification using neural networks and statistical parameters commercial partial discharge detector is firstly used to measure the 3-D partial discharge patterns of epoxy resin power transformers. Then, the gray intensity histograms extracted from the raw 3-D partial discharge patterns are statistically analyzed for the neural-network-based (NN-based) classification system. Noor Izzri Abdul Wahab and et..al in [7], presents transient stability assessment of electrical power system using probabilistic neural network (PNN) and principle component analysis. Transient stability of a power system is first determined based on the generator relative rotor angles obtained from time domain simulation outputs. In this paper we used Radial Basis and Error Backpropagation neural networks with Decoupled load flow method to raise the speed computation process and minimize the memory storage which required to the Load-Flow analysis of Iraqi National Super Grid (400 KV network).

Static Load-Flow Analysis:-

The objective of Load-Flow analysis is to determine the voltage and its angle at each bus, real and reactive power flow in each line and line losses in the power system for specified bus or terminal conditions. The power flow studies are conducted for the purpose of planning (viz. short, medium and long range planning), operation and control. For the purpose of power flow studies, it is

assumed that the three-phase power system is balanced and also mutual coupling between elements is neglected. Variable associated with each bus of the power system include four quantities viz. voltage magnitude Vi, its phase angle δi , real power Pi and reactive power Qi total 4n variable for n buses system. At every bus two variables are specified, the remaining two can be found by solving the 2n power flow equations. Out of these four quantities only two are generally specified at a few buses and depending upon which two are specified, we have three categories of buses, namely Swing Bus or Reference Bus, Generator Bus or PV Bus and Load Bus or PQ Bus. From the nodal current equations, the total current entering the i^{th} bus of m bus system is given by:-[5]

$$I_i = Y_{i1}V_1 + Y_{i2}V_2 + \dots\dots + Y_{im}V_m = \sum_{k=1}^{m} Y_{ik}V_k \qquad (1)$$

At i^{th} bus, complex conjugate power will be

$$S_i^* = P_i - jQ_i = V_i^* I_i = V_i^* \sum_{k=1}^{m} (Y_{ik}V_k)$$

$$or\ P_i - jQ_i = \sum_{k=1}^{m} \left[V_i |Y_{ik}| V_k e^{-j(\theta_{ik}+\delta_i-\delta_k)} \right] \qquad (2)$$

$$P_i = \mathrm{Re}al \sum_{k=1}^{m} \left[V_i |Y_{ik}| V_k e^{-j(\theta_{ik}+\delta_i-\delta_k)} \right]$$

$$\textbf{Or}\ P_i = \sum_{k=1}^{m} \left[V_i |Y_{ik}| V_k Cos(\theta_{ik}+\delta_i-\delta_k) \right]$$

$$P_i = \sum_{k=1}^{m} \left[V_i V_k [G_{ik} Cos\,(\delta_i-\delta_k) + B_{ik} Sin(\delta_i-\delta_k) \right] \qquad (3)$$

Similarly, the reactive power in the i^{th} bus will be

$$Q_i = \mathrm{Im}ajinary \sum_{k=1}^{m} \left[V_i |Y_{ik}| V_k e^{-j(\theta_{ik}+\delta_i-\delta_k)} \right]$$

$$\textbf{Or}\ Q_i = \sum_{k=1}^{m} \left[V_i |Y_{ik}| V_k Cos(\theta_{ik}+\delta_i-\delta_k) \right]$$

$$Q_i = \sum_{k=1}^{m} \left[V_i V_k [G_{ik} Sin\,(\delta_i-\delta_k) - B_{ik} Cos(\delta_i-\delta_k) \right] \qquad (4)$$

Equations (3) and (4) are known as *static Load-Flow equation*, the load flow equations used in Netown-Raphson method computation of voltage corrections are given as:

$$\begin{bmatrix} \Delta\delta \\ \dfrac{\Delta V}{V} \end{bmatrix} = \begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix}^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \qquad (5)$$

