Fast Voltage Contingency Screening using Radial Basis Function Neural Network

T Jain
L Srivastava
SN Singh
Abstract—Power system security is one of the vital concerns in competitive electricity markets due to the delineation of the system controller and the generation owner. This paper presents an approach based on radial basis function neural network (RBFN) to rank the contingencies expected to cause steady state bus voltage violations. Euclidean distance-based clustering technique has been employed to select the number of hidden (RBF) units and unit centers for the RBF neural network. A feature selection technique based on the class separability index and correlation coefficient has been employed to identify the inputs for the RBF network. The effectiveness of the proposed approach has been demonstrated on IEEE 30–bus system and a practical 75-bus Indian system for voltage contingency screening/ranking at different loading conditions.

Index Terms—Class separability index and correlation coefficient, power system security, radial basis function neural network, voltage contingency ranking.

I. INTRODUCTION

THE secure operation of grid, congestion management, power quality, frequency, and power regulation, etc. are the new challenges facing deregulated and unbundled electricity supply industry. Therefore, fast security assessment is of paramount importance in the open power market to provide reliable and secure electricity supply to its customers. The goal of security assessment is to provide information to the system operator about the secure or insecure nature of the operating state in the event of an unforeseen contingency, so that proper control actions can be taken.

Static security assessment of a power system deals with analyzing the system steady state performance after disturbances. Security assessment is the process whereby any violation of operating limit is detected. It has two functions. The first is the detection of violation of actual system operating states. The second, much more demanding, function of security assessment is contingency analysis and normally performed into three distinct stages: contingency definition, selection, and evaluation. The ranking of insecure contingencies in terms of their severity is known as contingency ranking. The severity of contingencies is assessed on the basis of a scalar performance index (PI). Several PI-based methods have been reported using ranking/screening methods in literature [1]–[5]. These traditional approaches are difficult to implement online due to high computational time requirements.

With the advent of artificial intelligence in recent years, expert system techniques [6] and fuzzy logic approaches [7] have been employed for contingency screening and ranking. The pattern recognition technique has been proposed in [8] to estimate the severity of various contingencies. Recently, artificial neural networks (ANNs) have shown great promise in power system engineering due to their ability to synthesize complex
mappings accurately and rapidly. Most of the published work in this area utilizes multilayer perceptron (MLP) model based on back propagation (BP) algorithm, which usually suffers from local minima and overfitting problems.

Various applications of ANNs approaches have been proposed for static security assessment as well as for dynamic security assessment. A hybrid neural network model was proposed in [9] for voltage contingency screening and ranking where the filter module screens the critical contingencies and a trained modular neural network classifies the filtered critical contingencies into different severity classes namely most severe, highly severe, severe, and least severe. However, this model does not provide ranking of critical contingencies belonging to the same class. Pao et al. [10] employed ANN with the combined use of unsupervised and supervised learning for dynamic security assessment. Fuzzy logic and neural networks were used together in [11] to determine the stability status of a contingency for dynamic security assessment. Neural networks have been applied for dynamic security assessment in [12] utilizing Fisher’s linear discrimination function for feature selection.

Radial basis function network (RBFN), which has nonlinear mapping capability, has become increasingly popular in recent years due to its structural simplicity and training efficiency. A potential advantage of RBFN is its ability to augment new training data without the need for retraining [14]. RBFN has only one nonlinear hidden layer and linear output layer. During training, all of the input variables are fed to hidden layer directly without any weight and only the weights between hidden and output layers have to be modified using error signal. Thus, it requires less training time in comparison to BP model. RBFN has been applied for active power contingency ranking/screening in [13] and a separate RBF network was trained for each contingency.

In this paper, both unsupervised and supervised learning is applied to radial basis neural network in order to reduce the number of neural networks required for voltage contingency screening and ranking. The unsupervised learning concept [10] is applied to discover similarities among unlabeled patterns and similar types of input patterns are grouped in one cluster. A separate RBFN would be trained to estimate severity of contingencies for each cluster. The real and reactive loads at different buses are used as input features to the RBF network while the normalized values of voltage performance index for selected contingencies are the output of the RBF network. An approach based on class separability index and correlation coefficient [8] is used to select the relevant features for the RBFN. The performance of the RBFN has been demonstrated on IEEE 30-bus system and 75-bus Indian system and found to be suitable for online screening/ranking of contingencies.

