International Journal of Power System Operation and Energy Management

Volume 1 | Issue 3 Article 5

January 2012

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Abstract **-** Load flow study is done to determine the power system static states (voltage magnitudes and voltage angles) at each bus to find the steady state working condition of a power system. It is important and most frequently carried out study performed by power utilities for power system planning, optimization, operation and control. In this paper a Particle Swarm Optimization Neural Network (PSO-ANN) is proposed to solve load flow problem under different loading/ contingency conditions for computing bus voltage magnitudes and angles of the power system. A multilayered feed-forward neural network is trained by using PSO technique. The results show the effectiveness of the proposed PSO-ANN based approach for solving power flow problem having different loading conditions and single-line outage contingencies in IEEE 14 bus system

Key words **-** *Load flow analysis, Particle Swarm Optimization, Artificial Neural Network, contingency analysis, Voltage magnitudes, Voltage angles.*

I. INTRODUCTION

The power flow study is one of the most frequently carried out study performed by power utilities and it is required to be performed at almost all the stages of power system planning, optimization, operation and control. In steady state security assessment of a power system, it is important to estimate the line flows and bus voltages at different loading conditions of a power system [1], [2]. In literature, several approaches such as PQ iteration method [2], distribution factor, the bounding method [3] and the concentric relaxation method [4] have been proposed to estimate bus voltage in real time applications.

The main objective of power flow (PF) studies is to determine the bus voltage magnitude with its angle at all the buses, real and reactive power flows (line flows) in different lines and the transmission losses occurring in a power system [5], [6].

The continuous growth and complexity of the power system have originated the adoption of complicated soft computing techniques for efficient planning, operation and control of their systems [7]. The load flow analysis is a time consuming task, because the set of non-linear algebraic equations of load flow are generally solved by employing iterative numerical methods. Therefore, these numerical methods are not fully suitable for on-line applications.

Fast security assessment is of paramount importance in a modern power system to provide reliable and secure electricity supply to its consumers. The contingency screening is one of the most CPU time consuming tasks for online security assessment. For the performance of contingency screening it is necessary to compute the operating state in every few minutes simulating the occurrence of several contingencies and different loading conditions [8].

With the advent of artificial intelligence in recent years, expert systems, pattern recognition, decision tree, neural networks, and fuzzy logic methodology have been applied to the power system problems. Amongst these approaches, the applications of Artificial Neural Network (ANNs) have shown great promises in power system engineering due to their ability to synthesize complex mappings accurately and rapidly. The work which is developed in this area utilizes mostly the multilayer perceptron (MLP) model based on back propagation (BP) algorithm which usually suffers from local minima and over fitting problems[9],[10]. Its generalization capability depends on various parameters like learning rate and the number of neurons (units) in hidden layer etc.

ANNs offer a relatively fast and flexible means of modeling any non-linear complex problem. ANNs do not impose functional relationship between independent and dependent variables. The functional relationship is determined by the data in the training process. The main advantage of ANNs is that a network with sufficient hidden units is able to approximate any continuous function to any degree of accuracy by performing efficient training.

Pao et al [11] employed ANN with the combined use of unsupervised and supervised learning for dynamic security assessment. Hsu et al. [9] developed a fast voltage estimation method using four layered ANN. In recent years, the neural networks have been proposed for solving many different problems of the power systems such as static and dynamic security assessments;[11,12] In the design of ANN, a set of system variables which affect bus voltage most were selected as an input to the ANN using an entropy function. In the above method, if the range of load variation at different buses is increased, the accuracy of voltage estimation greatly suffers. At the same time, learning of multilayer ANN becomes extremely slow, if the usual BP algorithm is used.

In this paper, authors have proposed to develop PSO-ANN to improve the ANN training speed for bus voltage magnitude and angle estimation by coupling ANN with PSO to form PSO-ANN .Two PSO-ANN's were trained, one for computation of bus voltage magnitudes at all the PQ buses and other for voltage angles at all the PV and PQ buses of a power system at different loading conditions.

The results show the effectiveness of the proposed PSO-ANN based approach for solving power flow problem having different loading conditions and single-line outage contingencies in IEEE 14 bus system [13].

II. PARTICLE SWARM OPTIMIZATION (PSO) ARTIFICIAL NEURAL NETWORK

In PSO-ANN, each neural network (NN) contains position & velocity. The position is related to weight of neural network, W. The velocity refers to updating of ANNs weights, ΔW. The function of PSO in ANN is to get the best set of weights (particle position) where several particles are trying to move to get best solution. Particle Swarm consist of many particles, where each particle keeps track if its position, velocity, best position, best fitness, current fitness and neighboring particles. For Neural Network implementation, the fitness value corresponds to a forward propagation through the network and position vector corresponds to the weight vector of the network. The particle's best neighbor and global best particle are used to guide the particle new solutions. At the end the global best particle's position serves as the answer.

