Fast Voltage and Power Flow Contingencies Ranking using Enhanced Radial Basis Function Neural Network

D. S. Javan*, H. Rajabi Mashhadi* and M. Rouhani**

Abstract: Deregulation of power system in recent years has changed static security assessment to the major concerns for which fast and accurate evaluation methodology is needed. Contingencies related to voltage violations and power line overloading have been responsible for power system collapse. This paper presents an enhanced radial basis function neural network (RBFNN) approach for on-line ranking of the contingencies expected to cause steady state bus voltage and power flow violations. Hidden layer units (neurons) have been selected with the growing and pruning algorithm which has the superiority of being able to choose optimal unit's center and width (radius). A feature preference technique-based class separability index and correlation coefficient has been employed to identify the relevant inputs for the neural network. The advantages of this method are simplicity of algorithm and high accuracy in classification. The effectiveness of the proposed approach has been demonstrated on IEEE 14-bus power system.

Keywords: Static Security Assessment, Neural Network, Feature Selection, Contingency, Performance Index.

1 Introduction

Power system security and contingency evaluation is one of the most important tasks encountered by planning and operation engineers of bulk power systems. Security assessment has been historically conducted in an offline operation-planning environment in which the steady-state and dynamic performance of the near-term forecasted system conditions are exhaustively determined using tools such as full AC power flow and time domain simulations. These deterministic computation methods exhaustively examine many contingencies and search for security limits using a rigorous approach. Although this approach provides the most accurate results available, it is computationally burdensome and, therefore, time consuming. The present trend toward deregulation has forced modern electric utilities to operate the systems under stressed operating conditions closer to their security limits. Under such fragile conditions, any disturbance could endanger system security and may lead to system collapse [1-2]. Therefore, fast and accurate security monitoring method has become a key issue to ensure secure operation of the system.

Variety of algorithms were developed for contingency analysis, the most popular being the Performance Index (PI) based method [3-4]. Performance index quantifies the severity of contingencies by calculating their PI values and to rank them accordingly. To achieve accurate ranking, each PI value would need to be calculated from the results of a full AC load flow [5-7]. This process is time consuming and unsuitable for on-line use.

To overcome these shortcomings, these applications can be linked to an Intelligent System (IS) [8-13] that can utilize the accumulated knowledge from previous calculations (stored in a database), utilize rules set by experts, and make inferences based on system conditions. In this way, security (and security limits) can be found rapidly without extensive simulations. In recent years, there is growing trend in applying these methods for the operation and control of a power system [14-17].

The artificial neural networks (ANNs) are the most popular method among machine learning methods and have been proposed for the static and dynamic security assessment [18-19], which usually encounters to local minimum and over-fitting problems. Application of Support Vector Machines (SVM) for security assessment has been reported in [20-21]. In these references, the superior performance of SVM over ANN

in terms of accuracy, speed and distribution of high-risk cases has been presented for security evaluation of a large-scale power system. However, SVM learning algorithms suffer from exceeding time and memory requirements, if the training pattern set is very large. SVM based binary classification for static and transient security evaluation is proposed in [22] and levels of power system security are just classified in two classes of secure and insecure. Also, literatures have reported the use of decision trees [23] for design of classifier.

In this paper, an enhanced Radial Basis Function Neural Network based on Growing and Pruning algorithm (GPRBFNN), which automatically selects the optimal units (neurons) and distributions, has been presented. The proposed method ranks the contingencies expected to cause steady state line power and bus voltage violations. Results of the contingency rankings by the proposed method are compared with those obtained by the classical performance index method (Newton Raphson). Different status for system security levels, such as secure, correctively secure, alert, correctable emergency and non-correctable emergency have been considered and the proposed neural network has been used to classify the power system security. Moreover, an approach based on the class separability index and correlation coefficient [24] is used to select the relevant features for the GPRBFNN. The performance of the presented method has been demonstrated on IEEE 14-bus system and found to be fitting for online ranking of contingencies.

2 Methodology

The comprehensive block diagram of the proposed method is presented in Fig. 1. A large number of load patterns are generated haphazardly in a wide range of load variation at each bus and for different contingency cases. The input features are preferred using the feature selection method to reduce the dimensionality of the input and the size of the neural network (block I). The selected input is normalized (block II). Proposed algorithm has been utilized to determine the number of nodes in the hidden layer and cluster position (block III). The input data are straightly fed to these hidden units and the weights between the hidden layer and the output layer are adjusted using supervised learning (block IV) so that the outputs of the RBFNN provide accurate values of the voltage and power flow ranking in each of the selected critical contingencies.