II. METHODOLOGY

The general block diagram of the proposed method is presented in Fig. 1. A large number of load patterns are generated randomly in wide range of load variation at each bus and for different contingency cases. The input features are selected using class separability index and correlation coefficient to reduce the dimensionality of the input as well as the size of the neural network (block I). The selected inputs as well as outputs are normalized (block II). Unsupervised learning is performed to group the similar type of patterns in one cluster (block III). For each cluster, a separate RBFN is trained using supervised learning. Euclidean distance-based clustering technique has been used to determine the number of nodes in hidden layer, cluster center, and its width (block IV). The input data are directly fed to these hidden units and the weights between the hidden layer and the output layer are modified using supervised learning (block V) so that the outputs of the RBFN provide the accurate values of the voltage performance index of the selected critical contingencies.

The diagram of RBFN used in the present work is shown in Fig. 2. The RBF network model consists of three layers viz. the input layer, hidden layer, and output layer. The nodes within each layer are fully connected 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 (units) contain the radial basis functions, and are analogous to the sigmoid function commonly used in the BP neural
networks. The RBF is similar to the Gaussian density function, which is defined by a center position and a width parameter. The width of the RBF unit controls the rate of decrease of function. The output of the \(i\)th unit \(a_i(X_p)\) in the hidden layer is given by

\[
a_i(X_p) = \exp \left( -\sum_{j=1}^{P} \frac{(X_{pj} - \bar{X}_{i})^2}{\sigma_i^2} \right),
\]

(1)

The connection between the hidden units and the output units are weighted sums. The output value \(o_{qp}\) of the \(qth\) output node is given as

\[
o_{qp} = \sum_{i=1}^{H} w_{iq} a_i(X_p) + w_{qq}. \tag{2}
\]

The parameters of the RBF units are determined in three steps of the training activity. First, the unit centers are determined by some form of clustering algorithm. Then the widths are determined by a nearest neighbor method. Finally, weights connecting the RBF units and the output units are calculated using multiple linear regression techniques. Euclidean distance-based clustering [15] technique has been employed in this paper to select the number of hidden (RBF) units and unit centers. The normalized input and output data are used for training of the RBF neural network.

During training of the RBF network, care has been taken to avoid network memorization or over training. When a neural network memorizes the training data, it produces acceptable results for patterns used for training but provides incorrect output when tested on unseen data. To ensure that the neural network has learned and not memorized [16], reshuffling of training patterns was performed to get almost equal errors during training and testing. It was observed that the training error decreases along with number of iterations, while the testing error decreases at first, bounces around, and then starts increasing [16], [17]. The optimal learning is achieved at the global minimum of testing error.

### A. Feature Selection

In ANN applications, if a large number of inputs are used, the number of input nodes as well as interconnection weights will increase and the training of a neural network will be extremely slow. It is neither desirable nor necessary to use all of the available variables viz. all bus, generation, and network data to correctly rank the contingencies under various system conditions. Hence, instead of managing large quantities of data, it would be beneficial if irrelevant or redundant attributes/data could be segregated from relevant and important ones [8], [17], [20]. ANNs are found to be good at interpolating within the training set, but do not extrapolate accurately outside it because of the nonlinear relationship between the input and output, and multiple correlated inputs [21].

Feature selection is performed to identify those features that contribute most to the discrimination ability of the neural network. Only these features are then used to train the neural network and the rest are discarded. By selecting only the relevant features of the data, higher predictive accuracy can be achieved and training time as well as size of the neural network can be reduced.

An approach based on class separability index and correlation coefficient [7] has been used to select appropriate training features for the RBF. Class separability index \(F\) is calculated for all the variables [i.e., real and reactive loads using (3) and correlation coefficient between the different variables is calculated using (4)]

\[
F_i = \left( \frac{m_i^{(S)} - m_i^{(I)}}{\sigma_i^{(S)} + \sigma_i^{(I)}} \right)^2 \tag{3}
\]

\[
C_{ij} = \frac{E(x_i x_j) - E(x_i)E(x_j)}{\sigma_i \sigma_j}. \tag{4}
\]

Those variables that contain more information about “class separability” and are less “correlated” are selected as features for RBF network.