Where: $J_{11}=\frac{\partial P_i}{\partial \delta_k}$, $J_{12}=\frac{\partial P_i}{\partial V_k}V_k$, $J_{21}=\frac{\partial Q_i}{\partial \delta_k}$, $J_{22}=\frac{\partial Q_i}{\partial V_k}V_k$

The solution of Equation (5) provides the correction vector i.e. .δ's for all the *PV* and *PQ* type buses and .*V*'s for all the *PQ* type buses, which are used to update the earlier estimates of δ's and *V*'s. This iterative process is continued till the mismatch vector i.e. .P's for all the PV and PQ type buses and .Q's for all the PQ buses become less than a pre-assigned tolerance value ε. As can be observed form (5), during each iteration, Jacobian elements are to be calculated and its inverse is also required, due to this fact, the Newton-Raphson method requires more time per iteration.

Decoupled Load-Flow Method:-

In the strictest use of the Newton-Raphson procedure, the jacobian is calculated and triangularized in each iteration. In practice, however, the jacobian is often recalculated only every few iterations and this speed up the overall solution process. The final solution is determined by the allowable power mismatches and voltage tolerance at the buses. When solving large scale transmission power systems, an alternative strategy for improving computational efficiency and reducing computer storage requirements is the decoupled Load-Flow method, which makes use an approximate version of the Newton-Raphson procedure. The principle underlying the decoupled approach is based on two observations:- [8]

- **Change in voltage angle δ at a bus primarily affects the flow of real power (P) in the transmission lines and leaves the flow of reactive power (Q) relatively unchanged.**
- **Change in voltage magnitude $|V|$ at a bus primarily affects the flow of reactive power (Q) in the transmission lines and leaves the flow of real power (P) relatively unchanged.**

We have noted that the first observation states essentially that $\partial P_i / \partial \delta_j$ is much larger than $\partial Q_i / \partial \delta_j$, which we now consider to be approximately zero. The second observation status that $\partial Q_i / \partial |V_j|$ is much larger than $\partial P_i / \partial |V_j|$, which is also considered to be zero. Incorporation of these approximations into jacobian of Newton-Raphson make the elements of the submatrices J_{12} and J_{21} zero, we are then left with two separated systems of equations;

$$\Delta P=\left[J_{11}\right]^{-1}\left[\Delta\delta\right] \quad \text{and} \quad \Delta Q=\left[J_{22}\right]^{-1}\left[|V|\right] \qquad \textbf{(6)}$$

To get fast computation in load flow solution, the decoupled load flow program has been developed in this paper and run to generate several training / testing patterns.

Neural Network Architecture:-[9]

A neural network functions like a human brain and is well known as a universal approximator. Due to the capability of dealing with highly nonlinear and complex problems, neural networks had been successfully applied to a wide variety of real world problems. An artificial neural network has three essential segments; an input layer, a hidden layer and an output layer. Depending on the complexity of a solution process an ANN may require more than one hidden layers. Each layer is made up of several neurons that transmit signal to the neurons at the next layer. Each signal path has its own weight, known as synaptic weight. By selecting the synaptic weights, an ANN can be made to simulate a complex solution process. Activation functions are used at the hidden and output layers to transform the input signals.

Radial Basis ANN: [10], [11]

The radial basis neural network consists of three layers, the input layer, hidden layer and output layer. The nodes within each layer are fully interconnected to the previous layer; the input variables are assigned to each node in the input layer and are passed directly to the hidden layer without weights. The hidden nodes contain the radial basis functions, and are analogous to the sigmoid function used in the Error Backpropagation (EBP) networks. The radial basis function (RBF) is defined by a center position and width parameter, the width of RBF unit controls the rate of decrease of function.