A. Architecture of the PSO based ANN

Architecture of the proposed PSO based neural network has been shown in Fig.1. The composition of the input variables for the proposed PSO-ANN has been selected to stimulate the solution process of a conventional power flow program. The input variables for PSO-ANN consist of electric network parameters represented by the diagonal elements of the bus conductance and susceptance matrix, voltage magnitudes Vg of generation and slack buses, the active power generations Pg of PV buses. In order to speed up the neural network training, the conductance and susceptance are normalized between 0.1 and 0.9. For this PSO-ANN based power flow model, the system loads, active and reactive power components are represented like constant admittance and they are included into the diagonal of the bus admittance matrix [Y]=[G]+j[B], where [G] and [B] are the bus conductance and susceptance matrices respectively. The function of PSO in ANN is to get the best set of weight where several ANNs are trying to achieve the best solution.

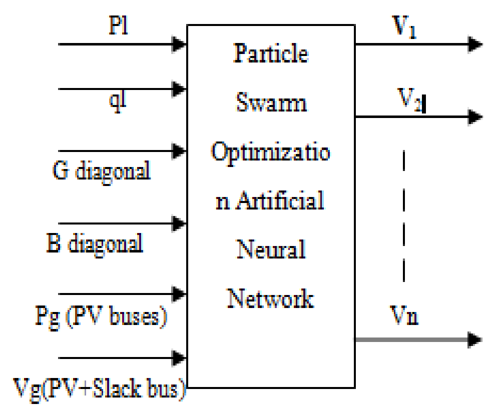

Fig. 1 : Architecture of PSO based ANN

No of inputs =29

- active powers of 9 PQ buses(load buses)
- reactive powers of 9 PQ buses(load buses)
- Conductance(G)
- Susceptance(B)
- Generated active powers of 4 PV buses (PG2-PG5)
- Voltage magnitudes of 4 PV buses (V2-V5)
- Voltage magnitude of slack bus (V1)

  No of outputs=9 (PSO-ANN1) (V6-V14)
- Voltage magnitudes of 9 PQ buses (load buses)

  No. of outputs= 13 (PSO-ANN2) (δ2-δ14)
- Voltage angles of 9 PQ buses and 4 PV buses.

III. SOLUTION ALGORITHM OF PSO-ANN

1. A large number of load patterns were generated by perturbing the load randomly at all the buses, real power generations at generator buses, voltage magnitudes of PV and slack buses.
2. An AC load flow (NR) programs were run for all the load patterns and also for single line outage contingencies cases to calculate bus voltage magnitude at all the PQ buses & voltage angle at PV and PQ buses.
3. The diagonal elements of the bus conductance and susceptance matrix, active and reactive loads, voltage magnitude at PV and slack and reactive power generation at PV buses are selected as input features.
4. 80% of total generated patterns were used for training and remaining 20 % were used for testing purpose.
5. The PSO-ANN model was developed for voltage magnitude & its angle estimation as follows:-
   a) For PSO-ANN, a population of ANN's was constructed, with different initial weights.
   b) For each ANN (particle), iterate over the training data set and calculate the sum of squared error.
   c) Compare all the ANN's error, to find the best ANN in the neighborhood.
   d) If one of the network has achieved the minimum error required (error goal) record its weights and go to step (f) otherwise go to step (e).
   e) For each ANN, apply the PSO algorithm to update its position i.e. its weight (W) and velocity vector i.e. (ΔW).
   f) The PSO-ANN has been trained to provide the set error goal.
6. Apply the testing pattern to evaluate the performance of the trained PSO-ANN's.

IV. IMPLEMENTATION OF TRAINING AND TESTING USING PSO-ANN

PSO is initialized with a group of random particles and then it searches for optima by updating generations. In every iteration, each particle (ANN's weights) is updated by two "best" values namely pbest and gbest. After finding the two best values, the particle updates its velocity and position.

The objective function (i.e. fitness function) is

$$f = \sum [\text{target-actual output}]^2 \qquad (5)$$

The fitness function for each particle is obtained by updating the weights of ANN as specified by the variables of the particle and finding the mean squared error obtained in ANN training as per Eq. (5). Similarly, the fitness functions of the particles in the population are determined. The particle having lowest fitness function is the gbest particle and the fitness function of the gbest particle is compared with the specified accuracy. If the required accuracy is obtained then the training is stopped. Otherwise, the velocity and new position of particles are updated. The same process is repeated until the specified accuracy is reached.

V. TEST RESULT

In IEEE-14 bus system there are 14 buses and 20 lines which have been used to test the proposed methodology. The data for IEEE-14 bus system were taken and buses renumbered to make bus-1 as slack bus having pre specified voltage as $1.06\angle 0^0$ p.u., buses 2-5 as PV buses and buses 6-14 as load (PQ buses).

The total number of inputs is 29, including diagonal values of G and B, real and reactive loads, real bus power generation at bus no.2, bus voltage magnitudes at 4 PV buses. For training and testing of PSO-ANN, 25 load scenarios were generated by perturbing the load at all the buses in the range of 50% to 150%, PV bus voltage magnitude between 0.9 to 1.1, real power generation between 80% to 120% and transformer tap settings between 0.9 to 1.1. Newton-Rapsons (NR) power flow program was used to generate training/testing patterns for 25 load scenarios and for the single line outage contingencies. The NR method converged for different loading conditions and for 19 line outage cases i.e. for 500 cases. Out of 500 generated patterns, 400 patterns corresponding to 20 load scenarios were arbitrarily selected and used for training of the PSO-ANN, while 100 patterns corresponding to 5 load scenarios were used for testing the performance of the trained PSO-ANN.

