New Parallel Radial Basis Function Neural Network for Voltage Security Analysis

T. Jain, L. Srivastava, S.N. Singh and I. Erlich

Abstract: **On-line monitoring of power system voltage security has become a very demanding task in competitive power market operation and fast estimation of bus voltage is essential for this. In this paper, a novel parallel radial basis function neural network (PRBFN) which is a multistage network, in which stages operate in parallel rather than in series during testing, has been developed to predict bus voltage magnitudes in an efficient manner. The non-linear mapping capability of radial basis function has been exploited along with forward-backward training. Entropy concept has been used to select the input features of PRBFN to reduce the size of the neural network. The proposed method using a single PRBFN is used to estimate bus voltages under different topological and operating conditions of IEEE 30-bus and a practical 75-bus Indian system.**

***Index Terms*: Entropy concept, Parallel radial basis function neural network, Stage neural network, Voltage security.**

NOMENCLATURE

SNN_i = i^{th} stage neural network of PRBFN
$S_i(n)$ = inputs for training of SNNs for n^{th} pattern after radial basis function applied
$V_d(n)$ = desired output voltage for n^{th} input pattern
$e_i(n)$ = error signal of SNN_i
$O_i(n)$ = outputs of SNN_i
$V_a(n)$ = final output of PRBFN for nth pattern
P_i = real power load at i^{th} bus
Q_i = reactive power load at i^{th} bus
P_{ij} = probability of bus voltage group i and load group j
n_{ij} = number of patterns common to group-i and group-j
H_i = entropy for each bus voltage group i
H_{avg} = average entropy
G = information gain
H_o = maximum entropy value corresponding to the condition when probability of all g groups is equal
x, $x_{\max}$, $x_{\min}$ = actual, maximum and minimum values of input variables for a particular pattern
$a_i(X_p)$ = output of the i^{th} unit in the hidden layer of each SNN
x_{jp} = j^{th} variable of input pattern p
$\bar{x}_{ji}$ = centre of i^{th} RBF unit for input variable j
ψ_i = width of i^{th} RBF unit
o_{qp} = output value of the q^{th} output node of each SNN p^{th} incoming pattern
w_{qi} = weight between i^{th} RBF unit and q^{th} output node
w_{qo} = biasing term at q^{th} output node
η = learning rate
δ_q = error signal for unit q
$\Delta w_{qi}(K)$ = change in weights connecting the hidden and output layers nodes at K^{th} iteration.
t_{qp} = target value at q^{th} neuron of output layer for p^{th} pattern
$\boldsymbol{T_q} = \lfloor t_{q1}, t_{q2}, \ldots\ldots\ldots, t_{qp^{\max}} \rfloor$
$\boldsymbol{O_q} = \lfloor o_{q1}, o_{q2}, \ldots\ldots\ldots, o_{qp^{\max}} \rfloor$ =the actual output vector of PRBFN for p^{th} pattern.
$P^{\max}$ = maximum number of patterns
NO = number of neurons in output layer.

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I. INTRODUCTION

RESTRUCTURING and deregulation of electricity industry has given birth to new problems in the operation and control of power system. The complexity of the system operation has increased many folds due to the involvement of several market entities. All parties try to get the benefits of cheaper source and greater profit margins leading to overloading and congestion of certain transmission corridors. This may result in violation of system operating limits thereby undermining the system security and reliability.

To maintain the system security, monitoring the power flows and bus voltages in a transmission network is very important [1] and fast prediction is essential for controlling these quantities in real time. The traditional procedure of voltage estimation involves the solution of full AC load flow. But, this method is no longer suitable due to the associated computational burden. In order to overcome this drawback several approaches such as 1P-1Q iteration method [2], distribution factor [3], the bounding method [4] and the concentric relaxation method [5] have been proposed in the literatures. However, the drastic decrease in the computational burden achieved by these approaches may not be sufficient for on-line purposes due to inaccuracy in the estimation of voltage magnitudes.

With the advent of artificial intelligence, in recent years, expert systems, pattern recognition, decision tree, neural networks and fuzzy logic methodologies have been applied to the security assessment problem [6-10, 18]. Amongst these, the application of artificial neural network (ANN) showed promising performances. This motivated many researchers to focus on ANN based voltage estimation problem. Hsu et al [11] employed MLP to estimate the bus voltages in normal and post fault conditions. But, if the range of load variation at different buses is increased, the accuracy of voltage estimation greatly suffers and at the same time training process is extremely slow due to the use of conventional back-propagation (BP) algorithm.