The parameters of RBF unit are determine in three steps of the training activity, first the unit centers are determined by some form of clustering algorithm, the widths are determined by a nearest neighbour methods. Finally weights connecting the RBF units and the output units are calculated using multiple regression techniques.

Test system:-

The INSG-400KV (Iraqi National Super Grid) which is composed 22-Bus and 29-Line has been used to test the proposed methodology. Bus BAJP make as slack bus having pre-specified voltage as $1.02\angle 0$, BAJG,MMDH,HDTH,QDSG,MSUP and NSRP as voltage-controlled buses and the remain buses as load buses. Figure (1) show the single line diagram of INSG network, and the line data and power data of this network are tabulated in Tables (1) and (2).[12]

Table (1): Line Data of Iraqi National Supper Grid System (400KV)

Line-Name	R (P.U)	X (P.U)	B (P.U)
MMDH-MSL4(1+2)	0.001436	0.011768	0.364392
MSL4-BAJp(1+2)	0.004195	0.034371	1.064256
BAJP-BAJG	0.000022	0.000197	0.005837
BAJG-KRK4	0.001799	0.016351	0.484471
BAJP-BGW4	0.004832	0.043931	1.301651
BAJP-BGW4	0.004962	0.045113	1.336673
BAJP-HDTH	0.003446	0.031323	0.928083
HDTH-QIM4	0.002918	0.02391	0.740352
HDTH- BGW4	0.004845	0.044049	1.305153
BGW4-BGN4	0.000932	0.008471	0.250991

BGW4-BGS4	0.001582	0.014383	0.426101
BGE4-BGN4	0.000288	0.00262	0.077632
BGN4-QDSG(1+2)	0.000152	0.001379	0.040859
BGE4-DAL4	0.000867	0.00788	0.23348
BGE4-BGS4	0.001261	0.011465	0.339713
BGS4-MUSP(1+2)	0.00122	0.010149	0.318967
BGS4-KUT4	0.000433	0.00394	0.11674
BGS4-KDS4	0.003075	0.027954	0.82827
MUSP-BAB4(1+2)	0.000809	0.006734	0.211651
BAB4-KDS4(1+2)	0.002326	0.019349	0.608124
KDS4-NSRP	0.003833	0.034849	1.032565
KUT4-NASP	0.004321	0.039282	1.163898
KUT4-QRNA	0.006248	0.05713	1.69273
NSRP-KAZG	0.004393	0.039932	1.18316
KAZG-HRTP	0.001183	0.010756	0.3187
HRTP-QRNA	0.0013	0.01182	0.35022
DAL4-KRK4	0.001625	0.014775	0.457775
BGS4-AMN4	0.000823	0.007486	0.221806
AMN4-BGE4	0.000433	0.00394	0.11674

Table (2): Bus-Bar's data of Iraqi National Supper Grid System (400KV)

Bus-Bar Name	V(p.u)	Pg(MW)	PL(MW)	QL(MVAR)
BAJP	1.02	0.0	200	98
BAJG	1.01	500	90	10
MMDH	1.0	500	50	20
HDTH	1.0	500	100	60
QDSG	1.01	242	60	70
MSUP	0.96	600	120	70
NSRP	0.98	650	100	54
HRTP	1.0	380	38	22
MSL4	0.0	0.0	300	180
KRK4	0.0	0.0	70	40
DAL4	0.0	0.0	150	80
BGE4	0.0	0.0	500	360
BGN4	0.0	0.0	300	200
BGW4	0.0	0.0	500	360
QIM4	0.0	0.0	60	40
BGS4	0.0	0.0	100	50
AMN4	0.0	0.0	350	47
KUT4	0.0	0.0	100	60
QRNA	0.0	0.0	70	30
KAZG	0.0	0.0	350	200
BAB4	0.0	0.0	100	50
KDS4	0.0	0.0	200	100