Two PSO-ANN models were developed, one for estimation of bus voltage magnitude at 9 PQ type buses (PSO-ANN1), while the other (PSO-ANN2) for estimation of bus voltage angle for 4 PV type buses and 9 PQ type buses(total=13). The number of hidden neurons could be decided using some trail and error method.

The optimum structures of neural networks were found to be (29-20-9) for PSO-ANN1 and (29-14-13) for PSO-ANNN2. The trained PSO-ANN's were tested for 100 unknown patterns and were found to be accurate and fast computation of bus voltage magnitude and voltage angles.

ESTIMATION OF VOLATGE MAGNITUDES FOR VARIOUS LINE OUTAGES

Table 1 No Line Outage (Base Case)

Voltage Mag.(V)(p.u.)	NR method	PSO-ANN1	Absolute Error	% Error
V6	0.9670	0.95954	0.00746	0.77135
V7	0.9583	0.95779	0.00051	0.05309
V8	0.9781	0.96760	0.01050	1.07371
V9	0.9549	0.95322	0.00168	0.17624
V10	0.9694	0.97089	0.00149	0.15332
V11	1.0323	0.95954	0.00099	0.09605
V12	1.0823	1.08176	0.00054	0.04962
V13	1.0675	1.06620	0.00130	0.12193
V14	0.9679	0.96585	0.00205	0.21224

Table 2 Outage of line No. 2

Voltage Mag.(V)(p.u.)	NR method	PSO-ANN1	Absolute Error	% Error
V6	0.9431	0.95438	0.01128	1.19601
V7	0.9484	0.95534	0.00694	0.73163
V8	0.9419	0.95336	0.01146	1.20219
V9	0.9458	0.95080	0.00500	0.52876
V10	0.9618	0.96925	0.00745	0.77506
V11	1.0285	0.95779	0.00386	0.37551
V12	1.0815	1.08161	0.00011	0.01028
V13	1.0662	1.06634	0.00014	0.01325
V14	0.9619	0.95980	0.00210	0.21863

Table 3 Outage of line No. 7

Voltage Mag.(V)(p.u.)	NR method	PSO-ANN1	Absolute Error	% Error
V6	0.9578	0.95408	0.00372	0.38799
V7	0.9293	0.92306	0.00624	0.67129
V8	0.9733	0.96836	0.00494	0.50752
V9	0.8978	0.90163	0.00383	0.42685
V10	0.8773	0.88060	0.00330	0.37652
V11	0.8625	0.85214	0.01036	1.20115
V12	1.0782	1.08406	0.00586	0.54384
V13	1.0584	1.06650	0.00810	0.76554
V14	0.9301	0.94317	0.01307	1.40522

Table 4 Outage of line No. 8

Voltage Mag.(V)(p.u.)	NR method	PSO-ANN1	Absolute Error	% Error
V6	0.9666	0.96378	0.00282	0.29175
V7	0.9571	0.96191	0.00481	0.50222
V8	0.9778	0.97635	0.00145	0.14862
V9	0.9527	0.95814	0.00544	0.57080
V10	0.9675	0.97171	0.00421	0.43507
V11	1.0313	1.06620	0.00379	0.36749
V12	1.0343	1.03939	0.00509	0.49250
V13	1.0539	1.05203	0.00187	0.17747
V14	0.9604	0.96944	0.00904	0.94155

Table 5 Outage of line No. 9

Voltage Mag.(V)(p.u.)	NR method	PSO-ANN1	Absolute Error	% Error
V6	0.9637	0.96217	0.00153	0.15916
V7	0.9486	0.94633	0.00227	0.23934
V8	0.9762	0.97526	0.00094	0.09585
V9	0.936	0.93439	0.00161	0.17197
V10	0.9534	0.95339	0.00001	0.00075
V11	1.024	0.96585	0.00244	0.23792
V12	1.029	1.03092	0.00192	0.18677
V13	0.9563	0.95387	0.00243	0.25422
V14	0.9064	0.90227	0.00413	0.45551

Table 6 Outage of line No. 10

Voltage Mag.(V)(p.u.)	NR method	PSO-ANN1	Absolute Error	% Error
V6	0.9601	0.95701	0.00309	0.32170
V7	0.9738	0.97047	0.00333	0.34208
V8	0.9726	0.96894	0.00366	0.37625
V9	0.9599	0.96596	0.00606	0.63091
V10	0.9731	0.96690	0.00620	0.63670
V11	1.0339	0.95438	0.00202	0.19525
V12	1.083	1.08267	0.00033	0.03036
V13	1.0679	1.06927	0.00137	0.12854
V14	0.9709	0.96301	0.00789	0.81277

Table 7 Outage of line No. 12

Voltage Mag.(V)(p.u.).	NR method	PSO-ANN1	Absolute Error	% Error
V6	0.9682	0.96673	0.00147	0.15135
V7	0.9543	0.94997	0.00433	0.45401
V8	0.9781	0.97793	0.00017	0.01770
V9	0.9465	0.94282	0.00368	0.38868
V10	0.9622	0.96338	0.00118	0.12212
V11	1.0285	0.96336	0.00040	0.03877
V12	1.0818	1.08128	0.00052	0.04834
V13	1.0661	1.06481	0.00129	0.12109
V14	0.9623	0.96678	0.00448	0.46577