### B. Voltage Performance Index

For online security assessment, critical contingencies are short-listed from a large list of credible contingencies and are ranked according to their severity. Voltage performance index is used as a measure of severity of contingencies. There are several types of performance indices in literature [4] but following voltage performance index [9] has been taken in this paper

\[
PI = \sum_{i \in LV} \left( \frac{u_i}{M} \right)^2 (f_i)^M \tag{5}
\]

and function \(f_i\) is defined as

\[
f_i = \begin{cases} 
V_i - V_i^{\text{max}}, & \text{for } V_i > V_i^{\text{max}} \\
V_i^{\text{min}} - V_i, & \text{for } V_i < V_i^{\text{min}} 
\end{cases}
\]

where \(f_i\) is a function of limit violated buses only (LV), \(V_i\) is the post contingent voltage at the \(i\)th bus, \(V_i^{\text{max}}\) and \(V_i^{\text{min}}\) are the upper limit and lower limit of voltage magnitudes at \(i\)th bus, \(u_i\) is the weighing coefficient, and \(M\) is the order of the exponent. It was observed that by using \(u_i = 1\) and \(M = 4\), masking effect is minimized for test samples studied. Here, summation is carried out only for limit violated buses.

If the computed PI value is greater than zero, then the corresponding contingency is identified as critical or insecure; otherwise, it is secure. The greater the value of PI, the more severe the contingency would be. Thus, it is very convenient to rank contingencies according to their PI values.

### C. Unsupervised Learning

The unsupervised learning is used for fast screening of system disturbances. Input patterns are clustered according to similarities discovered among the input features. The clustering process is governed by a threshold called the vigilance parameter and Euclidean metric function.

In clustering, the first pattern is selected as the center of the first cluster. Then, the next pattern is compared with the first cluster center. If the distance is less than the vigilance parameter, it is clustered with the first. Otherwise, it is a center of a new
cluster. This process is repeated for all of the patterns. Once all of the patterns are processed, the algorithm is reiterated until a stable cluster formation occurs [15].

D. Algorithm

The solution algorithm for contingency screening and ranking using RBFN is given below.

i) A large number of load patterns are generated randomly by perturbing the load at all of the buses.

ii) AC load flows are carried out for all the load patterns, simulating all of the single line outage contingencies and the corresponding value of voltage performance index is evaluated using (5).

iii) Input features (real and reactive power loads at buses) are selected on the basis of class separability index and correlation coefficient.

iv) Input data as well as output data (voltage) are normalized and an unsupervised learning algorithm is used to group the inputs of similar type in one cluster.

v) For each cluster, the number of hidden (RBF) units and unit centers are determined using Euclidean distance-based clustering technique. Then width of the RBF unit is determined.

vi) Set iteration count $K = 1$.

vii) For training of the RBF network, initialize all of the connection weights between hidden nodes and output nodes.

viii) Compute the Gaussian function at the hidden node using (1).

ix) Calculate the output of the RBF network using (2).

x) Calculate the mean squared error for the $p^{th}$ pattern using

$$ e_p = \frac{1}{2} \cdot \frac{1}{NO} \sum_{q=1}^{NO} (t_{qp} - o_{qp})^2. $$  

(7)

xi) Repeat steps (vii) to (ix) for all of the training patterns.

xii) Calculate the error function $E_K$ using

$$ E_K = \sum_{i=1}^{t_{\text{max}}} e_p = \frac{1}{2} \sum_{i=1}^{t_{\text{max}}} \frac{1}{NO} \sum_{q=1}^{NO} (t_{qp} - o_{qp})^2 $$  

(8)

where $t_{\text{max}}$ is the total number of training patterns.

xiii) Update the connection weights using equations

$$ w_{qp}(K + 1) = w_{qp}(K) + \Delta w_{qp}(K) $$  

(9)

where

$$ \Delta w_{qp}(K) = \eta(K) \cdot \sum_{i=1}^{t_{\text{max}}} \delta_{iq} \cdot A_{pi} + \alpha \cdot \Delta w_{qp}(K - 1) $$

$$ \delta_q = T_q - O_q. $$

xiv) Increase iteration count by one (i.e., $K = K + 1$) and continue the procedure until the error becomes negligible.

xv) Repeat steps (v) to (xiv) for each cluster.