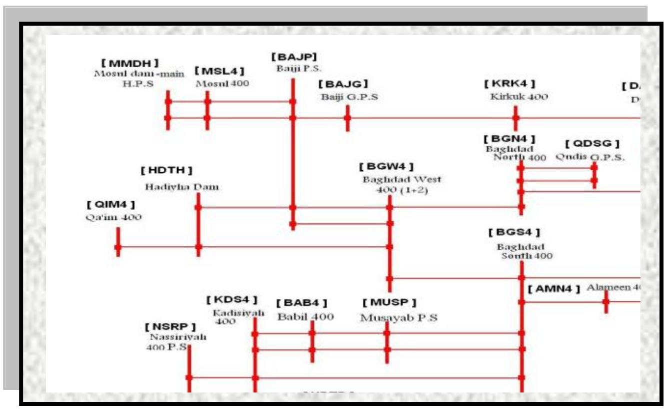

Figure (1): Single line diagram of Iraqi National Super Grid system. [12]

Proposed Solution Method:-

Three layers Radial Basis and Error Backpropagation Neural Networks have been used in this paper to provide the desired power system model. It is assumed that the neural network architecture would be sufficient enough to recognize any non-linearity in the simulated power system. The input vector of proposed neural networks is 2N (N is the number of system buses) and the output vector is 2(N-1), the size of hidden layer is based on educated trail and error approach; initially it is identical on output layer size and then increased as learning/identification process requires. Figure (2) shows the architecture of proposed neural networks, during the training process of this network, a set of input values are fed to both neural networks model and numerical decoupled load-flow iterative method, then the output of three systems are compared to produce the error signals. The network architecture specification is as the following:-

- **Input layer size equal to 44 neurons represent the slack bus phase angle and voltage magnitude, and real and reactive powers of other buses.**
- **Output layer size of equal to 42 neurons representing all buses (except slack bus), estimated voltage magnitude and phase angle.**
- **Hidden layer size equal to 56 neurons found by educated trial and error procedure.**

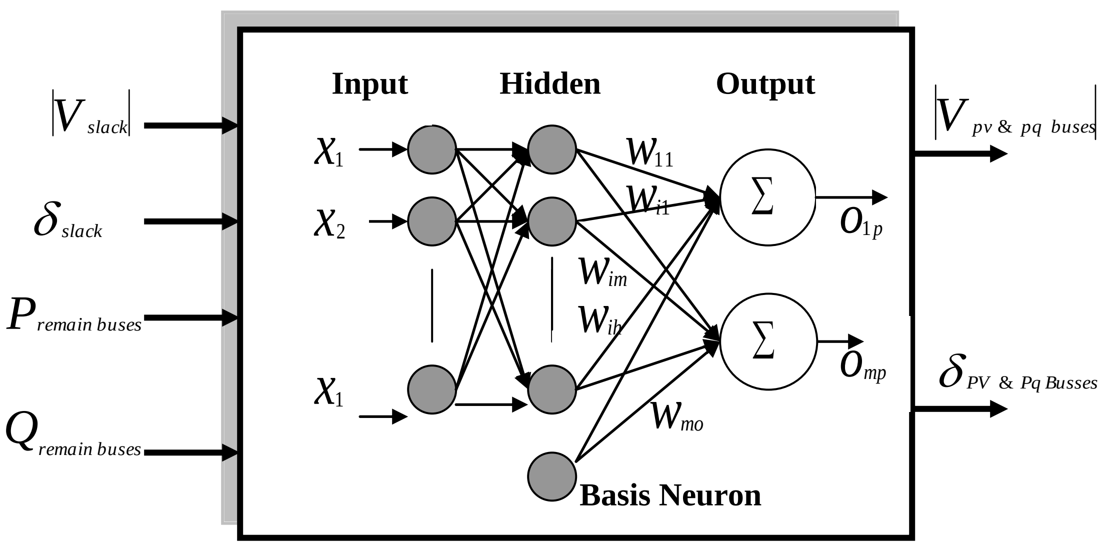

Figure (2): Architecture of proposed Radial Basis Neural Network

Simulation Results:-

After the implementation of conventional Load-Flow method program, the training data of radial basis and error backpropagation neural networks are

