

On-line voltage stability assessment using radial basis function network model with reduced input features

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ABSTRACT

In recent years, voltage instability has become a major threat for the operation of many power systems. This paper presents an artificial neural network (ANN)-based approach for on-line voltage security assessment. The proposed approach uses radial basis function (RBF) networks to estimate the voltage stability level of the system under contingency state. Maximum L -index of the load buses in the system is taken as the indicator of voltage stability. Pre-contingency state power flows are taken as the input to the neural network. The key feature of the proposed method is the use of dimensionality reduction techniques to improve the performance of the developed network. Mutual information based technique for feature selection is proposed to enhance overall design of neural network. The effectiveness of the proposed approach is demonstrated through voltage security assessment in IEEE 30-bus system and Indian practical 76 bus system under various operating conditions considering single and double line contingencies and is found to predict voltage stability index more accurate than feedforward neural networks trained by back propagation algorithm and AC load flow. Experimental results show that the proposed method reduces the training time and improves the generalization capability of the network than the multilayer perceptron networks.

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1. Introduction

The intensive loading of existing generation and transmission facilities and drawing transmission lines from remotely-located generation station has resulted in voltage related problems in many power systems. Several incidents of voltage instability have been initiated by tripping of a critical line in the system. In order to save the system from voltage collapse under contingencies, it is necessary to estimate the effect of contingencies on the voltage stability, so that corrective measures can be taken to avoid system black-out.

Several approaches have been proposed for analyzing the voltage stability problem. They can be broadly classified into static and dynamic approaches. The static approach [1–6] is based on the steady-state load flow model. In the dynamic approach [7,8] the power system is represented by a dynamic model and time domain simulations are carried out using a comprehensive set of initial and transient conditions to compute the voltage stability level. These methods require comparatively large computation time and are not suitable for on-line applications.

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In recent years, research endeavors in the area of security assessment have been directed towards artificial neural network [9–13]. Two separate models are proposed to estimate the voltage security of the system, a unified network to provide the voltage stability level under all the selected contingency state and a set of trained networks one each for every selected contingencies. Most of the authors have used feedforward neural networks with sigmoidal nonlinearities for model development. Also, the networks were developed based on the complete input variables, which significantly reduce their performance. With feedforward neural networks any continuous function can be approximated to within an arbitrary accuracy by carefully choosing the parameters in the network provided the network structure is sufficiently large. But the shortcoming of this network is that it takes long time for training. Also, feedforward network with sigmoidal activation function in the hidden nodes has no inherent ability to detect the outliers. Even though training is done in off-line, short training time is preferred as one may have to retrain the networks on a regular basis as the topology or the system condition changes. Outliers can occur in practice, because it is difficult to produce a complete training set representing all possible operating conditions of a power system.

In [14], a radial basis function neural network with a fast hybrid learning method is proposed in which a function approximation problem is used. An adaptive RBF network is proposed in [15] for

multicontingency voltage stability monitoring in which sequential learning strategy is used along with regularization technique to design RBFNN and weights in output layer are determined using linear optimization. A network pruning strategy is used to limit the growth of network size due to adaptive training. Jayashankar et al. [16] proposed feedforward back propagation network to estimate voltage stability index for various load conditions and the optimal location for placement of TCSC is identified for improving the voltage stability in power system. Thukaram et al. [17] proposed a feedforward neural network under various training functions for on-line voltage stability assessment and monitoring.

In this paper, we use Radial Basis Function (RBF) networks [18] for fast voltage security assessment. Radial basis function networks take less time for training and the distance-based activation function used in the hidden nodes gives the ability to detect the outliers during estimation [19]. The L -index proposed in [3] is adopted as the voltage stability index. The value of this index ranges from 0 (no load of system) to 1 (voltage collapse). The bus with the highest L -index value will be the most vulnerable bus in the system and hence this method helps in identifying the weak areas in the system which need critical reactive power support.