In [12], parallel self-organizing hierarchical neural network (PSHNN) was proposed to predict accurate bus voltage in wider range of load variation utilizing both unsupervised and supervised learning. Though the results demonstrated the superiority of PSHNN over multilayer feed forward ANN in terms of accuracy and training time, a separate PSHNN was required for each bus voltage. It is not practical to build and manage a large number of ANNs simultaneously to estimate bus voltages for a large power system due to large CPU time during training. Reference [13] used a radial basis function neural network (RBFN) to predict the post fault power flows and bus voltages. RBFN has been compared to progressive learning network (PLN) and the self organizing map (SOM) for fast voltage prediction task [14] but a separate RBFN was employed for each bus voltage.

Two main issues are important in the application of ANN for voltage estimation in large power systems. Firstly, the training of the neural network must be fast which can be achieved by having limited number of neural networks and secondly, the estimation of voltages must be accurate for large range of operating and topological conditions. The proposed method, in this paper, overcomes these shortcomings. It was observed in [12] that the total network consisting of small BP stages converges mush faster as compared to a single BP network of the same total size for similar error performance. Hence, the idea of stage neural networks has been utilized. Radial basis function neural network has been used in each stage as it learns much faster than multilayer perceptron model. Furthermore, it does not get stuck in local minima. By implementing the parallel radial basis function neural network (PRBFN), the speed of processing with several stages is almost the same as with one stage.

A parallel radial basis function neural network is being proposed in the present paper to estimate bus voltages under different topological and operating conditions. PRBFN is a multistage network in which during training each SNN requires the error signal of previous SNN but during testing all stages operate simultaneously without waiting for data from each other. In an earlier attempt, the authors applied PRBFN based approach [15] for voltage estimation of IEEE test system under different loading and generating conditions and is found to be superior to parallel self-organizing hierarchical neural network (PSHNN) in terms of speed and accuracy. But when a contingency takes place, the system topology changes and the trained neural network will fail to predict the accurate values of bus voltages as it would be unable to capture the input-output relationship properly. To incorporate topological changes, a topology number in the form of bipolar digits is used as an additional input to the PRBFN to represent the corresponding contingency. Thus a single PRBFN has been trained to predict bus voltage magnitudes for the base case as well as for the line outages in IEEE 30-bus and a practical 75-bus Indian system.

II. METHODOLOGY

A conceptual diagram using PRBFN for voltage magnitude estimation is shown in Fig. 1. Input features are selected to reduce the dimensionality of the input as well as size of the neural network, using entropy concept (Block I). The selected inputs are normalized (Block II). A topology number representing the corresponding line outage is also used as an input to the PRBFN. Euclidean distance based clustering technique has been used to determine the number of nodes in hidden layer, cluster centre and its width (Block III). Supervised learning is applied for accurate estimation of bus voltages using a parallel radial basis function neural network (Block IV). The line outages are simulated using a topology number in the form of bipolar digits (+1 or –1) used as an input to the PRBFN to represent the corresponding case.

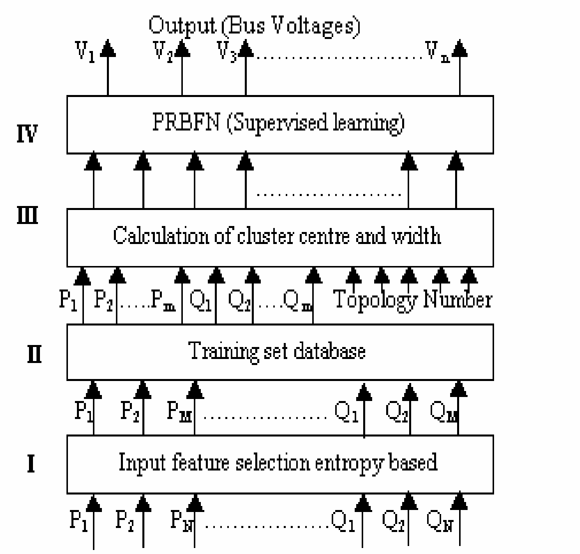

Fig. 1: Conceptual diagram of learning model for voltage estimation

The block diagram of PRBFN used in the present work is shown in Fig. 2. The PRBFN consists of four stage neural networks (SNNs). Each SNN is a three-layered radial basis function network (RBFN) having linear input and output units and only one non-linear hidden unit. During training of RBF, all the input variables are fed to hidden layer without any weight and only the weights between hidden and output layers have to be modified using error signal. After the first stage neural network (SNN1) has been trained using the RBF algorithm, the error signal of SNN1 is considered as the desired output for the next stage neural network (SNN2) and the weights are updated accordingly. This has been done to reduce the final error effectively and the final output of PRBFN is the sum of actual output of each SNN. The RBF is applied identically to all four stages as shown in Fig. 2, which constitutes one sweep. The training of the PRBFN is continued for a number of sweeps until convergence is obtained. For faster learning, the forward-backward training is also adopted.