Table 8 Outage of line No. 18

Voltage Mag.(V)(p.u.)	NR method	PSO-ANN1	Absolute Error	% Error
V6	0.9596	0.96652	0.00692	0.72107
V7	0.9346	0.92208	0.01252	1.34002
V8	0.9742	0.97826	0.00406	0.41656
V9	0.908	0.90971	0.00171	0.18860
V10	0.8941	0.90806	0.01396	1.56136
V11	1.0993	1.06634	0.01103	1.00348
V12	1.0789	1.07802	0.00088	0.08163
V13	1.0602	1.06601	0.00581	0.54770
V14	0.937	0.92851	0.00849	0.90575

The above table's (Table 1-8) present's voltage magnitude at different PQ buses calculated by NR method and proposed PSO-ANN method as well as it also shows the absolute error and the percentage error for various line outages. Among all the 19 results of base case and 18 single line outage the results of selected line outages (No line outage, line outage 2, line outage 7, line outage 8, line outage 9, line outage 10, line outage 12 and line outage 18) are being selected to show the effectiveness of results as in these cases percentage error was found maximum which is approx. 1%.Further to illustrate results of proposed PSO-ANN method graphs of bus voltage magnitudes at all PQ buses (bus no. 6- bus no. 14) are shown in figures.

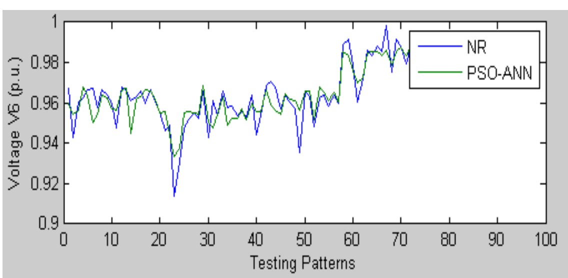

Fig. 2 : Error in Estimation of Voltage magnitude (p.u.) at bus No.6

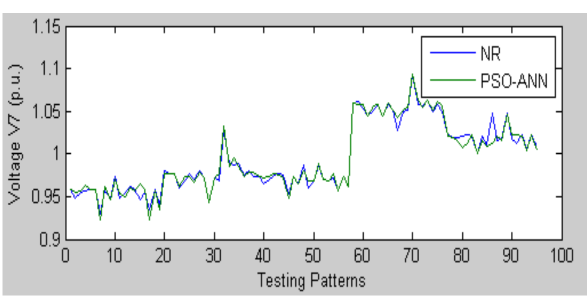

Fig. 3 : Error in Estimation of Voltage magnitude (p.u.) at bus No.7

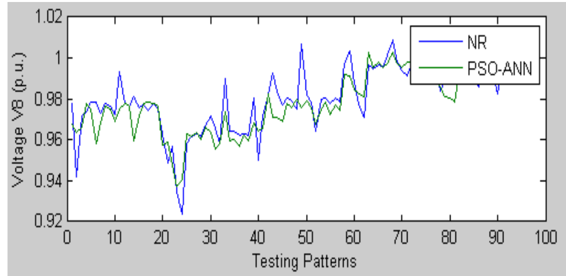

Fig. 4 : Error in Estimation of Voltage magnitude (p.u.) at bus No.8

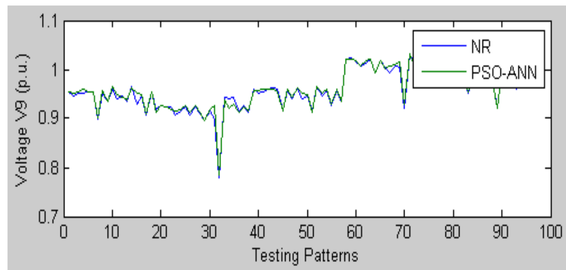

Fig. 5 : Error in Estimation of Voltage magnitude (p.u.) at bus No.9

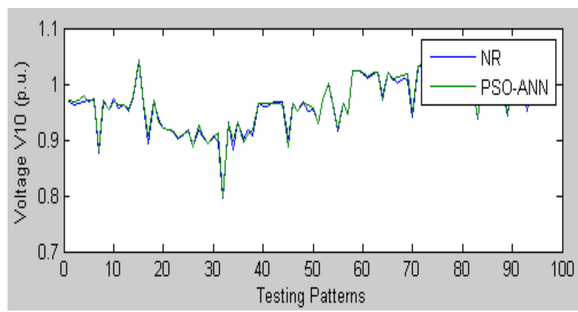

Fig. 6 : Error in Estimation of Voltage magnitude (p.u.) at bus No.10

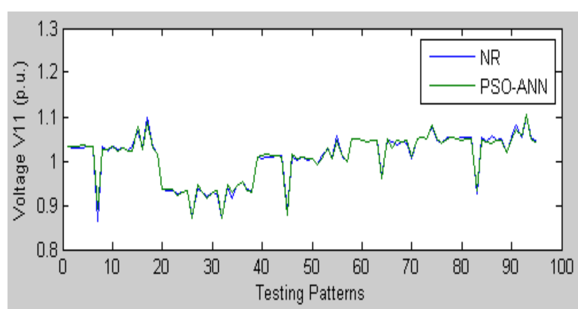

Fig. 7 : Error in Estimation of Voltage magnitude (p.u.) at bus No.11

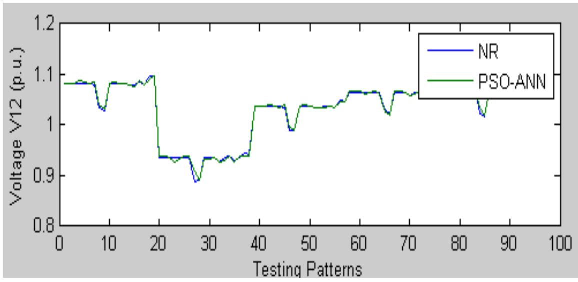

Fig. 8 : Error in Estimation of Voltage magnitude (p.u.) at bus No.12

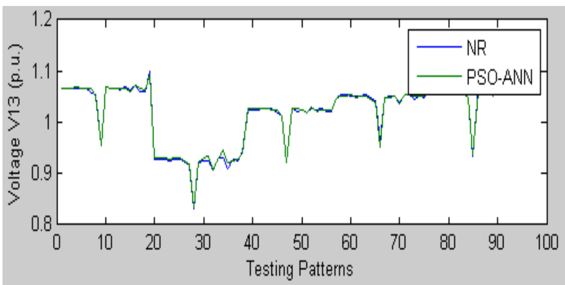