III. RESULTS AND DISCUSSIONS

To demonstrate the effectiveness of the proposed RBFN model, it has been tested for voltage contingency screening and ranking of IEEE 14-bus system [18], IEEE 30-bus system [18], a practical 75-bus Indian system [19] representing 400-kV and 220-kV buses of the UP State Electricity Board’s (India) network. The method is found to work satisfactorily on all these systems, but due to limited space, the results of only IEEE 30-bus system and a highly stressed practical 75-bus Indian system are presented in this paper.

The load patterns were generated randomly by changing the load at each bus in wide range. Full ac load flow was performed for each load pattern for single line outage contingencies to evaluate the voltage performance index. The steps described in Section II-D are applied for voltage contingency screening and ranking. During the training of the RBF network, it was observed that if the number of hidden nodes is close to the number of patterns, the training is very fast but the network memorizes the training patterns soon. In that case, it gives acceptable results for training patterns but inaccurate results for testing patterns. If the number of hidden nodes is much less than the number of patterns, then the training of RBF network is slow. Therefore, it is necessary to select optimal number of hidden nodes. The performance of the proposed method is presented in terms of errors which are defined as

$$ \text{Max Error (}$ e_{\text{max}} $)$

$$ = \max \left\{ \left| T_q - O_q \right| \right\}, q = 1, \ldots, NO $$  

(10)

$$ \text{RMS Error (}$ e_{\text{rms}} $)$

$$ = \sqrt{\frac{1}{t_{\text{max}}} \sum_{i=1}^{t_{\text{max}}} \frac{1}{NO} \sum_{q=1}^{NO} (t_{qp} - o_{qp})^2} $$  

(11)

where $t_{qp}$ is the target output and $o_{qp}$ is the actual output of RBFN for $p^{th}$ pattern.

A. IEEE 30-Bus System

The IEEE 30-bus system consists of six generator buses, 24 PQ buses, and 41 lines. Out of 41 lines of the system, the load flow converged for 37 line outage cases only. Changing the load at each bus randomly from 50 to 150% of their base values, 300 load scenarios were generated and for each scenario, the voltage performance index was estimated, simulating each of the 37 contingencies. Out of 37 contingencies, 26 line outage cases were found to be noncritical for all of the load patterns. Thus, 11 cases of single line outages were selected in contingency list. The operating point of a power system is dynamic in nature mainly because of continually changing loads connected to it. Hence, real loads at all the PV and PQ buses and reactive loads at PQ buses only were used as a data set for input features selection for RBF network. Thus out of 53 variables, considering only nonzero values, 39 real and reactive loads at different buses were selected as the variables of the input vector. 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. For this system, two methods of feature selection were considered:

- Method 1: input features selected by inspection of network;
- Method 2: input features selected by statistical method based on class separability factor and correlation coefficient method.

**Method 1:** Line outage in a power system results in changes in voltages at a number of buses and power flows in several lines. It is observed that the terminal voltages of the contingent line and power flows in the vicinity of contingent line change a lot. Real and reactive load variations at a bus affect the bus voltage and, hence, the voltage performance index. Therefore, in this method, real and reactive loads at the terminal buses of the critical lines were selected as input features. Eighteen input features (ten for real loads and eight for reactive loads) were selected excluding the buses with zero real/reactive loads. As shown in Table I, the real load at buses 2, 5, 8, 11, 12, 19, 20, 21, 24, and 26, and reactive load at buses 8, 11, 12, 19, 20, 21, 24, and 26 were selected as input features. Reactive powers at bus 2 and bus 5 are not selected in the input features as they are PV buses.