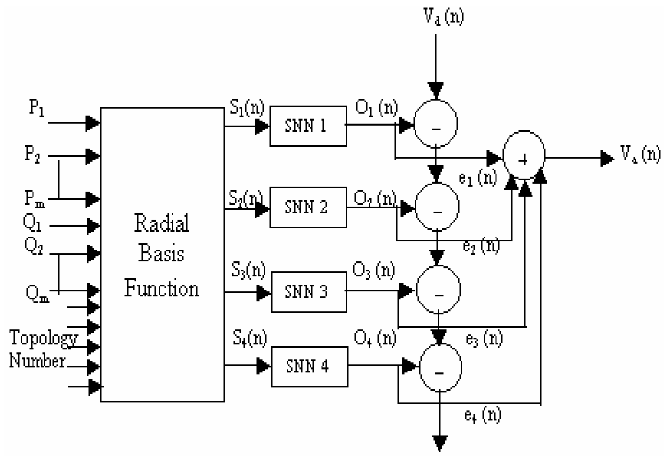

Fig.2 Block diagram for four stage PRBFN

A. Input Selection for PRBFN

The bus voltage magnitudes are affected by several parameters of the power system. Some of them are having larger effect and some are having lesser impact. It is not necessary to use all the available variables to train the PRBFN as it will increase the number of input nodes and will result in a complex structure requiring large training time. An approach based on system entropy [16] has been used to identify the input features, i.e. real and reactive loads affecting the bus voltage most. The term entropy has been used to describe the degree of uncertainty about an event. A large value of entropy indicates high degree of uncertainty and minimum information about an event.

The change in entropy for given information is defined as the information gain or entropy gain The information gain is computed by observing the voltages at each bus for load disturbance at various buses in the power system and on this basis the input features i.e. real and reactive loads affecting a bus voltage most are selected for training the PRBFN. The information gain is computed using the following algorithm.

- At each bus, corresponding to different patterns, arrange the real load in decreasing order and then divide the range into g groups.
- For each bus, also arrange the value of bus voltages for each load pattern into decreasing order and divide them into g groups.
- The probability of bus voltage group i and load group j is calculated by the following equation

$$P_{ij} = \frac{n_{ij}}{\sum_{j=1}^{g} n_{ij}} \quad \text{for } i = 1,2,\ldots\ldots,g \tag{1}$$

- For each bus voltage group i, the entropy H is calculated by

$$H_i = \sum_{j=1}^{g} P_{ij} \ln\left(\frac{1}{P_{ij}}\right) \tag{2}$$

- The average entropy H_{avg} and information gain G are calculated using the following relation

$$H_{avg} = \frac{1}{g}\sum_{i=1}^{g} H_i \tag{3}$$

$$G = H_o - H_{avg} \tag{4}$$

- At each bus, real loads are ranked according to the magnitude of their information gain. The real loads with higher ranking in almost all the buses are selected. The above procedure is repeated for reactive loads also. Thus, the selected real and reactive loads are used as features for training the network.

B. Normalization of the Data

Normalization of the data is an important aspect for training of the neural network. Without normalization, the higher valued input variables may tend to suppress the influence of smaller ones. To overcome this problem neural networks are trained with normalized input data. The value of input variables is scaled between some suitable values (0.1 and 0.9 in the present case) for each load pattern. The variable having highest value is assigned a value equal to 0.9 and that having lowest value is assigned 0.1. The normalized value x_n presented to the neural network as input is calculated using the equation

$$x_n = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} 0.8 + 0.1 \tag{5}$$

C. Solution Algorithm

The solution algorithm for bus voltage prediction using PRBFN is given below:

(i) Several load patterns are randomly generated for different topology and operating conditions and AC load flows are carried out to calculate bus voltage.