RBFNN is used for solving problems such as pattern classification and nonlinear functional approximation [25]. The form of the radial basis function, $O_j(x)$, is strictly positive and symmetric with a unique maximum at the center. The most commonly used form is the Gaussian function according to:

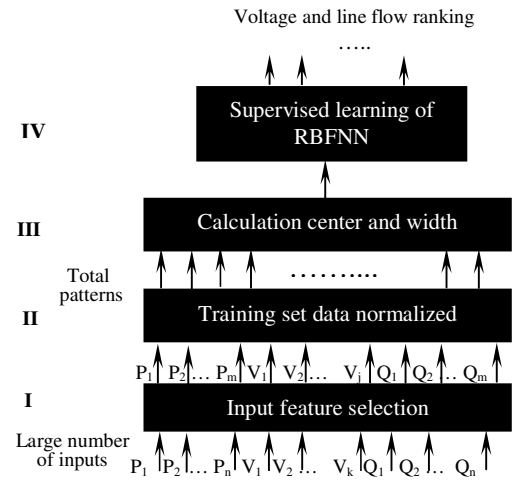$$Q_j(x) = \exp\left(-\left(\frac{\| x - C_j \|}{2\sigma_j}\right)^2\right) \quad (1)$$

Fig. 1 Conceptual diagram of a supervised learning model for voltage and power line contingency ranking.

where, $C_j = \left[c_{j_1}, c_{j_2}, \ldots, c_{j_m}\right]^T$ is the field centers matrix and σ_j is the radius in the function.

3 Proposed Algorithm of Enhanced Radial Basis Function Neural Network

In the traditional RBFNN, if the number of neurons in hidden layer is too small, the generalized output vectors may be in low accuracy. Conversely, too large a number may cause over-fitting of the input data, as well as upsetting the global generalization performance. A problem significantly found in RBFNN design, however, is selecting the appropriate number and positions of the radial basis functions in the hidden layer space. If the number of RBFN neurons is not selected properly, the network may give out poor global generalization capability, slow training speed, and large memory space request. Still, a second problem, from a classification point of view, is the boundary patterns where clusters of each class contain data from other classes. In the proposed algorithm, the boundary region separates various classes and the patterns of each class lie in their corresponding clusters.

The incremental training algorithm is outlined as follows:
a) Suppose the classes A and B follow m and n patterns respectively.
b) Calculate the distance between m patterns in class A and n patterns in class B:

$$P_i = \begin{bmatrix} \|a_1 - b_1\| & \cdots & \|a_1 - b_n\| \\ \vdots & \ddots & \vdots \\ \|a_m - b_1\| & \cdots & \|a_m - b_n\| \end{bmatrix} \quad (2)$$

c) Find the minimum distance from pattern a_i to patterns of class B in every row of P_i:

$$\text{Dis}(a_1, B) = \min((\|a_1 - b_1\|, \ldots, \|a_1 - b_n\|)$$
$$\vdots \qquad\qquad \vdots \qquad\qquad (3)$$
$$\text{Dis}(a_m, B) = \min((\|a_m - b_1\|, \ldots, \|a_m - b_n\|)$$

d) Determine the maximum distance from (4); then, consider R_{a_j} and a_j as the radius and center for the first neuron and cluster of class A:

$$R_{a_j} = \max(\text{Dis}(a_1, B), \ldots, \text{Dis}(a_m, B)) \qquad (4)$$

e) Calculate the distance between patterns of class A with each other:

$$Q_i = \begin{bmatrix} \|a_1 - a_1\| & \cdots & \|a_1 - a_m\| \\ \vdots & \ddots & \vdots \\ \|a_m - a_1\| & \cdots & \|a_m - a_m\| \end{bmatrix} \qquad (5)$$

f) Sort the distance from other patterns in class A:

$$\|a_j - a_1\|, \|a_j - a_2\|, \ldots, \|a_j - a_m\| \qquad (6)$$

g) Remove the patterns of class A for smaller distances than R_{a_j} and label it as the first cluster.