Fig. 9 : Error in Estimation of Voltage magnitude (p.u.) at bus No.13

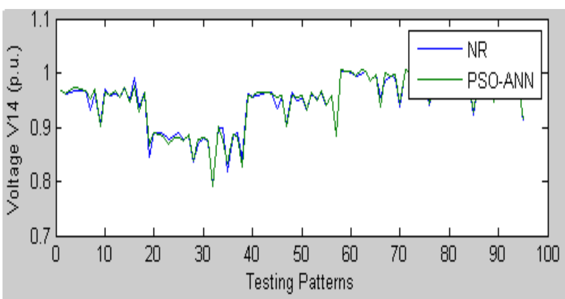

Fig.10 : Error in Estimation of Voltage magnitude (p.u.) at bus No.14

ESTIMATION OF VOLATGE ANGLES FOR VARIOUS LINE OUTAGES

Table 9 No line Outage (Base Case)

Voltage Angle (δ) (in Deg.)	NR method	PSO-ANN2	Abs. Error	% Error
δ2	-8.7723	-8.69772	0.07458	0.8502
δ3	-17.2138	-17.09961	0.11419	0.66339
δ4	-18.3025	-18.046	0.25650	1.40143
δ5	-16.728	-16.93326	0.20526	1.22707
δ6	-13.3204	-13.12696	0.19344	1.45220
δ7	-16.726	-14.45124	0.03116	0.18631
δ8	-11.8988	-11.84542	0.05338	0.44861
δ9	-18.6146	-18.59829	0.01631	0.08761
δ10	-18.6866	-18.8694	0.18280	0.97823
δ11	-18.5696	-18.43993	0.12967	0.69829
δ12	-18.9687	-19.05897	0.09027	0.47589
δ13	-18.9342	-18.89606	0.03814	0.20145
δ14	-19.7879	-19.8309	0.04300	0.21731

Table 10 Outage of line No. 2

Voltage Angle (δ) (in Deg.)	NR method	PSO-ANN2	Abs. Error	% Error
δ2	-12.0025	-11.85997	0.14253	1.18749
δ3	-21.9127	-22.0297	0.11700	0.53391
δ4	-25.2228	-25.22424	0.00144	0.00571
δ5	-23.1175	-23.2197	0.10220	0.44209
δ6	-19.649	-19.67699	0.02799	0.14246
δ7	-23.1157	-10.3493	0.12621	0.54598
δ8	-19.2052	-18.865	0.3402	1.77138
δ9	-25.0975	-25.06896	0.02854	0.11371
δ10	-25.2497	-25.28088	0.03118	0.12347
δ11	-25.3129	-25.31561	0.00271	0.01072
δ12	-25.8588	-25.92872	0.06992	0.27041
δ13	-25.7962	-25.87462	0.07842	0.30398
δ14	-26.4358	-26.46812	0.03232	0.12225

Table 11 Outage of line No.7

Voltage Angle (δ) (in Deg.)	NR method	PSO-ANN2	Abs. Error	% Error
δ2	-8.8011	-8.73627	0.06483	0.73663
δ3	-17.3096	-17.10136	0.20824	1.20303
δ4	-17.5461	-17.87473	0.32863	1.87294
δ5	-17.2004	-17.19579	0.00461	0.02678
δ6	-13.4472	-13.53827	0.09107	0.67725
δ7	-17.197	-17.85668	0.30940	1.79917
δ8	-11.8352	-11.69722	0.13798	1.16584
δ9	-19.3862	-19.46732	0.08112	0.41842
δ10	-19.6759	-19.93425	0.25835	1.31304
δ11	-19.9474	-19.55468	0.39272	1.96877
δ12	-18.3298	-18.66163	0.33183	1.81035
δ13	-18.3732	-18.57872	0.20552	1.11858
δ14	-19.9952	-20.22215	0.22695	1.13503