(ii) Inputs for PRBFN (P_i and Q_i) are selected on the basis of entropy gain as discussed in section II.A and are normalized.

(iii) The number of hidden units and unit centers for the RBFN used in each stage of the PRBFN are determined using Euclidean distance based clustering technique [17]. Then width of the RBF unit is determined.

(iv) A PRBFN consisting of four stage neural networks (SNN) is designed. The output of the i^{th} unit $a_i\,(X_p)$ in the hidden layer of each SNN is given by

$$a_i(X_p) = \exp\left(-\sum_{j=1}^{r}\left[x_{jp} - \bar{x}_{ji}\right]^2 / \psi_i^2\right) \tag{6}$$

(v) The output value o_{qp} of the q^{th} output node of each SNN is given as

$$o_{qp} = \sum_{i=1}^{H} w_{qi} a_i(X_p) + w_{qo} \tag{7}$$

(vi) After SNN_1 is trained with the RBF algorithm, the error signal is :

$$e_1(n) = V_d(n) - O_1(n) \quad (8)$$

(vii) Use the error signal $e_1(n)$ as the desired output of SNN_2. The error signal for the second stage is:

$$e_2(n) = e_1(n) - O_2(n) \quad (9)$$

(viii) The same procedure is adopted to train SNN_3 and SNN_4. The final output of PRBFN is :

$$V_a(n) = O_1(n) + O_2(n) + O_3(n) + O_4(n) \quad (10)$$

(ix) The RBF is applied identically to all four stages and the connection weights are updated using equations:

$$\Delta w_{qi}(K) = \eta \delta_q O_i(n) \quad (11)$$

(x) The iterations are continued until the error becomes negligible.

(xi) The same procedure from step (ix) to (x) is adopted for the succeeding stages and the final error signal of the PRBFN becomes:

$$e(n) = V_d(n) - V_a(n) \quad (12)$$

(xii) After all four SNNs are trained, retraining of SNN3 and SNN2 is performed. This constitutes one sweep and is referred to as forward-backward training.

(xiii) Training of the PRBFN (step (xi) to step (xii)) is continued for a number of sweeps until convergence is obtained.

III. Results and Discussion

To demonstrate its suitability, the PRBFN is employed to estimate bus voltages under different operating conditions on different sizes of power systems. Firstly, it was tested on IEEE 14-bus system to estimate pre-contingent (base case) and post-contingent voltage at all the PQ buses which were nine in number. The test results demonstrated that the proposed approach was feasible and this encouraged the authors to investigate its application to IEEE 30-bus system and a practical 75-bus Indian system. The performance of the proposed method is presented in terms of errors which are defined as

$$\text{Maximum error } (e_{max}) = \max\ [\{T_q - O_q\},\ q = 1, NO] \quad (13)$$

$$\text{RMS error}(e_{rms}) = \sqrt{\frac{1}{P^{\max}} \sum_{p=1}^{p^{\max}} \frac{1}{NO} \sum_{q=1}^{NO} [t_{qp} - o_{qp}]^2} \quad (14)$$

A. IEEE 30-Bus System

Since IEEE 30-bus system consists of 6 generator buses and 24 PQ type buses, the output layer of the PRBFN would contain 24 neurons. Out of 41 lines, the load flow solution converged for 37 line outage cases only. Changing the load and generation between ± 50% and ± 10% respectively, 25 load scenarios were generated and for each scenario the voltages at all the PQ buses were estimated for each of the 37 contingencies.

A large number of input features increases complexity of the neural network as well as its training time. Hence it is essential to select optimum number of inputs which are able to clearly define the input-output mapping. Since the variations in reactive power loads have significant effect on the bus voltage, all the 18 non-zero reactive loads at the PQ buses were used as input features. To identify the relevant real loads as input features, entropy reduction approach is used. Out of 21 real loads, 8 real loads with higher entropy gain in almost all the buses were selected as input features. Thus, 26 input features corresponding to the loads, as shown in Table I, were selected to train the PRBFN.

TABLE I

Features Selected for IEEE 30-Bus System

S. No.	Feature selection method	No. of features selected	Features
1	Entropy reduction method	26	P_2,P_8,P_{12},P_{17},P_{21},P_{24},P_{26},P_{27} Q_8,Q_9,Q_{11},Q_{12},Q_{14},Q_{15},Q_{16}, Q_{17},Q_{18},Q_{19},Q_{20},Q_{21},Q_{23},Q_{24}, Q_{26},Q_{27},Q_{29},Q_{30}

Since only one PRBFN with multi-output node is designed to predict the bus voltages for the base case as well as for the line outage cases, a topology number in the form of six bipolar digits (+1 or –1) is used as an input to the PRBFN to represent the corresponding case. For example, the base case is represented by a bipolar string (−1 −1 −1 −1 −1 -1) and the first line outage by (-1 −1 −1 −1 −1 + 1). Thus the total input features used to train the PRBFN are 32 in number.