For the remainder of the patterns of class A which have larger distances than R_{a_j}, continue the process until all patterns in class A are eliminated.

h) Repeat the algorithm for the n patterns of class B.

Fig. 2 graphically illustrates the procedure of clustering stages for an artificial data set. In the presented algorithm, Steps (b) to (d) seek the optimum center and radius:

$$\forall a_i \in A \,\&\, b_j \in B \Rightarrow R_{a_i} = \text{Max}_i \text{Min}_i \quad \text{norm}_2(a_i, b_{j=1,2,\ldots,n}) \quad (7)$$

where, R_{a_i} and a_i are the selected radii and center set for class A. Steps (e) to (g) contrast the pattern selected as the centre with other patterns of class A and if distances are smaller than the selected radius, they are placed in one cluster and the algorithm is repeated for the remainder of patterns in class A which are outside the cluster [Fig. 2(a) and Fig. 2(c)]. Therefore, the proposed algorithm is repeated until all patterns of class A sit in their optimum clusters [Fig. 2(b) and Fig. 2(d)]. Finally, by performing the proposed algorithm, three optimum clusters can be found for each of the two classes of Fig. 2.

The construction of GPRBFNN, in its most basic form, involves three layers with entirely different roles as shown in Fig. 3. The first layer is an input layer of which each node corresponds to an attribute of an input pattern. The second layer is a hidden layer and the transformation from the input layer to the hidden layer is nonlinear, whereas it is constructed using the proposed algorithm. The third layer gives the network output vector which is a linear combination of the basis function outputs. Thus, for the GPRBFNN having l-neurons, the relationship between an n-dimensional output vector $Y = [y_1, y_2, \ldots, y_n]^T$ and an m-
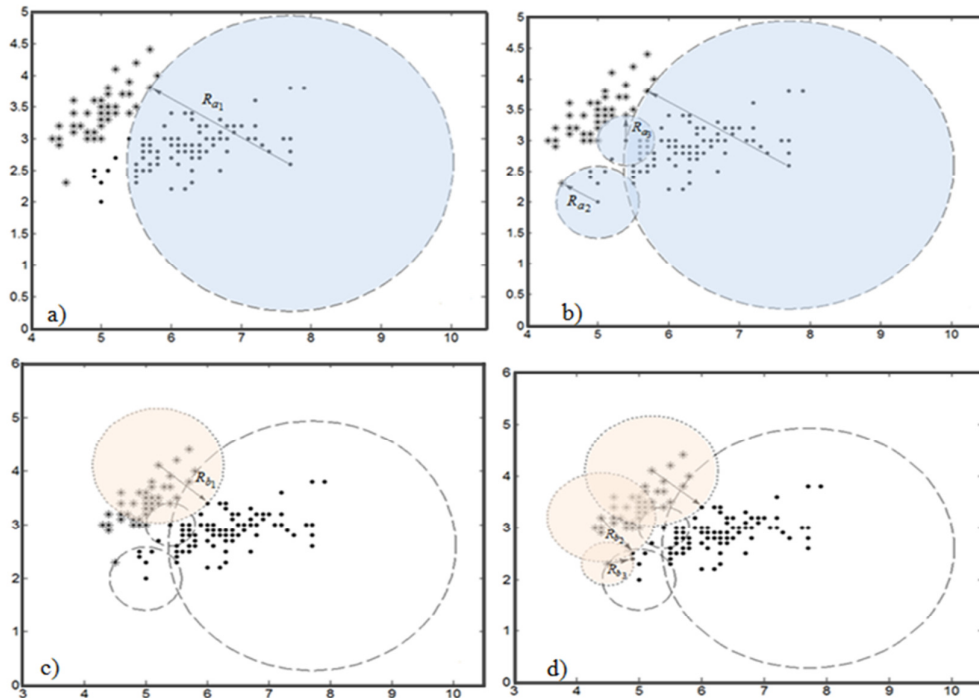