Table 12 Outage of line No.8

Voltage Angle (δ) (in Deg.)	NR method	PSO-ANN2	Abs. Error	% Error
δ2	-8.7809	-8.86713	0.08623	0.98197
δ3	-17.231	-17.25393	0.02293	0.13311
δ4	-18.2734	-18.26357	0.00983	0.05379
δ5	-16.7856	-16.95252	0.16692	0.99442
δ6	-13.4367	-13.51786	0.08116	0.60404
δ7	-16.7835	-17.91052	0.07031	0.41894
δ8	-11.907	-11.73226	0.17474	1.46755
δ9	-18.6982	-18.52235	0.17585	0.94046
δ10	-18.7491	-18.72684	0.02226	0.11875
δ11	-18.5853	-18.55548	0.02982	0.16045
δ12	-19.4393	-19.24413	0.19517	1.00401
δ13	-19.2126	-19.14226	0.07034	0.36609
δ14	-19.9701	-19.83546	0.13464	0.67422

Table 13 Outage of line No.9

Voltage Angle (δ) (in Deg.)	NR method	PSO-ANN	Abs. Error	% Error
δ2	-8.824	-8.88588	0.06188	0.70131
δ3	-17.3207	-17.47493	0.15423	0.89043
δ4	-18.1209	-18.47363	0.35273	1.94656
δ5	-17.0655	-17.25381	0.18831	1.10344
δ6	-13.5038	-13.5756	0.07180	0.53167
δ7	-17.0627	-3.44565	0.06947	0.40712
δ8	-11.9389	-11.8918	0.04711	0.39450
δ9	-19.1197	-19.03718	0.08252	0.43159
δ10	-19.0599	-18.97608	0.08382	0.43978
δ11	-18.6554	-18.74178	0.08638	0.46304
δ12	-19.9356	-19.59764	0.33796	1.69526
δ13	-20.1908	-19.92147	0.26933	1.33392
δ14	-20.7277	-20.53457	0.19313	0.93176

Table 14 Outage of line No.10

Voltage Angle (δ) (in Deg.)	NR method	PSO-ANN2	Abs. Error	% Error
δ2	-8.7332	-8.78935	0.05615	0.64293
δ3	-17.0293	-17.28752	0.25822	1.51634
δ4	-20.6784	-20.57799	0.10041	0.48556
δ5	-23.4427	-23.2863	0.15640	0.66716
δ6	-13.3529	-13.47456	0.12166	0.91114
δ7	-23.4376	-14.62172	0.17896	0.76358
δ8	-12.1154	-11.95602	0.15938	1.31551
δ9	-23.4339	-23.36653	0.06737	0.28749
δ10	-23.043	-22.9248	0.1182	0.51297
δ11	-21.9082	-21.91402	0.00582	0.02655
δ12	-21.5196	-21.61042	0.09082	0.42201
δ13	-21.6256	-21.6969	0.0713	0.32972
δ14	-23.6861	-23.74879	0.06269	0.26468

Table 15 Outage of line No.12

Voltage Angle (δ) (in Deg.)	NR method	PSO-ANN2	Abs. Error	% Error
δ2	-8.7588	-8.68153	0.07727	0.88221
δ3	-17.1454	-17.16656	0.02116	0.12344
δ4	-19.2983	-18.96128	0.33702	1.74635
δ5	-17.855	-17.71119	0.14381	0.80546
δ6	-13.3823	-13.35784	0.02446	0.18277
δ7	-17.8523	-11.61096	0.20609	1.15441
δ8	-11.9856	-11.85161	0.13399	1.11792
δ9	-20.457	-20.2364	0.22060	1.07835
δ10	-20.3666	-20.17821	0.18839	0.92501
δ11	-19.8953	-19.68333	0.21197	1.06543
δ12	-20.0315	-20.01193	0.01957	0.09771
δ13	-20.039	-19.98295	0.05605	0.27968
δ14	-21.3216	-21.19701	0.12459	0.58433

Table 16 Outage of line No.18

Voltage Angle (δ) (in Deg.)	NR method	PSO-ANN2	Abs. Error	% Error
δ2	-8.785	-8.69640	0.08860	1.00857
δ3	-17.2651	-17.24235	0.02275	0.13174
δ4	-17.8489	-17.69952	0.14938	0.83694
δ5	-16.9802	-17.09666	0.11646	0.68585
δ6	-13.4191	-13.38647	0.03263	0.24313
δ7	-16.9773	-14.03551	0.02785	0.16407
δ8	-11.8496	-11.68193	0.16767	1.41511
δ9	-19.0408	-18.92263	0.11817	0.62062
δ10	-19.1996	-19.0577	0.14190	0.73910
δ11	-18.0554	-18.26962	0.2 1422	1.18645
δ12	-18.5853	-18.73457	0.14927	0.80316
δ13	-18.5933	-18.70068	0.10738	0.57754
δ14	-19.8939	-19.92389	0.02999	0.15076

The above table's (9-18) shows bus voltage angle computed by NR and PSO-ANN methods for PQ buses i.e. bus no. 6-14 and PV i.e. 2-5 buses, absolute and percentage error for outage of various line outages. Among 19 total cases base case and including 18 line outage cases, it is found that results obtained for line outages (No line outage, line outage 2, line outage 7, line outage 8, line outage 9, line outage 10, line outage 12 and line outage 18) are having maximum error of approx. 1% .The graphs of voltage angles at various buses (PQ and PV buses) are shown in figures as they are having maximum absolute and percentage error.