obtained then the conventional and neural programs are performed to achieve the simulation results which are tabulated in Tables (3) and (4). Depending on the results of Decoupled Load-Flow method which are considered as a main reference in comparison due to its high accuracy with respect to neural methods, it was found that the results of proposed neural networks method obtains a good average time and accuracy that the neural network results not acceded in estimated values the permitted error level percentage. Table (5) shows the results of solution methods in the point of view of the execution time and accuracy. Figures (3) and (4) show the training curve of proposed Error Back-propagation and Radial Basis Neural Networks and voltage profile of test system calculated by three proposed methods has been illustrated in Figure (5).

Table (3): Simulation results of Solution Methods from Voltage Magnitude Point of View

Bus Name	Bus No.	*DLF Method* V_{Bus} (P.U)	*EBPNN Method*		*RBNN Method*	
			V_{Bus} (P.U)	$\lvert Error \rvert$ %	V_{Bus} (P.U)	$\lvert Error \rvert$ %
BAJG	2	1.00000	1.0000	0.0000	0.998	0.2000
MMDH	3	1.0000	1.0031	0.3100	0.990	1.0000
HDTH	4	1.0000	1.0046	0.4600	1.009	0.9000
QDSG	5	1.0100	1.0140	0.3960	1.000	0.9900
MSUP	6	0.9600	0.9645	0.4680	0.979	0.1979
NSRP	7	0.9800	0.9833	0.3367	0.988	0.8163
HRTP	8	1.00082	1.0	0.0819	0.986	0.0819
MSL4	9	0.9784	0.971	0.7560	0.989	1.0834
KRK4	10	0.9882	0.977	1.1330	0.980	0.8297
DAL4	11	0.9775	0.974	0.3580	0.983	0.5626
BGE4	12	0.9827	0.990	0.7420	0.995	1.2516
BGN4	13	0.9973	0.993	0.4310	0.981	1.6344
BGW4	14	1.0041	1.000	0.4083	1.000	0.4038
QIM4	15	0.9803	0.983	0.2754	1.000	1.7341
BGS4	16	0.9885	0.984	0.4552	0.995	0.6630
AMN4	17	1.0015	1.001	0.0499	0.988	1.3479
KUT4	18	1.0023	1.00	0.2294	0.992	1.0276
QRNA	19	0.9585	0.964	0.5738	0.975	1.7214
KAZG	20	1.0188	1.020	0.1177	1.009	0.9619
BAB4	21	1.0422	1.040	0.2110	1.0392	0.8878
KDS4	22	0.9667	0.967	0.0310	0.972	0.2379

Table (4): Simulation results of Solution Methods from Phase Angle Point of View

Bus Name	Bus No.	*DLF Method* δ (radian)	*EBPNN Method*		*RBNN Method*	
			δ (radian)	$\lvert Error \rvert$ %	δ (radian)	$\lvert Error \rvert$ %
BAJG	2	0.0342	0.0346	1.1695	0.0348	1.7543
MMDH	3	0.0963	0.0971	0.8307	0.0973	1.0384
HDTH	4	0.0231	0.0226	2.1645	0.0235	1.7316
QDSG	5	0.0765	0.0755	1.3071	0.0733	1.5686
MSUP	6	0.0707	0.0694	1.8387	0.0722	2.1216
NSRP	7	0.0734	0.0720	1.9073	0.0752	2.4523