Out of 950 (25×38) generated patterns corresponding to 25 load scenarios and 37 contingencies, 760 (20×38) patterns were selected for training the network and remaining 190 (5×38) patterns were used for testing the performance of the network. A four-stage PRBFN (four stages found adequate) was designed having 32 neurons in the input layer and 24 neurons in the output layer. On applying Euclidean distance based clustering, 19 clusters were formed when the vigilance parameter was set to 0.44. Thus the hidden layer of PRBFN contains 19 neurons. The PRBFN (32-19-24) was trained using supervised learning.

TABLE II

Voltage Estimation for Outage of Line-5

Bus No.	Full AC Load flow	PRBFN Output	Abs. Error
7	1.009	1.005	0.004
8	0.987	0.982	0.005
10	1.033	1.036	0.003
12	0.990	0.994	0.004
14	0.989	0.987	0.002
15	0.984	0.982	0.002
16	0.992	0.985	0.007
17	0.985	0.976	0.009
18	0.971	0.966	0.005
19	0.967	0.961	0.006
20	0.971	0.967	0.004
21	0.973	0.969	0.004
22	0.975	0.972	0.003
24	0.970	0.972	0.002
26	0.976	0.983	0.007
29	1.016	1.008	0.008
30	1.007	0.998	0.009

Once the PRBFN was trained, it was tested for the remaining 190 load patterns. The maximum absolute error in voltage estimation was found to be 0.0204 pu and rms error was equal to 0.0084 pu. Testing results of PRBFN having errors more than 0.001 pu for only one load scenario during outage of the most heavily loaded line-5 connected between bus-2 and bus-13 are presented in Table II. It can be seen that the maximum value of voltage is 1.033 pu at bus-10 and minimum value is 0.967 pu at bus-19 during this outage condition. In spite of wide variation in voltage magnitudes, PRBFN is able to estimate post-contingent voltages accurately. The errors in estimation of pre-contingent and post-contingent voltages with PRBFN and AC load flow method at bus-11, bus-19 and bus-27 are shown in Fig. 3. A graphical comparison between PRBFN approach and a standard AC load flow algorithm results for bus voltage estimation under different line outage conditions are shown in Fig. 4, Fig. 5 and Fig. 6.