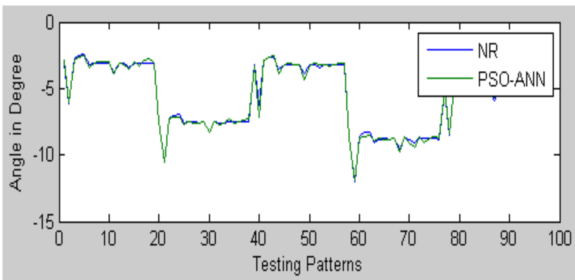

Fig. 11 : Error in Estimation of Voltage Angle (p.u.) at bus No.2

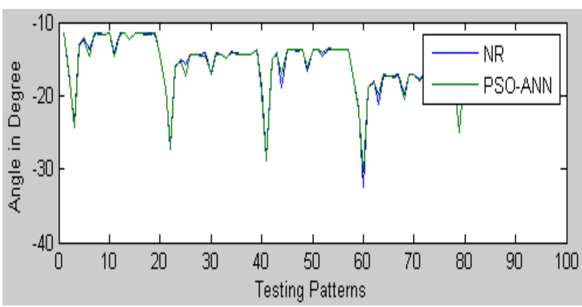

Fig. 12 : Error in Estimation of Voltage Angle (p.u.) at bus No.3

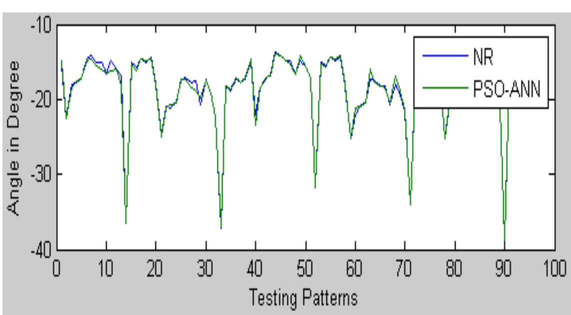

Fig. 13 : Error in Estimation of Voltage Angle (p.u.) at bus No.4

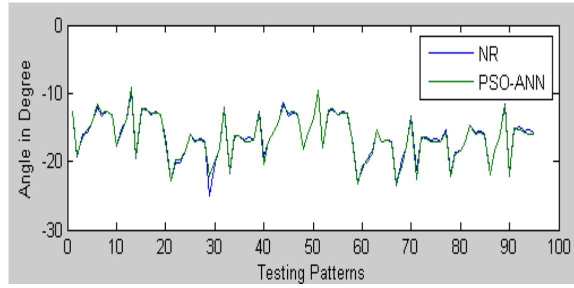

Fig. 14: Error in Estimation of Voltage Angle (p.u.) at bus No.5

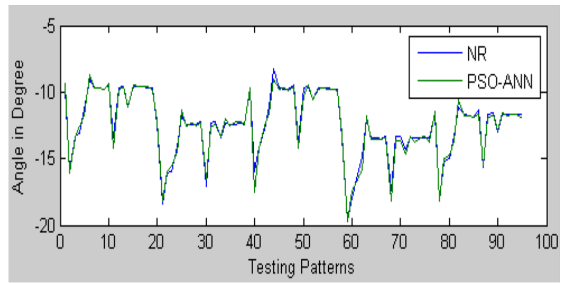

Fig.15 : Error in Estimation of Voltage Angle (p.u.) at bus No.6

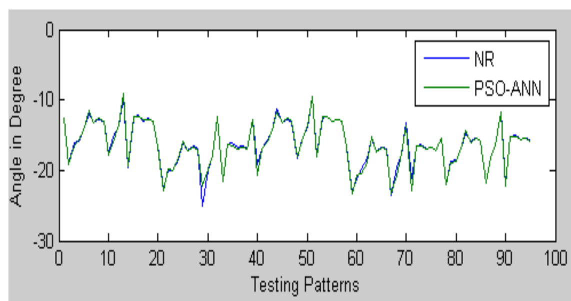

Fig. 16 : Error in Estimation of Voltage Angle (p.u.) at bus No.7

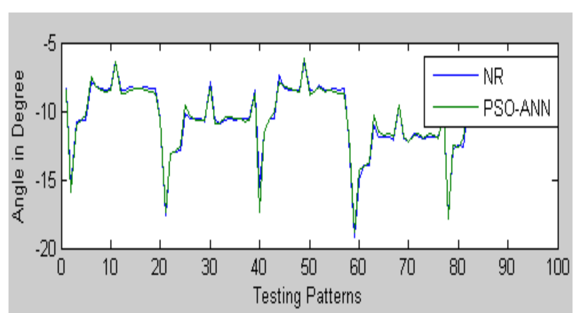

Fig. 17 : Error in Estimation of Voltage Angle (p.u.) at bus No.8

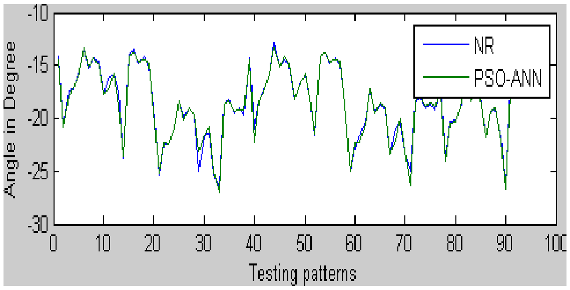

Fig. 18 : Error in Estimation of Voltage Angle (p.u.) at bus No.9

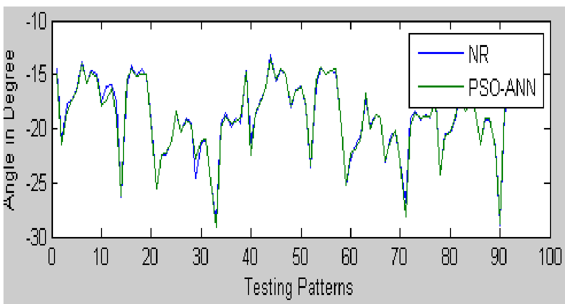

Fig. 19 : Error in Estimation of Voltage Angle (p.u.) at bus No.10

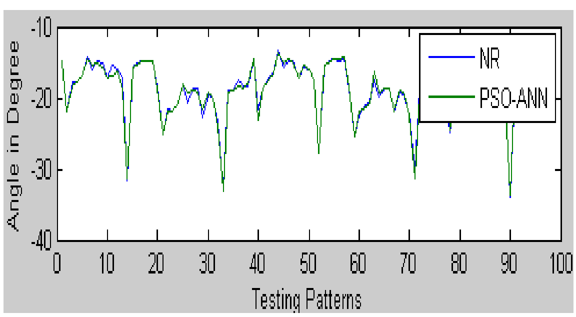

Fig. 20 : Error in Estimation of Voltage Angle (p.u.) at bus No.11

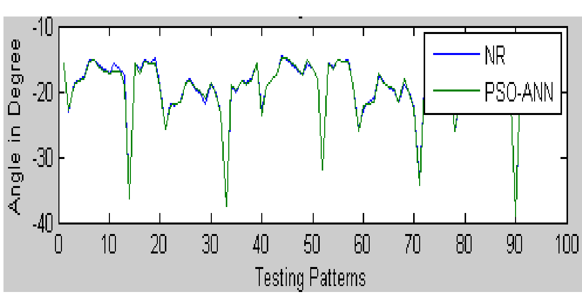

Fig. 21: Error in Estimation of Voltage Angle (p.u.) at bus No.12

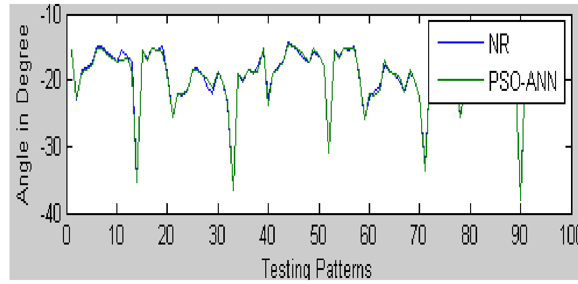

Fig. 22 : Error in Estimation of Voltage Angle (p.u.) at bus No.13

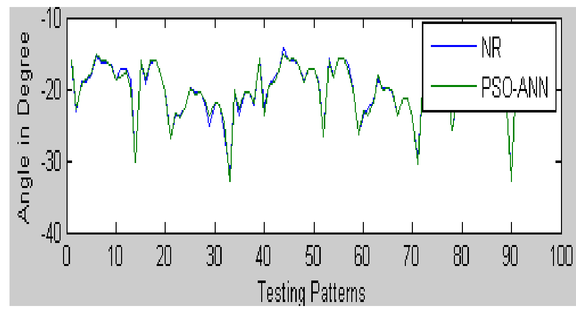

Fig. 23 : Error in Estimation of Voltage Angle (p.u.) at bus No.14

VI. CONCLUSION