HRTP	8	0.0671	0.0659	1.7883	0.0689	2.6825
MSL4	9	0.0779	0.0766	1.6688	0.0753	1.7971
KRK4	10	0.0542	0.0531	2.0295	0.0554	2.2140
DAL4	11	0.0642	0.0629	2.0249	0.0627	2.3364
BGE4	12	0.0601	0.0593	1.3311	0.0611	1.6638
BGN4	13	0.0587	0.0593	1.0221	0.0595	1.3628
BGW4	14	0.0589	0.0594	0.8488	0.0596	1.1884
QIM4	15	0.0363	0.0365	0.5509	0.0366	0.8264
BGS4	16	0.0888	0.0893	0.5630	0.0895	0.7882
AMN4	17	0.0540	0.0538	0.3703	0.0543	0.5555
KUT4	18	0.0417	0.0419	0.4796	0.0422	1.1990
QRNA	19	0.0547	0.0538	1.6453	0.0551	0.7312
KAZG	20	0.0429	0.0422	1.6317	0.0433	0.9324
BAB4	21	0.0437	0.0444	1.6018	0.0446	2.0594
KDS4	22	0.0218	0.0215	1.3761	0.0222	1.8348

Table (5): The results of solution methods in the point of view of the execution time and accuracy

Solution Method		DLF	EBPNN	RBNN
Execution Time(s)		4.46	1.48	0.65
Accuracy	$\|V\|$	-	99.618 %	99.117 %
	δ	-	98.659 %	98.436 %