While training the neural network, by selecting only the relevant attributes of the data as input features and excluding redundant ones, higher performance is expected with smaller computational effort. Principal Component Analysis (PCA) is presumably the most commonly used feature extraction method [20]. The total system variability can be presented by a smaller number of principal components, because there is almost as much information in the first p principal components as there is in the original variables. Principal Component Analysis yields a k -dimensional linear subspace of feature space that best represents the full data according to a minimum square error criterion. Although PCA reduces the dimension of the data in a larger manner still it has some serious limitations. If the data represent complicated interactions of features, then the linear subspace representation by PCA will be a poor representation. Secondly, if the noise is high compared to the difference between categories, then the component analysis will find the directions of the noise rather than the signal. Hence if we pool all the samples, the directions that are discarded by PCA might be exactly the directions that are needed for distinguishing between classes. Hence the alternate approach is to select the most significant features that best describe the studied phenomena and to discard the redundant variables. This work uses mutual information based feature selection [11] to reduce the dimension of the input features. The effectiveness of the proposed method is demonstrated through voltage stability assessment in IEEE 30-bus system and Indian Practical 76 bus system.

The remainder of this paper is organized as follows: In Section 2, the use of L -index for voltage stability analysis is reviewed. In Section 3, the details of RBF networks are explained and the methodology followed to configure the network from the input–output training data is explained. Various issues involved in developing the ANN-based model for contingency selection are given in Section 4. Section 5 presents the details of the application of the proposed model for contingency selection in IEEE 30-bus system and Indian Practical 76 bus system.

2. Voltage stability index

The static voltage stability analysis involves determination of an index known as voltage stability index. This index is an approximate measure of closeness of the system operating point to voltage collapse. There are various methods of determining the voltage stability index. One such method is the maximum L -index of the load buses in the system proposed in [3]. The value of L -index ranges from 0 (no load of system) to 1 (voltage collapse). The bus with

the highest L index value will be the most vulnerable bus in the system. The L -index calculation for a power system is briefly presented below.

Consider a N -bus system in which there are N_g generators. The relationship between voltage and current can be expressed by the following expression:

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \quad (1)$$

where I_G , I_L and V_G , V_L represent currents and voltages at the generator buses and load buses. Rearranging the above equation we get,

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (2)$$

where

$$F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}] \quad (3)$$

is the sub matrix of the above hybrid matrix H .

The L -index of the j th node is given by,

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ji} \frac{V_i}{V_j} \angle(\theta_{ji} + \delta_i - \delta_j) \right| \quad (4)$$

where V_i is the voltage magnitude of i th generator bus, θ_{ji} the phase angle of the term F_{ji} , δ_i is voltage phase angle of i th generator bus and N_g is the number of generating units.

It was demonstrated that when a load bus approaches the voltage collapse point, the L -index approaches the numerical value of 1. Hence, for a system-wide voltage stability, the index evaluated at any of the buses must be less than unity, and the maximum value of the L -index gives an indication of how far the system is from voltage collapse.

3. Proposed methodology for voltage security assessment

The proposed method for voltage security assessment is based on RBF neural networks. The objective is to estimate the voltage stability level for each contingency and rank them according to their severity level. The study presented in this paper focuses on single line outages and the voltage stability level is expressed by the maximum L -index value.

3.1. Training data generation

The generation of the appropriate training data is an important step in the development of ANN models. For the ANN to accurately predict the output the training data should represent the complete range of operating conditions of the system under consideration. For model development, a large number of training data is generated through off-line power system simulation. Pre-contingency state power flows are the input to the neural network and the maximum value of L -index following a contingency is the output of the network. The training data for the development of ANN is generated through the following procedure:

- First, a range of situations is generated by randomly perturbing the load at all buses from the base case value and by adjusting the generator output in proportion to the output in the base case condition.
- For each load-generation pattern, pre-contingency line flows are obtained by solving the load flow equations using Newton Raphson algorithm.
- Next, for each load-generation pattern, the single line-outages specified in the contingency list are simulated sequentially and the L -index values are evaluated by conducting AC load flow.

3.2. Dimensionality reduction

Real power systems have thousands of variables at the system level. If all the measured variables are used as inputs to neural network, it results in large size of the network and hence larger training time. To make the neural network approach applicable for large scale power system problems, some dimensionality reduction is mandatory. As most of the contingencies are localized in nature, all the variables in the input vector may not exert equal influence on the post-contingency L -values. Irrelevant and redundant attributes in the input not only complicate the network structure, but also degrade the performance of the networks. By selecting only the relevant variables as input features and excluding irrelevant ones, higher performance is expected with smaller computational efforts. Also, networks involving too many input variables suffer from curse of dimensionality. This work uses mutual information based feature selection to reduce the dimension of the input features.