Particle Swarm Optimization-Artificial Neural Network (PSO-ANN) has been developed to solve power flow problem in an efficient manner. In multi-layer feed forward 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 PSO-ANN is very fast, at the same time the generalization capability of the PSO-ANN allows it to produce a correct output even when it is given an input vector that is partially incomplete or partially incomplete or partially incorrect. Two PSOANNs were trained, one for computation of voltage magnitude at all the PQ type buses (PSO-ANN1) and other for voltage angles at all the PV and PQ buses (PSO-ANN2). The trained PSOANNs were able to compute bus voltages magnitudes and voltage angles accurately for previously unseen patterns having changing load / generation conditions of the power system and for single-line outage contingencies as well. Full AC load flow takes long time, as it should be run for any change in load/ generations. On the other hand, once the PSO-ANN networks are trained they provide accurate values of bus voltage magnitudes at all the PQ buses and voltage angles at all the PQ and PV buses almost instantaneously. These values of voltage magnitudes and voltage angles can be used to compute line flows and line losses etc .The PSO-ANN based power flow method can be implemented for on-line security assessment in Energy Management Systems. The similar power flow study can be carried out for generator outage and multiple contingency cases as well.

ACKNOWLEDGEMENT

The authors sincerely acknowledge the financial support provided by Department of Science and Technology (D.S.T), India under Research grant no F.No.SR/S3/EECE/0064/2009 dated 22-01-10 and Director, MITS, Gwalior, India to carry out this work.

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