The RBF network contains 18 neurons in the input layer and 11 in the output layer giving the values of voltage performance index corresponding to 11 critical line outages. Real and reactive load variations at a bus affect the bus voltage and, hence, the voltage performance index. Therefore, in this method, real and reactive loads at the terminal buses of the critical lines were selected as input features. Eighteen input features (ten for real loads and eight for reactive loads) were selected excluding the buses with zero real/reactive loads. As shown in Table I, the real load at buses 2, 5, 8, 11, 12, 19, 20, 21, 24, and 26, and reactive load at buses 8, 11, 12, 19, 20, 21, 24, and 26 were selected as input features. Reactive powers at bus 2 and bus 5 are not selected in the input features as they are PV buses.

The RBF network contains 18 neurons in the input layer and 11 in the output layer giving the values of voltage performance index corresponding to 11 critical line outages. Using these input features for training patterns, Euclidean distance-based clustering was applied to calculate the number of hidden units of RBF network. When the vigilance parameter was set to be 0.154, 188 clusters formed. The RBF network (18-188-11) required 35.324 s for 5000 iterations of training. After 5000 iterations, the training error was found to be 0.0435 while the maximum testing error was 0.7372. Further iterations did not result in improved testing performance.

**Method II:** In this case, separability factor $F$ of every variable [i.e., real and reactive load and correlation coefficient for all of the 39 variables were calculated as per (3) and (4) respectively]. For comparison of this method with method I, 18 features were selected, having high separability factor and low correlation coefficient among them. Table I lists the separability factor of the selected variables. It can be observed from Table I that most of the features selected by this method are different from those selected by the first method. The input features are mostly the reactive power injections (16 out of 18 features) that are desirable also as voltage is directly affected with the reactive power loads.

The RBFN model used contained 18 neurons in the input layer, 11 neurons in the output layer, and 187 neurons in the hidden layer when the vigilance parameter was set to 0.19. The developed RBF network (18-187-11) took 35.214 s for 5000 iterations of training. After 5000 iterations, the training error was found to be 0.0213 and the maximum testing error was 0.4484. Further training resulted in reduced training error; still the testing performance was satisfactory. It was observed that the training in this case was faster and also its performance was better as compared to the first method. Hence, this method is adopted in this work.

The trained RBF network produces inaccurate estimates of voltage PI for some of the testing patterns. This may be due to the existence of noncontiguous pockets in the input space [10]. Hence, unsupervised learning was performed to group similar types of input patterns in one cluster. Taking tolerance parameter of 0.313, three stable clusters were formed in 11 iterations. Hence, three separate RBF networks were trained. Table II gives the training and testing details and number of hidden nodes for each cluster. One-hundred eighteen, 89, and 93 patterns were grouped in first, second, and third cluster, respectively. The optimum size of the three RBF network was found to be (18-85-11), (18-67-11), and (18-65-11) with vigilance parameters equal to 0.164, 0.18, and 0.164, respectively. CPU time required for training of the three RBF networks was 33.872, 24.073, and 21.521 s, respectively. During testing phase, the RBF networks provided the results almost instantaneously while ac load flow (NR) method required 0.031 s to calculate the voltage performance indices of the 11 critical contingencies.

When comparing the performance of this model with MLP model, it was observed that RBF network (18-85-11) required CPU time of 11.693 s for 5000 iterations with training error reduced to 0.0869, while the three-layered MLP model of the same structure required 20.471 s for 5000 iterations with total training error reduction to 1.953. In both cases, same values of initial learning rate and momentum were used along with adaptive learning rate. Testing performance of RBF network was
comparable with MLP model but faster learning and testing of RBF made it superior to MLP for online implementation. Furthermore, RBF does not get stuck in local minima and generalize well after training. The numbers of hidden nodes in RBF are determined by the clustering algorithm but in MLP it is difficult to decide about the number and size of hidden layers and a hit and trial method is used.