3.3. Data normalization

The first stage of RBF network learning is the identification of the cluster centers through K-means clustering algorithm which uses Euclidean distance as a measure of dissimilarity. Distance norms are sensitive to variations in the numerical ranges of the different features. For example, the Euclidean distance assigns more weighting to features with wide ranges than to those with narrow ranges. To overcome this problem, input data is normalized before presenting it to the clustering algorithm. The input data is normalized between 0 and 1 using the expression,

$$x_n = \frac{(x - x_{\min}) \times \text{range}}{(x_{\max} - x_{\min})} + \text{starting value} \quad (5)$$

where x_n is the normalized value and x_{\min} and x_{\max} are the minimum and maximum values of the variable x .

3.4. Network development

The selected features after normalization are presented to the RBF networks for training. After training, the networks are evaluated through a different set of input–output data. Once the networks are trained and tested, they are ready for estimating the L -index values at different operating conditions.

4. Review of radial basis function network

Radial basis function network [19] is a class of single hidden layer feedforward neural network. Fig. 1 shows the schematic diagram of a RBF neural network. The input nodes pass the input directly and the first layer connections are not weighted. The transfer functions in the hidden nodes are similar to the multivariate Gaussian density function,

$$\phi_j(x) = \exp\left(-\frac{\|x - \mu_j\|^2}{2\sigma_j^2}\right) \quad (6)$$

where x is the input vector, μ_j and σ_j are the center and the spread of the corresponding Gaussian function. Each RBF unit has a significant activation over a specific region determined by μ_j and σ_j , thus each RBF represents a unique local neighborhood in the input space. The connections in the second layer are weighted and the output nodes are linear summation units.

The value of the k th output node y_k is given by,

$$y_k(x) = \sum_{j=1}^h w_{kj} \phi_j(x) + w_{k0} \quad (7)$$

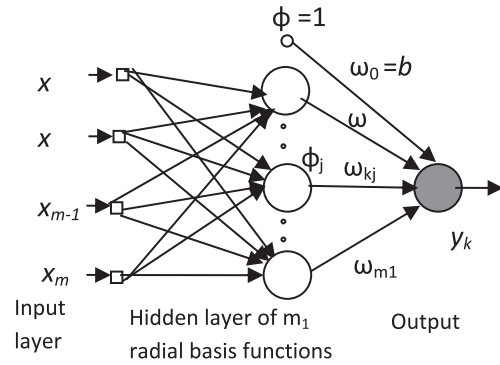


Fig. 1. Schematic diagram of RBF neural network.

where w_{kj} is the connection weight between the k th output node and j th hidden node and w_{k0} is the bias term.

The training in RBF networks is done in three sequential stages as against the single optimization procedure followed in back propagation network training. The first stage of the learning consists of determining the unit centers α_j by the K-means clustering algorithm [19].

Next, we determine the unit widths σ_j using a heuristic approach that ensures the smoothness and continuity of the fitted function. The width of any hidden node is taken as the maximum Euclidean distance between the identified centers. Finally, the weights of the second layer connections are determined by linear regression using a least-squares objective function.

RBF networks can be viewed as an alternative tool for learning in neural networks. While RBF networks exhibit the same properties as back propagation networks such as generalization ability and robustness, they also have the additional advantage of fast learning and ability to detect outliers during estimation. The attractive feature of RBFNN lies in the linear dependence in the parameters which greatly simplifies the design and analysis of such networks. It also has an advantage of easy and effective learning algorithm compared to other MLPNN.

5. Mutual information based feature selection

The application of “mutual information” between the input variables and the output provides the basis for feature selection. If the information regarding a certain system variable results in significant reduction in the system entropy, then this variable must have significant impact on the security index which is to be estimated. Therefore, this variable will be selected as a feature for security index estimation. On the other hand, the system variables which result in minor reduction in the system entropy will be regarded as having minor effects on the security index and will not be selected as feature.

Once the mutual information value of input variables is evaluated, the variables are ranked, with the variable having the high mutual information value at the top and so on. The optimum number of features can be selected by consequent training of the neural networks using a progressively increasing number of features until the minimum required accuracy is obtained.