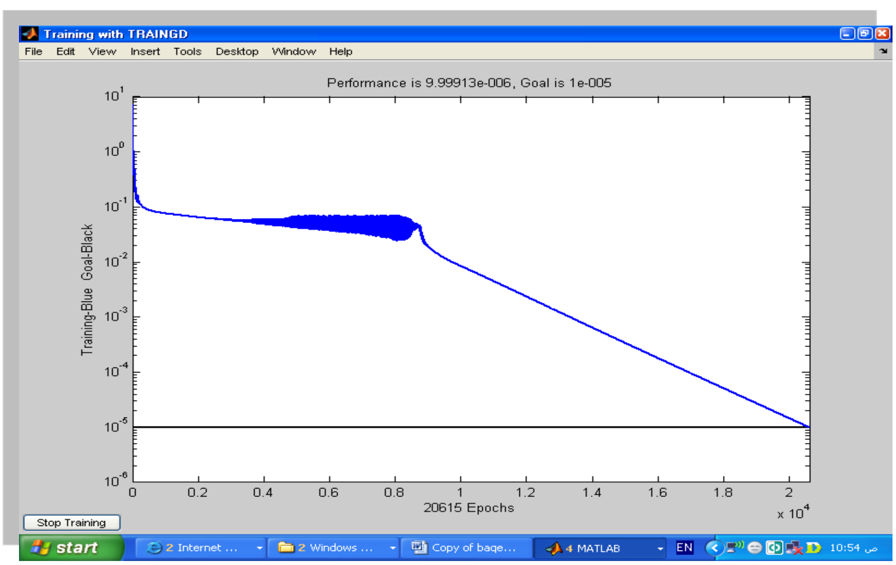

Figure (3): Training curve of proposed EBP Neural Network

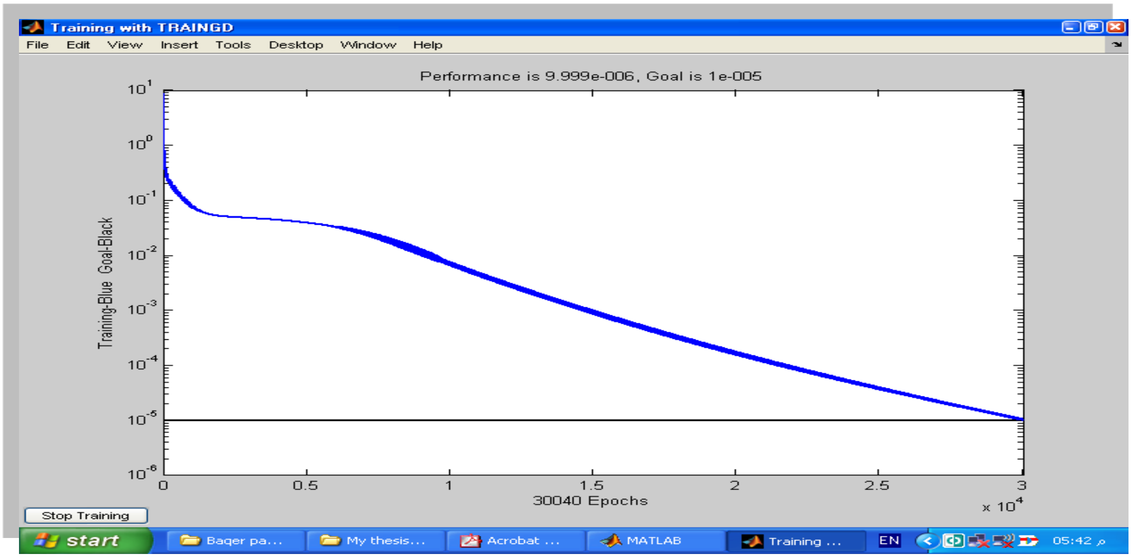

Figure (4): Training curve of proposed Radial Basis Neural Network

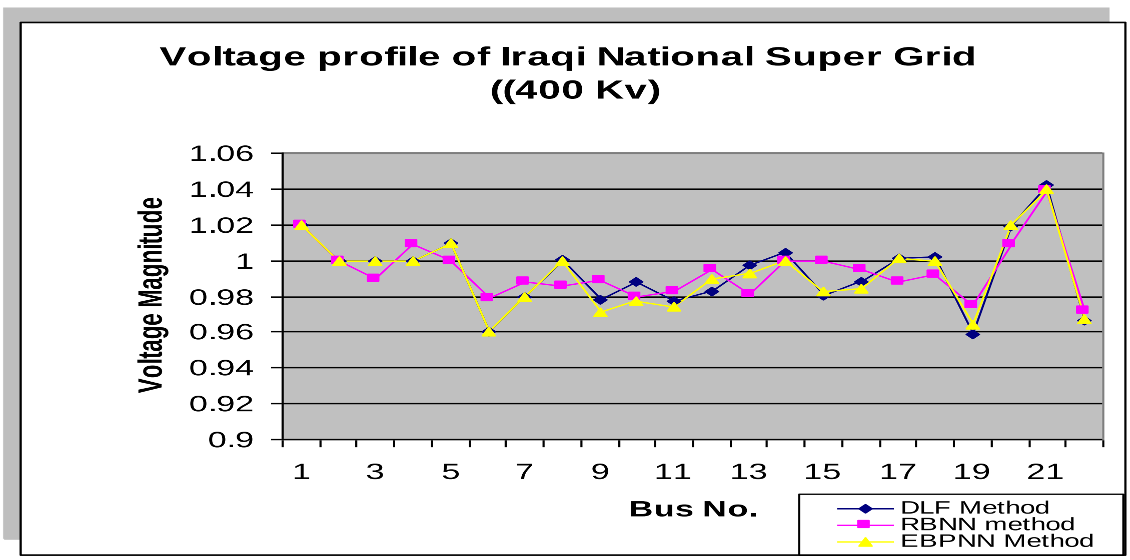

Figure (5): Voltage profile of test system calculated by proposed methods

Conclusions:-

Radial basis neural networks have been developed to solve power flow problem in an efficient manner. In error backpropagation neural network the training process is slow, and its ability to generalize a pattern-mapping task depends on the learning rate and the number of neurons in the hidden layer. On the other hand training of a radial basis neural network is very fast, at the same time the generalization capability of the RBNN allows it to produce a correct output even when it is given an input vector that is partially incomplete or partially incorrect. The proposed solution method tested on Iraqi National Supper Grid (400 KV) using 7.5-MATLAB language in program implementation.

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