Ranking, based on the PI output of RBFN, of all the critical contingencies for only five testing patterns of cluster-1 are presented in Table III, according to their severities due to limited space. As it can be observed from Table III, the ranking order of contingencies is not the same for different load scenarios, though outage of line number 20 is most severe in all of these cases. It is found that the ranking by ac load flow and the RBFN method are the same for all of the patterns. Table IV compares the ranking performance of the trained RBFN with full ac load flow for a particular pattern of cluster-2. It is observed that the ranking by the RBFN closely matches to the ranking by load flow for all of the clusters. The errors in computation of PI with RBF network is very close to the value obtained by the full ac load flow method. Outage of line-20 connected between bus 15 and 18 is found to be most severe for all the loadings. From Fig. 3, it is seen that the maximum error occurs in the case of line-2 outage.

These results are given for a given topology (base case). Change in the system topology due to outage of lightly loaded line, the same weights of RBF will give the accurate results. The results of change in topology due outage of line-32 for a pattern is given in Table V. However, for critical lines, trained weights can be stored and used for ranking the contingencies of the changed topology. Moreover, the training of the weight required less time compared to other ANN approach which makes this possible to update the weights offline.

**B. Indian 75-Bus System**

The 75-bus Indian system has 15 generator buses, 60 load buses, and 114 lines. 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 line are viewed as one kind of single outage. Therefore, 70 single line outages are chosen in the contingency set. The training and testing patterns were created by varying the load at each bus from 80% to 120% of the base case in the 400 randomly selected steps. Out of 76 real and reactive loads (nonzero), 25 features were selected as input features to the RBF based on class separability index and correlation coefficient. Here, input features based on the general observation are not considered as it is not giving the accurate results. For this system with above load variations, MLP gives misranking [17].

Table VI shows the list of the selected 25 variables. Thirteen single line contingencies are short listed as critical out of 70 contingencies. Thus, the input layer of the RBFN contains 25 neurons and the output layer consists of 13 neurons. Taking a vigilance parameter of 0.289, input patterns of similar types were grouped into one cluster using unsupervised learning (Euclidean distance-based clustering) and, thus, three stable clusters were formed in 11 iterations. Hence, three separate RBF

---

**TABLE III**

IEEE 30-Bus System - Ranking of Line Outages in Cluster 1

<table>
<thead>
<tr>
<th>Pattern No.</th>
<th>Methods</th>
<th>Ranking of contingencies according to severities (line outage numbers)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Load Flow</td>
<td>20, 27, 1, 2, 29, 4, 5, 11, 30, 23, 31</td>
</tr>
<tr>
<td>2</td>
<td>RBFN</td>
<td>20, 27, 1, 2, 29, 4, 5, 11, 30, 23, 31</td>
</tr>
<tr>
<td>3</td>
<td>RBFN</td>
<td>20, 27, 1, 2, 29, 4, 5, 11, 30, 23, 31</td>
</tr>
<tr>
<td>4</td>
<td>Load Flow</td>
<td>20, 27, 1, 2, 29, 4, 5, 11, 30, 23, 31</td>
</tr>
<tr>
<td>5</td>
<td>RBFN</td>
<td>20, 27, 1, 2, 29, 4, 5, 11, 30, 23, 31</td>
</tr>
</tbody>
</table>

**TABLE IV**

IEEE 30-Bus System - Ranking Performance of RBFN for Cluster 2

<table>
<thead>
<tr>
<th>Line outage</th>
<th>Full AC load flow</th>
<th>RBF</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>0.9000</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>0.7572</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>0.5479</td>
<td>3</td>
</tr>
<tr>
<td>23</td>
<td>0.7367</td>
<td>4</td>
</tr>
<tr>
<td>27</td>
<td>0.5479</td>
<td>3</td>
</tr>
<tr>
<td>29</td>
<td>0.1810</td>
<td>7</td>
</tr>
<tr>
<td>11</td>
<td>0.1810</td>
<td>7</td>
</tr>
<tr>
<td>1</td>
<td>0.1810</td>
<td>7</td>
</tr>
</tbody>
</table>