Fig. 2 Classification of an artificial dataset. Patterns of class A and B are shown with bold dots and stars.
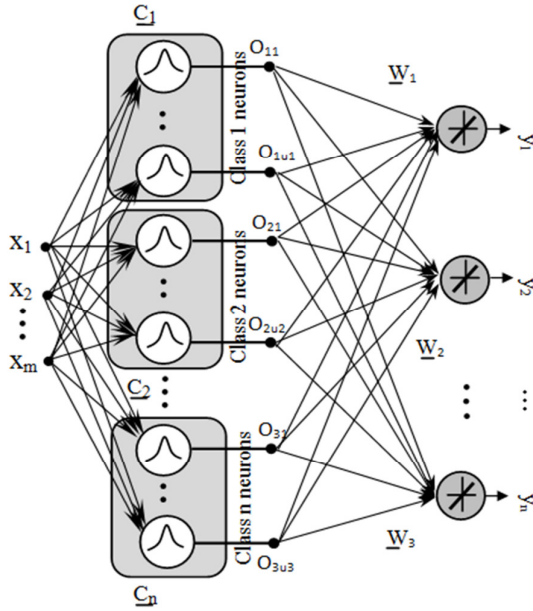
Fig. 3 Structure of GPRBF neural network.

dimensional input vector $X = [x_1, x_2, \ldots, x_m]^T$ can be expressed as:

$$y_i(x) = \sum_{j=1}^{l} w_{ij} O_j(x) \tag{8}$$

By minimizing the Sum of Square Error (SSE), the weight matrix (W) is defined as:

$$SSE = \sum_{p=1}^{P} \left\| d_p - W \times O_p \right\|^2 \tag{9}$$

where, d_p is a desirable output and P is number of patterns. In the matrix form:

$$SSE = (\underline{D} - W \times \underline{O})^T \times (\underline{D} - W \times \underline{O}) \tag{10}$$

where, $\underline{D} = [\underline{d}_1, \underline{d}_2, \ldots, \underline{d}_P]_{n \times P}$ and $\underline{O} = [\underline{o}_1, \underline{o}_2, \ldots, \underline{o}_P]_{l \times P}$ are desirable matrix and output matrix of the hidden layer respectively. Finally, objective function is the minimized SSE that can be expressed as:

$$\underset{W}{\text{Min}} \quad (\underline{D} - W \times \underline{O})^T \times (\underline{D} - W \times \underline{O}) \Rightarrow$$
$$\Rightarrow W = \underline{D} \times \underline{O}^T \times (\underline{O} \times \underline{O}^T)^{-1} \tag{11}$$

4 Performance Index

The standard approach for steady state contingency checking is to run a load flow for the post-transient steady state status following each outage. Some of the outages may lead to system constraint violations such as load bus voltages outside their normal limits and transmission line (transformer) overloads. The system performance index is described as a penalty function to penalize gravely any violation of bus voltage limitations or line flow constraints.

By adding the penalty functions together, the method may suffer from a masking effect. In fact, the lack of discrimination in which the performance index for a case with many small violations can be comparable in value to the index for a case with one huge violation, is known as masking effect. Masking effect, to some extent, can be avoided by using higher order performance indices. However, to avoid the misranking, proper selection of weights for performance indices is required. Some of the efforts in reducing these effects include the works of [26-27]. To overcome the masking, one can try to raise the exponent used in the penalty functions.

4.1 Voltage and Power Line Performance Indices

The voltage performance index is selected to quantify system lack due to out-of limits bus voltages and measures the severity of contingencies. There are several types of performance indices in literature [28] but following voltage performance index has been acquired in this paper:

$$PI_V = \sum_{i=1}^{LV} \left(\frac{W_i}{M} \right) \left(\frac{f_i}{\Delta V_{lim}} \right)^M \tag{12}$$

$$f_i = \begin{cases} V_i - V_i^{max}, & V_i \rangle V_i^{max} \\ V_i^{min} - V_i, & V_i \langle V_i^{min} \end{cases} \tag{13}$$

where, f_i is a function of limit violated buses only, V_i is the post contingent voltage at the ith bus, ΔV_{lim} the voltage deviation limit, V_i^{min} and V_i^{max} are the lower and upper limit of voltage magnitudes at i^{th} bus, W_i (=1) is the weighting coefficient, and M is the order of the exponent. If the enumerated PI_V value is greater than zero, then the corresponding contingency is recognized as critical or insecure; otherwise, it is secure.

An index for quantifying the extent of line overloads may be defined in terms of MW performance index:

$$PI_{MW} = \sum_{l=1}^{N_L} \left(\frac{W_{l_i}}{2n} \right) \left(\frac{P_l}{P_l^{lim}} \right)^{2n} \tag{14}$$

where, P_l and P_l^{lim} are the MW flow of line l and the MW capacity of line l, N_L is the number of system lines, W_{li} and n are real nonnegative weighting factor(=1) and exponent of penalty function, respectively. This index PI_{MW} has a small value, when all line flows are within their limits and a high value when there are line overloads. Thus, it provides a measure of the severity of line overloads for a given state of the power system.