5.1. Definition of mutual information

Consider a stochastic system with input X and output Y . Let the discrete variable X has N_x possible values and Y has N_y possible values. Now the initial uncertainty about Y is given by the entropy $H(Y)$ which is defined as,

$$H(Y) = - \sum_{j=1}^{N_y} P(y_j) \cdot \log(P(y_j)) \quad (8)$$

where $P(y_j)$ are the probabilities for the different values of Y . The amount of uncertainty remaining about the system output Y after knowing the input X is given by the conditional entropy $H(Y|X)$ which is defined as,

$$H(Y|X) = - \sum_{i=1}^{N_x} P(x_i) \cdot \left(\sum_{j=1}^{N_y} P(y_j|x_i) \cdot \log(P(y_j|x_i)) \right) \quad (9)$$

where $P(y_j|x_i)$ is the conditional probability for output y_j given the input vector x_i . Now the difference $H(Y) - H(Y|X)$ represents the uncertainty about the system output that is resolved by knowing the input. This quantity is called the mutual information between the random variables X and Y . Denoting it by $I(Y;X)$, we may thus write, $I(Y;X) = H(Y) - H(Y|X)$ (10)

The mutual information is therefore the amount by which the knowledge provided by X decreases the average uncertainty about the random experiment represented by the variable Y . Mutual information is a symmetrical measure. That is, the amount of information gained about Y after observing X is equal to the amount of information gained about X after observing Y . For the contingency selection problem under consideration, X corresponds to the pre-contingency line flows and Y corresponds to the post-contingency security index.

5.2. Mutual information for feature selection

For feature selection first the mutual information between each variable and the model output is calculated using (8)–(10). If a variable has high value of mutual information with respect to the output, then this variable must have significant effect on the output value which is to be estimated. Therefore, this variable is selected as a feature for the neural network. On the other hand, those variables which have low values of mutual information will be regarded as having minor effects on the output and are not selected for network training. Next, the mutual information among the selected input variables is calculated. If any two input variables have high value of mutual information between them, then they will have similar effect on the output and hence one is considered for network training discarding the other one.

6. Simulation results

This section presents the details of the simulation study carried out on IEEE 30-bus system and 76-bus practical Indian system. For these two test systems, based on contingency analysis conducted at different loading conditions, seven single line outages were identified and the ANN models were developed to estimate the voltage security level corresponding to these contingencies. The details of the ANN models developed are presented here.

6.1. Voltage security assessment in IEEE 30 bus system

IEEE 30-bus system consists of six generators, 24 load buses and 41 transmission lines of which lines (6–9), (6–10), (4–12) and (28–27) are with tap changing transformer. The transmission line parameters and generator cost coefficients are given in [21]. The L -index proposed in [3] and presented in Section 2 is used as the voltage stability index. Seven single line outages (1–2), (1–3), (10–20), (28–27), (4–12) (6–7) and (9–10) were identified as severe cases based on contingency analysis. For generating training data for the RBFNN, active and reactive powers at the load buses and generator real power outputs are varied randomly between

70% and 140% of operating conditions. Based on the algorithm given in Section 3.1, a total of 1000 input–output pairs were generated, with 750 for training and 250 for testing. Separate networks dedicated for each contingency are developed using the data set. To select the input features, the input variable is divided into five levels and output is divided into three groups. Mutual information of each variable with respect to the output is evaluated using (8) and (10). For illustration, the mutual information between the input variables and the output for contingency (1–2) is shown in Fig. 2. From this figure, it is evident that only a few variables are having significant information and the remaining variables have very less amount of information. The first few variables which have high mutual information value are selected as features to train the ANN, and the remaining variables are discarded from further consideration. The selected features for the seven models are given in Table 1. The selected variables after normalization are presented to the network. Twenty iterations of the clustering algorithm followed by linear regression are performed to estimate the parameters of the network. As the value of basis functions is not known in advance, a trial-and-error procedure is followed to select the optimum number. After training, the networks are tested with the test data set to assess the generalization capability of the developed network.

The performance of the network during training and testing phase for all the seven models are presented in Table 1. The results clearly show that the training of the RBF networks has been successful and the correct estimation of L -index has been achieved by the RBF network even for previously unseen data.