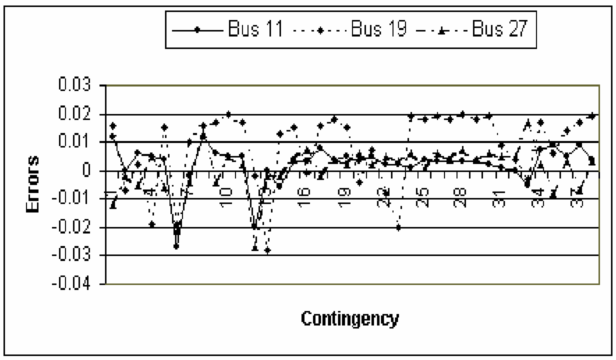

Fig.3: Errors in voltage estimation at bus-11, bus-19 and bus-27

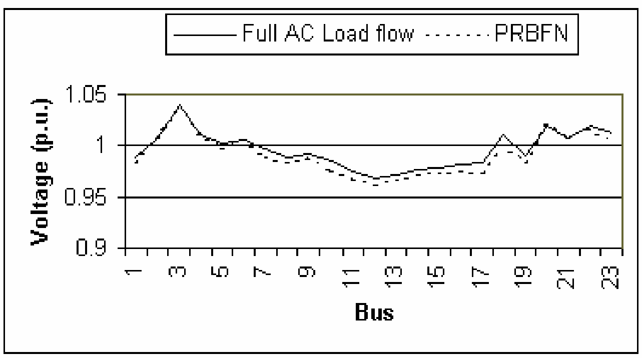

Fig. 4: Voltage at all PQ buses under outage of line 6

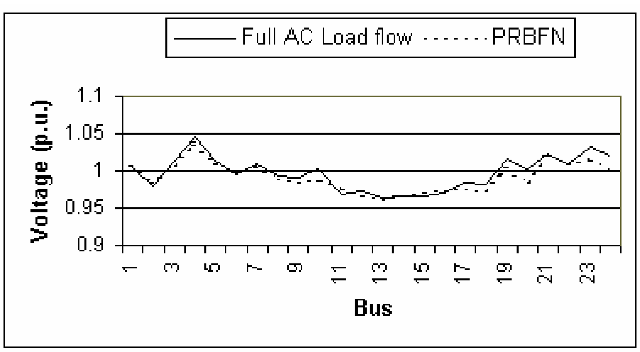

Fig. 5: Voltage at all PQ buses under outage of line 18

From Figs. 4-6, it can be seen than voltage estimations using the proposed PRBN are very close to the AC load flow solution.

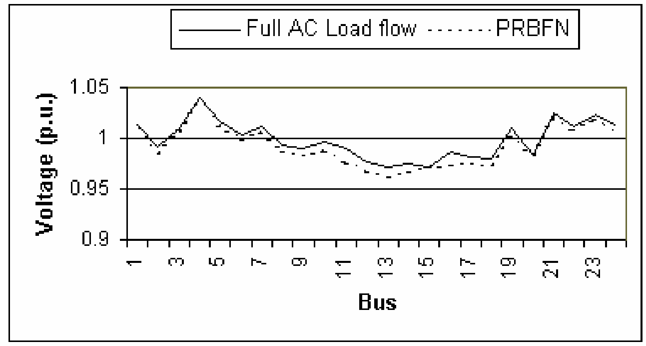

Fig. 6: Voltage at all PQ buses under outage of line 26

B. *Indian 75-Bus System*

The Indian 75-bus system consists of 60-PQ type buses, 14-PV type buses, one slack bus and 114 lines. As the bus voltage magnitude has to be estimated at each PQ bus, the number of neurons in the output layer of PRBFN would be 60. Generator outages, shunt outages and some single line outages which cause an islanding of the system are not considered in this work. Single line outages of a parallel transmission lines are viewed as one kind of single outage. In this case, 15 load scenarios were generated by perturbing load and generation between ± 20% and ± 10% respectively. Full AC load flow was performed to estimate voltage at all the PQ buses for each scenario simulating 69 single line contingencies.

As voltage is directly affected with the reactive power loads, all the 38 non-zero reactive loads were used as input to the PRBFN and out of 42 non-zero real loads, 25 were selected on the basis of high information gain. The 63 real and reactive loads selected as input features for the training of the PRBFN are shown in Table III. Similar to the IEEE 30-bus system, a string of bipolar digits (- 1, + 1) was used as an additional input to the neural network to represent a particular line outage. To represent 69 line outages seven bipolar digits were required, making the total number of input features to be 70.

TABLE III

FEATURES SELECTED FOR INDIAN 75-BUS SYSTEM

S. No.	Feature selection method	No. of features selected	Features
1	Entropy reduction method	63	$P_{16}, P_{25}, P_{28}, P_{30}, P_{34}, P_{37}, P_{39}, P_{46}, P_{47}, P_{48}, P_{49}, P_{50}, P_{52}, P_{55}, P_{56}, P_{57}, P_{60}, P_{63}, P_{64}, P_{65}, P_{67}, P_{68}, P_{69}, P_{70}, P_{71}$ $Q_{16}, Q_{20}, Q_{24}, Q_{25}, Q_{27}, Q_{28}, Q_{30}, Q_{32}, Q_{34}, Q_{37}, Q_{39}, Q_{46}, Q_{47}, Q_{48}, Q_{49}, Q_{50}, Q_{51}, Q_{52}, Q_{53}, Q_{54}, Q_{55}, Q_{56}, Q_{57}, Q_{58}, Q_{59}, Q_{60}, Q_{61}, Q_{62}, Q_{63}, Q_{64}, Q_{65}, Q_{66}, Q_{67}, Q_{68}, Q_{69}, Q_{70}, Q_{71}, Q_{72}$

The numbers of neurons in the hidden layer were determined using Euclidean distance based clustering. Taking a vigilance parameter of 0.39, 52 clusters were formed. Thus, the structure of PRBFN used to estimate bus voltage magnitude in this case was (70-52-60). Out of 1050 (15×70) patterns corresponding to 15 load scenarios and 69 contingencies, 770 (11×70) patterns were selected for training the network and remaining 280 (4×70) patterns were used for testing the performance of the network when training was complete. The maximum absolute error in voltage estimation was found to be 0.0151pu and rms error was equal to 0.0052 pu.