It should be pointed out that the weighting factors W_i and W_{li} can be regarded as tuning parameters. These factors are selected on the basis of experience with the system and on the relative importance placed on the various limit violations. Moreover, it is observed from simulation that for M=4 and n = 2, masking effect has been removed for the IEEE 14-bus test system.

4.2 Security Index

In order to quantify the concept of secure and insecure operating states, five severity levels have been determined. The four critical levels are correctively secure, alert, correctable emergency and non-correctable emergency and are represented by the hypotheses $\{H_1, H_2, H_3, H_4\}$, and one non-critical level is shown by $\{H_0\}$. In this way, term of $\{H_4\}$ represents which all loads supplied but operating limits are violated. These cannot be corrected without loss of load. For ranking the severity of contingencies, single line and generator outages corresponding to each load pattern are also simulated by full AC load flow to calculate the voltage and power line performance index. Based on the calculated performance index, the voltage and power flow security status can be determined, according to Table 1.

5   Generation of Training Data

The RBFNN learning methods are found on our knowledge about the behavior of the system, performed from a large number of off-line simulations. In this way, load patterns were generated randomly by changing the load at each bus in a wide range. Training data should be able to represent the whole operating space of power system. For this purpose, for each load bus a corresponding upper and lower limit (P_L^{max}, P_L^{min}) is defined which represent boundary of daily load variation. Considering this point, Fig. 4 shows the methodology used in generating data for training and testing of the proposed neural network. For each data set, in order to obtain an estimate of the generalization error, five-fold cross-validation was used, i.e., five experiments were conducted, just one of the folds used for testing.

6   Feature Selection

Feature selection is performed to recognize 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 proper features of the data, training time and size of the neural network can be reduced [29]. Many feature selection algorithms are available in the literature such as fisher discrimination analysis [30] and entropy maximization. The main problem with the existing feature algorithms is that it

works well with linearly separable classes, but not well established on non-linearly separable classes [31].

A usual procedure includes exploiting the crisp secure-insecure classification provided by class separability index (F) and correlation coefficient [24] is used to select appropriate training feature for the GPRBFN. F is defined by expression according to:

$$F_i = \frac{\left| m_i^{(S)} - m_i^{(I)} \right|}{\sigma_i^{(S)} + \sigma_i^{(I)}} \tag{15}$$

where, $m_i^{(S)}$ and $m_i^{(I)}$ are the mean values of variable i in the secure and insecure classes, respectively, $\sigma_i^{(S)}$ and $\sigma_i^{(I)}$ are the corresponding standard deviations. Variables with greater F have more discriminating power, and are chosen as relevant attributes. Correlation coefficient between the variables with greater F is calculated using the expression below:

$$C_{ij} = \frac{E\{x_i x_j\} - E\{x_i\} E\{x_j\}}{\sigma_i \sigma_j} \tag{16}$$

7   Results and Discussion

To demonstrate the effectiveness of the proposed GPRBFNN model, it has been tested for static security evaluation of IEEE 14-bus system to rank the contingencies expected to cause steady state power flow and bus voltage violations at different loading conditions (%60 to %140 of base load) and contingencies. Load flow analysis has been carried out using the Power System Analysis Toolbox (PSAT) [32]. Training and testing results are simulated on Pentium IV 2.8 GHz, 512 MB RAM, 40GB Hard drive.

The performance of the GPRBFN is determined by evaluating the following measures during training and testing phases:

1) Mean of Absolute Percentage Error (MAPE):

$$APE_i(\%) = \left| \frac{NNO_i - DO_i}{DO_i} \right| \times 100 \tag{17}$$

$$MAPE(\%) = \frac{1}{N} \sum_{i=1}^{N} APE_i \tag{18}$$

where N, NNOi and DOi are the number of samples in the data set, neural network output and desired output obtained from off-line simulation, respectively.

Table 1 Security levels for classification of line overloads and out-of limits bus voltages.