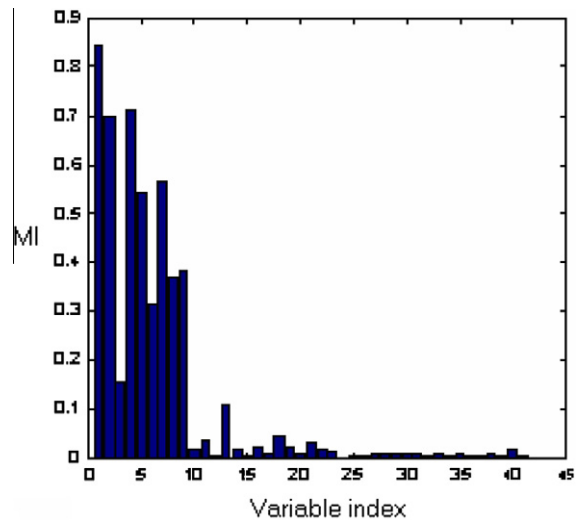


Fig. 2. Mutual information for variables in models 1–2 in IEEE 30 bus system.

Table 1 Training and testing performance of RBF network.

S. no	Line outage	Selected features	No. of basis functions	Training time (s)	Testing error (ms)
1	1–2	S_j : 1, 4, 2, 7, 5	25	0.6100	1.1020×10^{-6}
2	1–3	S_j : 2, 4, 1	15	0.3430	2.5387×10^{-6}
3	4–12	S_j : 15, 12, 14, 11, 18, 28	35	0.7190	6.5960×10^{-4}
4	6–7	S_j : 9, 5, 8, 1	25	0.5940	8.8545×10^{-5}
5	9–10	S_j : 14, 12, 27, 15, 28, 11, 18, 13	25	0.7350	3.8046×10^{-4}
6	10–20	S_j : 25, 24, 18, 22, 15, 12, 14	25	0.6090	3.1721×10^{-4}
7	28–27	S_j : 36, 37, 38, 12, 14, 39, 11, 28, 15, 18	25	0.6870	8.4978×10^{-4}

Table 2 presents the L -index values estimated using the developed RBF model for one particular loading condition along with the ranking of the contingencies. For comparison, the actual values of L -index calculated from AC load flow study are also presented. The result shows the agreement between the actual ranking and the ranking based on the output of the neural networks.

To compare the performance of the proposed RBF network-based approach with the commonly used neural network architecture, multilayer perceptron (MLP) networks are developed to estimate the L -index values. The networks are trained with the conjugate gradient algorithm to reach the same error level achieved by the RBF networks during the training. After training, the networks are tested with the test data.

The time taken for training is presented in Table 3. From this table, it is observed that RBF networks take less time for training, but they require more number of hidden nodes as compared to multilayer perceptron networks. Apart from that the RBF network exhibits better generalization performance than the MLP network in most of the cases.

For comparison, a unified neural network model with pre-contingency power flow as the input and the L_{max} values of all seven contingencies as output was developed. The network was trained and tested with the data set used in the previous case and the per-

formance of the network is given in Table 4. On comparing Tables 1 and 4, it is found that the individual networks take less time for training than the unified network and the generalization capability of the individual networks is also better than the unified network.

6.2. Voltage security assessment in Indian practical 76 bus system

Next, the proposed approach was applied for voltage security assessment in a practical Indian power system. The considered system consists of 76 buses, 13 generators, 63 load buses and 115 transmission lines. The transmission level parameters and generator cost coefficients are given in [22]. The training and test data required to develop the RBF network are generated by adopting the procedure given in Section 3.1. RBFNN models were developed for seven severe single line outages (18–57), (23–70), (74–19), (57–17), (67–21), (35–73) and (31–65). Input features of the network are selected using the mutual information based method explained in Section 4. The number of basis functions is selected by trial and error method.

Table 5 shows the performance of RBF NN during the training and testing period. The results presented in the tables show the

Table 2 Comparison of RBF output and load flow result.

Line outage	RBF output		Load flow result	
	L_{max}	Rank	L_{max}	Rank
1–2	0.2958	I	0.3220	I
1–3	0.1754	V	0.1867	V
4–12	0.2058	III	0.2154	III
6–7	0.2106	II	0.2209	II
9–10	0.1902	IV	0.2059	IV
10–20	0.1752	VI	0.1857	VI
28–27	0.1645	VII	0.1823	VII

Table 3 Comparison of RBF NN with MLP net for model (1–2).

Type of network	No. of hidden neurons	Training time (s)	Testing error (ms)
RBF	25	0.6100	1.1020×10^{-6}
MLP	8	2.9060	4.0813×10^{-4}

Table 4 Results of unified neural network.