The performance of PRBFN with full AC load flow is compared in Table IV for only one load scenario when the outage of line-64 connected between bus-41 and bus-42 takes place. The results are presented in the table for which the error is more than 0.003 pu only. It was found that in this case also, besides having wide variations in voltage from maximum value of 1.040 p.u. at bus-33 and minimum value of 0.948 pu at bus-69, PRBFN is able to estimate post-contingent voltages accurately.

TABLE IV
VOLTAGE ESTIMATION FOR OUTAGE OF LINE 64

Bus No.	Full AC Load flow	PRBFN Output	Abs. Error
23	1.014	1.019	0.005
24	1.001	1.006	0.005
27	0.991	0.995	0.004
32	1.037	1.031	0.006
34	1.011	1.021	0.010
46	0.988	0.977	0.011
50	0.987	0.991	0.004
51	0.978	0.983	0.005
52	0.979	0.985	0.006
54	1.000	1.006	0.006
55	0.990	0.995	0.005
60	0.992	0.996	0.004
61	1.012	1.006	0.006
62	1.023	1.015	0.008
63	0.992	0.997	0.005
66	0.983	0.979	0.004
67	1.000	1.005	0.005
69	0.948	0.956	0.008
71	0.991	0.995	0.004
73	1.034	1.041	0.007

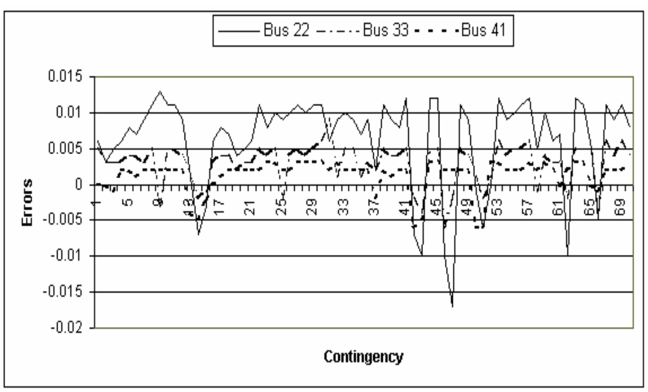

Fig. 7: Errors in voltage estimation at bus 22, bus 33 and bus 41

Fig. 7 and Fig. 8 show the graphical representation of errors in estimation of pre-contingent and post-contingent voltages by PRBFN and AC load flow method at bus-22, bus-33, bus-41 and bus-47, bus-56, bus-71 respectively. A graphical comparison between PRBFN model and a standard AC load flow algorithm results for bus voltage estimation under different line outage conditions are shown in Figs. 9-12. Figures show voltage estimation at only those buses for which error is more than 0.001 pu.