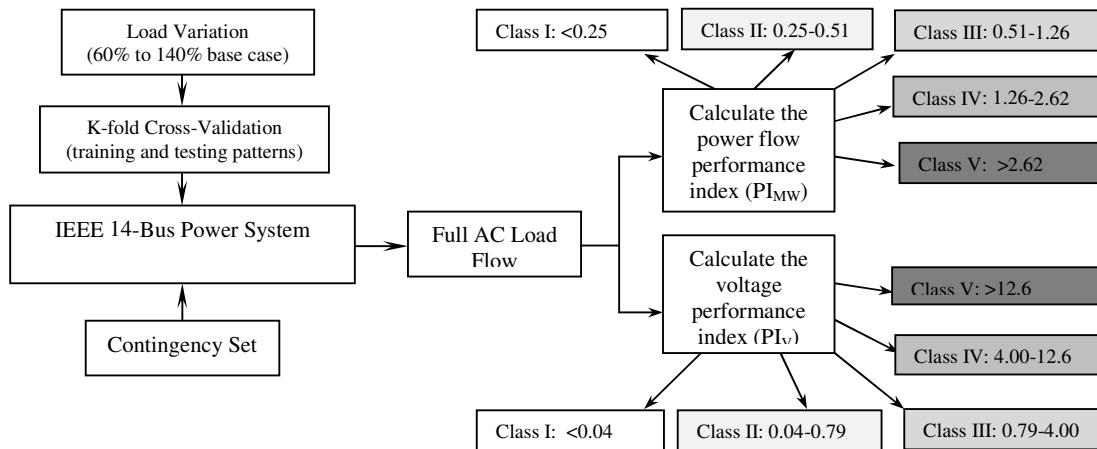| Security level	Line flow (%)	PI$_{MW}$	Voltage Deviation (%)	PI$_V$
Secure (H$_0$)	<100	<0.25	<10	<0.04
Correctively Secure (H$_1$)	100-120	0.25-0.51	10-20	0.04-0.79
Alert (H$_2$)	120-150	0.51-1.26	20-30	0.79-4.00
Correctable Emergency (H$_3$)	150-180	1.26-2.62	30-40	4.00-12.60
Non-correctable Emergency (H$_4$)	>180	>2.62	>40	>12.60

Fig. 4 Methodology for data generation contingency analysis using neural network.

2) Mean of Square Error (MSE):

$$MSE = \frac{1}{N}\sum_{k=1}^{N}\left|NNO_k - DO_k\right|^2 \qquad (19)$$

3) Classification Accuracy (CA):

$$CA(\%) = \frac{\text{No. of samples classified correctly}}{\text{Total No. of samples in data set}} \times 100 \quad (20)$$

7.1 IEEE 14-Bus System

IEEE 14-bus is the test system which contains 2 generators, 14 buses, 20 lines and 3 condensers. This power system is shown in Fig. 5.

Input features are selected by a statistical method based on class separability index and correlation coefficient technique. Separability factor of every variable of the power system was calculated as per (15) and (16), respectively. In Table 2, 12 features were selected, having high separability factor and low correlation coefficient among them.

A total of 800 (contingencies) load flow cases are selected for the load scenarios using different lines and generation outages to compute the voltage performance indices and determine the security levels as pointed out in Table 1. After training, the optimum size of the GPRBFNN was found to be (12-284-5) which each of the security status of secure, correctively secure, alert, correctable emergency and non-correctable emergency has 42, 105, 94, 40 and 3 neurons (clusters) in the hidden layer, respectively. GPRBFNN was tested using different sets of load flow cases that were not used during the training process. For testing, 80 load flow cases are selected using different transmission lines and generator outages.

It can be observed from Table 3 that the column corresponding to the voltage contingency ranking obtained by GPRBFNN for different loading conditions is almost same as that obtained by the Newton Raphson (NR). The ranking order of similar contingencies is not the same for different load scenarios such as the line outage between bus 1 and bus 2. In addition, it can be seen that GPRBFNN method has a considerable performance than classical RBFNN. As it can be observed from Table 3, the outage of L_1 is most severe in all of these cases. The bold outages indicate the misclassified contingencies.

Table 2 Class separability index F for IEEE 14-bus system.