Model	No. of input features	No. of hidden nodes	Training time (s)	Testing error (ms)
Unified network	41	80	0.9350	3.1154×10^{-4}

Table 5 Performance of RBF NN for (n – 1) contingencies in 76 bus Indian system.

Line outage	RBF output		Training time (s)	Testing error (ms)
	Selected features			
18–57	$S(10) = 78, 80, 37, 79, 110, 113, 101, 4, 62, 41$		0.2184	3.0514×10^{-4}
23–70	$S(7) = 78, 4110, 92, 80, 112, 79$		0.1560	2.200×10^{-3}
74–19	$S(9) = 25, 113, 11041, 4112, 80, 62, 40$		0.2028	7.9870×10^{-4}
57–17	$S(20) = 39, 41, 112, 4113, 61, 110, 60, 103, 40, 58, 107, 109, 106, 5, 79, 30, 105, 62, 59$		0.2496	7.3180×10^{-4}
67–21	$S(18) = 39, 41, 112, 4113, 61, 110, 60, 103, 40, 58, 107, 109, 106, 5, 79, 30, 105$		0.2028	8.4685×10^{-4}
35–73	$S(18) = 4, 78, 80, 79, 110, 62, 60112, 59, 88, 41, 107, 18, 113, 25106, 87, 61$		0.2652	6.400×10^{-3}
31–65	$S(20) = 78, 80, 4, 79, 59, 110, 1862, 88, 87, 60, 112, 17, 11, 3, 41, 25, 61, 107, 64, 106$			8.300×10^{-3}

Table 6 Comparison of RBF, MLPNN and conventional method in estimating L_{max} value.

Line outage	RBF output		MLPNN		Load flow result	
	Ranking	L_{max}	Ranking	L_{max}	Ranking	L_{max}
18–57	2	0.4741	2	0.4753	2	0.4246
23–70	6	0.3515	6	0.3594	6	0.3335
74–19	1	0.5228	1	0.5205	1	0.5320
57–17	4	0.4345	4	0.4367	4	0.4060
67–21	3	0.4355	3	0.4380	3	0.4065
35–73	7	0.3473	7	0.3535	7	0.3276
31–65	5	0.3593	5	0.3636	5	0.3389

Table 7 Performance of RBF network for multiple contingencies.

S. no	Line contingencies	Selected features	No of basis functions	Training time (s)	Testing error (ms)
1	18–57 and 23–70	$S(20) = 78, 80, 37, 79, 110, 113, 101, 4, 62, 112, 41, 106, 107, 105, 111, 108, 25, 104, 3, 8$	50	0.2028	3.4177×10^{-4}
2	18–57 and 74–19	$S(20) = 25, 41, 110, 113, 4112, 107, 62, 106, 40, 108, 105, 3111, 109, 79, 58, 103, 29, 80$	50	0.2340	1.700×10^{-3}

ability of the proposed model to estimate the voltage security level even for a larger test system. Table 6 shows the comparison between the RBFNN and MLPNN output and result of conventional AC load flow for one particular condition along with ranking of contingencies. The result shows the agreement between ranking made by the neural network approaches and actual ranking by conventional method. This shows that the proposed RBFNN is computationally efficient and hence is suitable for on-line voltage security assessment.

Table 7 shows the performance of RBFNN for ($n - 2$) contingencies with outages of 18–57/23–70 and 18–57/74–19. The test results indicate the effectiveness of proposed method for on-line voltage security assessment for multiple contingencies also.

7. Conclusion

This paper has presented a radial basis function network-based fast voltage security assessment method for on-line applications. A set of RBF networks has been trained to map the nonlinear relationship between the pre-contingency operating conditions and the post-contingency voltage stability index. Feature selection is addressed through mutual information between the input variables and the output stability index. Computer simulation was carried out on the IEEE 30-bus system and Indian Practical 76 bus system for voltage security assessment. Test results show that the proposed RBF network-based approach provides accurate estimation of post-contingency L -values for various operating conditions for single line and double line contingencies. The proposed RBF network-based approach significantly reduces the training time compared to the back propagation algorithm. By reducing the dimension of the input features using feature selection the efficiency of the ANN model has been significantly increased both in the learning and estimation stages. Further, the reduction in the dimension of the input data results in the reduction in the demand for measurements within the power system.

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