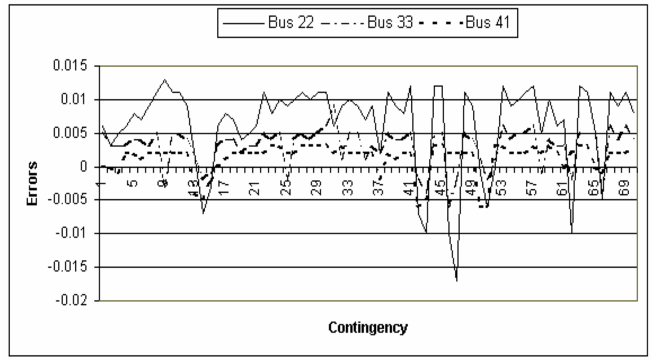

Fig. 8: Errors in voltage estimation at bus 47, bus 56 and bus 71

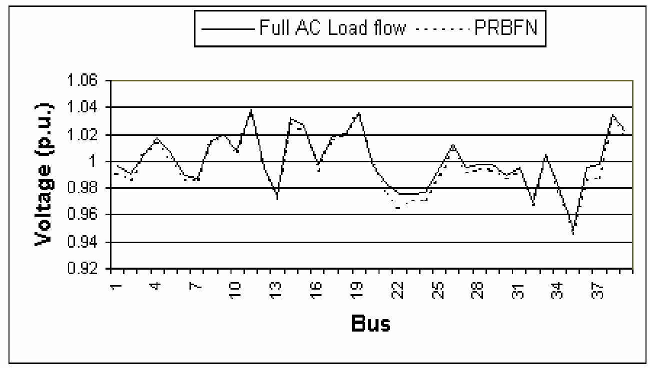

Fig. 9: Voltage at PQ buses under outage of line 16

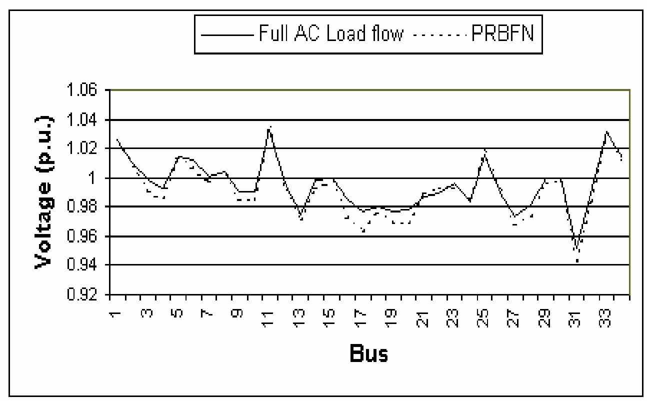

Fig. 10: Voltage at PQ buses under outage of line 29

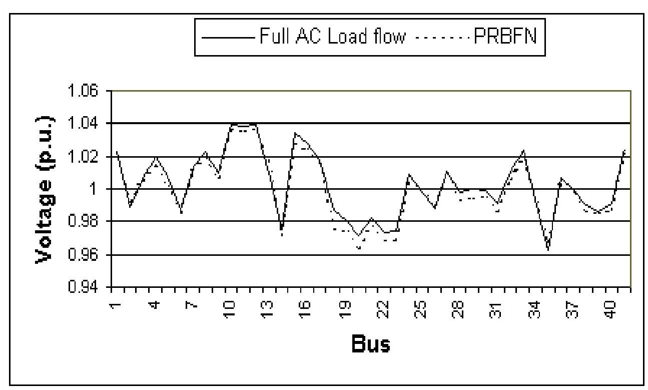

Fig. 11: Voltage at PQ buses under outage of line 38

C. Computational Time

In order to compare the computational time taken by the proposed method with AC load flow, CPU times were computed on a Pentium III, 533 MHz, computer. The CPU time for the training of all the patterns for IEEE 30-bus system was 2424.23 s whereas testing time for one pattern was 9.2×10^{-5} s. The CPU time for training of 75-bus system was 10499.94 s whereas testing time for one pattern was 9.94×10^{-4} s. It is observed that CPU time required by the proposed method is much smaller than the time required for one pattern by AC load flow method for one pattern which is 0.171 s for IEEE 30-bus system and 6.591 s for 75-bus Indian system.

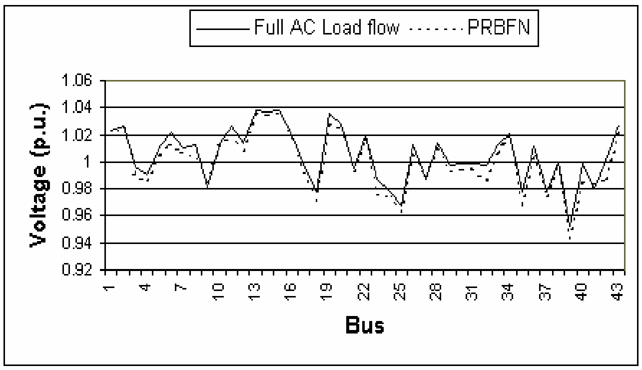

Fig. 12: Voltage at PQ buses under outage of line 55

V. CONCLUSION

A novel parallel radial basis function neural network has been developed to estimate bus voltage magnitudes in an efficient manner for voltage security analysis. To reduce the training time and enhance the accuracy of the PRBFN, four-stage neural networks were employed in PRBFN and inputs to the neural network were selected on the basis of information gain. The designed PRBFN has been applied to predict bus voltages under different loading and generating conditions along with single line outages of the power system. The computation of bus voltages by conventional method requires large computation time as the load flows are to be run every time in the event of an outage of a line, change in load or generation. On the other hand, by the proposed method, once the training of the PRBFN is successfully completed, the prediction of the voltages at all the PQ buses is almost instantaneous. Thus, the proposed approach can be effectively used for on-line applications in power system voltage security analysis.

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