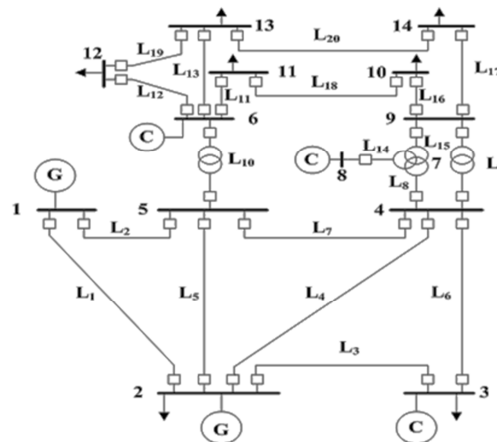| Feature No.	Variables	Separability Index F
1	V_9	0.74
2	$Phase_{14}$	0.33
3	$Qload_{13}$	0.99
4	$Qload_{11}$	0.80
5	Qsc_8	0.65
6	$Pline_{7-9}$	0.60
7	$Pline_{6-13}$	0.34
8	$Qline_{4-9}$	0.36
9	$Qline_{5-6}$	0.37
10	$Qline_{6-3}$	0.68
11	$Qline_{7-8}$	0.62
12	$Qline_{12-13}$	0.36

Fig. 5 IEEE 14-bus test system.

Table 3 IEEE 14-bus system-Voltage ranking at different loading conditions.

No	Loading		Line/Gen From/To	PI_V	Contingency Ranking		
	P (MW)	Q (MW)			Load Flow (NR)	RBFNN	GPRBFNN
1	360.48	50	1-2	5.72	H_3	$\mathbf{H_0}$	H_3
2	412.87	60	2-3	0.43	H_1	H_1	H_1
3	26861	80	9-14	0.89	H_2	$\mathbf{H_4}$	H_2
4	423.37	55	G_8	0.11	H_1	H_1	$\mathbf{H_0}$
5	353.32	73	1-2	14.65	H_4	$\mathbf{H_2}$	H_4
6	306.65	40	G_1	0.53	H_1	H_1	H_1
7	310.60	62	6-11	0.92	H_2	H_2	H_2
8	299.34	85	10-11	0.51	H_1	$\mathbf{H_0}$	H_1
9	378.33	63	5-6	0.80	H_2	$\mathbf{H_0}$	H_2
10	324.39	78	G_6	0.31	H_1	H_1	H_1

The proposed algorithm is performed for contingencies ranking of line overload severity and the optimum size of the GPRBFNN was found to be (12-215-5) which each of the security classes has 31, 53, 72, 49 and 10 neurons (clusters) in the hidden layer.

In Table 4, the IEEE 14-bus system was tested for 20 single line outage cases and five generator outage cases to identify the most severe lines or generators contingencies on line overloads at 120% loading. Such critical contingencies should be quickly identified for further detailed evaluation or, where possible, corrective measures taken.

In all of the obtained results, the preference of GPRBFNN method in fast and accurate ranking of the contingencies expected to cause steady state line power and bus voltage violations is obvious respect to the classical RBFNN method.

Table 5 shows the obtained results of the GPRBFNN and RBFNN for steady state security evaluation in a wide range of loading. The proposed method has enough speed to evaluate the power system security in ranking of voltage violated buses and line overload severities. As we know, the RBF neural network is a famous tool for pattern classification and nonlinear functional approximation. However, the results of Tables imply that in almost all cases, the classical RBFNN gives the largest errors due to their limitations in optimum clustering.

7.2 Computation Burden

One of the main shortcomings attributed to classical radial basis function neural network (RBFNN) is their long training process. This is basically because of the iterative nature of training of such networks. Inability in choosing proper unit's center and width (radius) and also numbers of optimal neurons in hidden layer causes to take long time for training process. In this neural network, neurons are being added to the hidden layer till the classical algorithm converges to a tuning error.

However, using the proposed algorithm, the enhanced neural network determines automatically appropriate centers and radii.

As shown in Table 5, the training process of RBF neural network for voltage and power flow contingencies ranking takes 40.60 and 33.13 seconds, respectively. On the other hand, the training process of the proposed method (GPRBFNN), for the same data and on the same computer, takes 9.8 seconds. The main reason is the non-iterative nature of the GPRBFNN, which also brings more stability over the classical RBFNN.

8 Conclusion

The analytical method for contingency evaluation consists of the computation of the performance indices by running full AC load flow for all contingencies which is both time consuming and susceptible to miss ranking effects.