**TABLE V**

Ranking Performance of RBFN for Different Topology

<table>
<thead>
<tr>
<th>Line outage</th>
<th>Full AC load flow</th>
<th>RBF</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>0.9000</td>
<td>1</td>
</tr>
<tr>
<td>27</td>
<td>0.7000</td>
<td>2</td>
</tr>
<tr>
<td>30</td>
<td>0.6191</td>
<td>3</td>
</tr>
<tr>
<td>11</td>
<td>0.3952</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>0.3679</td>
<td>5</td>
</tr>
<tr>
<td>23</td>
<td>0.3017</td>
<td>6</td>
</tr>
<tr>
<td>17</td>
<td>0.2870</td>
<td>7</td>
</tr>
<tr>
<td>31</td>
<td>0.2668</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>0.2446</td>
<td>9</td>
</tr>
<tr>
<td>4</td>
<td>0.2190</td>
<td>10</td>
</tr>
<tr>
<td>29</td>
<td>0.1012</td>
<td>11</td>
</tr>
</tbody>
</table>

Fig. 3. IEEE 30-bus system - errors in PI calculations in cluster-3.
networks were trained. The number of hidden nodes for each cluster and the training and testing details are given in Table VII. In first, second, and third clusters, 168, 118, and 114 patterns, respectively, were grouped. In this case, the optimum size of the three RBF network was found to be (25-122-13), (25-83-13), and (25-81-13) with vigilance parameter of 0.18 for clusters 1, 2, and 3, respectively.

Ranking of all the critical contingencies for only five testing patterns of cluster-1 are presented in Table VIII according to their severities. It is found that the ranking by ac load flow and the RBFN method are the same for all of the patterns except for few misranking; however, all of the critical contingencies are selected with minor change of their severity order. From Table VIII, it is seen that for pattern 2, line outage contingency 13 is ranked lower to line outage 47 because the PI values of both the contingencies are very close to each other. Similar situation is also observed in some other patterns. It is found that line-46 outage connected between bus 38 and 29 ranks the topmost in the severity list for the most of the cases. The ranking performance of the RBFN is compared with full ac load flow and is given in Table IX for only one pattern of cluster-2 due to space constraint. It can be seen that the ranking order of RBFN closely matches with ranking based on full ac load flow. Fig. 4 shows errors in the PI calculation between ac load flow and RBFN for all of the patterns for line outages numbers (LO) 13, 14, and 43 of cluster-3.

IV. CONCLUSIONS

Radial basis function neural network model has been developed to estimate and rank the severity of selected critical contingencies accurately and rapidly. Linear output layer and radial basis hidden layer structures of RBF neural networks provide the possibility of learning the connection weights efficiently without local minima problem. The training of RBF neural network requires less computation time as compared to the MLP model, since only the second layer weights have to be calculated using error signal. The training of RBF networks has been made still faster by applying adaptive learning rate and momentum.
Class separability index and correlation coefficient-based technique has been used to identify the relevant features as inputs to the RBF network.

Once trained, the RBF networks are able to estimate the voltage performance indices of all the critical contingencies under any loading condition almost instantaneously and screens them accurately whereas the computation of voltage performance index 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. The ranking of the contingencies are almost the same except few misranking because the PI values of misranked contingencies are very close to each other. Test results of the two sample systems given in this paper and of other systems also reveal that the trained RBF network is capable of online voltage contingency ranking under uncertain loading conditions and is expected to perform similarly on even larger systems and handle even greater number of contingencies than reported here. The proposed approach can be used for multiple contingency cases as well.

REFERENCES


L. Srivastava received the M.Tech. degree from the Indian Institute of Technology, Kanpur, India, in 1996, and the Ph.D. degree from University of Roorkee, Roorkee, India, in 1998. Currently, she is a Reader in the Department of Electrical Engineering at Madhav Institute of Technology and Science, Gwalior, India. Her research interests include power systems security and artificial neural network (ANN) application to power systems.

S. N. Singh (SM’02) received the M. Tech. and Ph.D. degrees from the Indian Institute of Technology, Kanpur, in 1989 and 1995, respectively. Currently, he is an Associate Professor in Electrical Engineering at the Indian Institute of Technology. His research interests include power system restructuring, power system optimization and control, voltage security and stability analysis, power system planning, artificial neural network, and genetic algorithm (GA) application to power system problems and transient stability.