Table 4 IEEE 14-bus system-PI_{MW} ranking of generator and power line outages at 120% loading.

Loading (%)	Methods	Ranking of contingencies according to severities (line & generator outages)				
		Secure	Correctively secure	Alert	Correctable emergency	non-Correctable emergency
120	Load Flow	G_8	L_{14}	G_3,G_6,L_{19}	$G_2,L_{13},L_9,L_{15},L_{11},L_5,L_{20},L_8$ $L_{17},L_6,L_{12},L_{16},L_{18}$	$L_1,L_3,L_{10},L_2,L_4,L_7$
	RBFNN	$\mathbf{L_3, L_5}$ $\mathbf{L_8}$	$\mathbf{G_8}$	G_3,G_6,L_{19} $\mathbf{L_4,L_{10},L_{18}}$	$G_2,L_{13},L_9,L_{15},L_{11},\mathbf{L_{14}}$ $L_{17},L_6,L_{12},L_{16},L_{20}$	L_1,L_2, L_7
	GPRBFNN	G_8	L_{14}	$G_3,\mathbf{L_{15}},G_6,L_{19}$	$G_2,L_{13},L_9,L_{11},L_5,L_{20},L_8,L_{17}$ L_6,L_{12},L_{16},L_{18}	$L_1,L_3,L_{10},L_2,L_4,L_7$

Table 5 IEEE-14 bus system- obtained results of voltage and power flow ranking performance at different loading conditions.

| | Voltage Performance Index Ranking | | | | Power Flow Performance Index Ranking | | | |
| | Train Set | | Test Set | | Train Set | | Test Set | |
	RBFNN	GPRBFNN	RBFNN	GPRBFNN	RBFNN	GPRBFNN	RBFNN	GPRBFNN
No. Neuron	431	284	431	284	512	215	512	215
MSE	0.163	0.009	0.83	0.012	0.093	0.010	0.563	0.015
MAPE (%)	2.93	1.07	12.03	3.77	2.10	0.69	9.98	1.150
CA (%)	93.14	97.12	88.14	95.20	94.03	98.12	84.30	96.03
Time (s)	40.60	9.8	1.03	0.52	33.13	9.8	1.14	0.65

Radial basis function neural network based on Growing and Pruning algorithm has been proposed to evaluate static security of IEEE 14-bus power system. The proposed neural network approach to contingency analysis consists of training the ranking module for different contingencies corresponding to voltage violated buses and power flow (MW) violated lines. The ranking module provides accurate levels of performance indices (PI$_V$, PI$_{MW}$) for unknown load patterns, which are compared with Newton Raphson method. In the presented algorithm, optimum centers and corresponding radii are obtained. So, the training of RBFN based on Growing and Pruning algorithm requires less computation time and the testing accuracy of RBFN has been made higher by applying it. Test results reveal that the proposed network involve less time and is suitable for online static assessment under uncertain loading conditions and is expected to perform similarly on even larger systems and handle even greater number of contingencies than reported here.

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Dawood Seyed Javan was born in Mashhad, Iran, in 1984. He received the B.Sc. degrees in electrical engineering from the Azad University of Mashhad. He is currently pursuing the M.Sc. degree in the Department of Electrical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran. His research interests are power system security assessment, load and price forecasting in electricity markets, neural networks and genetic algorithms.

Habib Rajabi Mashhadi was born in Mashhad, Iran, in 1967. He received the B.Sc. and M.Sc. degrees with honor from the Ferdowsi University of Mashhad, both in electrical engineering, and the Ph.D. degree from the Department of Electrical and Computer Engineering of Tehran University, Tehran, Iran, under joint cooperation of Aachen University of Technology,

Germany, in 2002. He is as Associate Professor of electrical engineering at Ferdowsi University of Mashhad. His research interests are power system operation and planning, power system economics, and biological computation.

Modjtaba Rouhani received the B.S. and M.S. degrees in electrical engineering from Ferdowsi university of Mashad, Mashad, Iran, in 1990 and 1993, respectively, and the Ph.D. degree in electrical engineering from Amir Kabir university of Technology, Tehran, Iran, in 2001. He is currently with Azad Islamic university, Gonabad branch, Gonabad, Iran, where he is an assistant Professor in control engineering, electrical engineering department, engineering faculty. His research interests are neural networks, computational intelligence and nonlinear adaptive control.