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TWO COMPARATIVE APPROACHES FOR ONLINE VOLTAGE STABILITY MONITORING AND CONTINGENCY RANKING

Benyamin MORADZADEH, Seyed Hossein HOSSEINIAN, Mohammad MONFARED
Department of Electrical Engineering, Amirkabir University of Technology (Tehran Polytechnic), Iran

Abstract: Voltage stability is one of the major concerns in competitive electricity market. In this paper, two new neural network based approaches are presented in order to predict the static voltage stability index and to rank the critical line outage contingencies. These algorithms speedup the neural network training process by reducing the dimensions of neural network training vectors. Based on the weak buses identification method, the first developed algorithm introduces a new feature extraction technique. The second algorithm is based on Principal Component Analysis algorithm which is a statistical method. A clustering method is applied to reduce the number of neural network training vectors. The proposed algorithms have been tested on the IEEE-30 bus test system. Fast performance, accurate evaluation and good prediction accuracy for voltage stability index and contingency ranking have been obtained

Keywords: Neural Networks, Contingency Ranking, Minimum Singular Value, Principal Component Analysis.

1. Introduction

Voltage stability is defined as the ability of a power system to maintain steadily acceptable bus voltage at each node under normal operating conditions, after load increase, following system configuration changes or when the system is being subjected to disturbances like line outage, generator outage and etc [1]. Voltage collapse may be caused by a variety of single or multiple contingencies known as voltage contingencies in which the voltage stability of the power system is threatened [2]. Conventional evaluation techniques based on the full or reduced load flow Jacobian matrix analysis such as, singular value decomposition, eigen value calculations, sensitivity factor, and modal analysis are time consuming [3]-[5]. So they are not suitable for online applications in large scale power systems. Recently, artificial neural networks (ANNs) have shown great promise in power system engineering due to their ability to synthesize complex mappings accurately and fast. Radial basis function network (RBFN), with nonlinear mapping capability, has become increasingly popular in recent years due to its simple structure and training efficiency. RBFN has only one nonlinear hidden layer and one linear output layer. In this paper, two new RBFN based algorithms are presented for voltage stability index prediction and contingency ranking.

2. Voltage stability index

Minimum singular value of the load-flow Jacobian matrix is proposed as an index for quantifying the proximity to the voltage collapse point. Right Singular Vector (RSV), corresponding to a minimum singular value of the Jacobian matrix, can be utilized for indicating sensitive voltages that identify the weakest node in the power system [5].

3. Proposed algorithms

In this paper two different algorithms are proposed for feature extraction. Theses algorithms reduce the training time of the RBF neural network remarkably.

3.1. First algorithm

In this algorithm, three groups of parameters are considered for feature extraction. The first group includes the active and reactive loads on the weak PQ buses. Load variations on these buses have great effects on the voltage stability index. The second important parameter group consists of the active and reactive loads on terminal buses of critical lines. The third parameter group is the ratio between the sum of the active and reactive loads on the remained PQ buses to the sum of their base values of active and reactive loads.

3.2. Second algorithm

In this algorithm, Principal Component Analysis (PCA) method is employed in order to reduce the dimension of the neural network training vectors. PCA is a well-known statistical technique for feature extraction. Each $M \times N$ vector in the training set is row concatenated to form $MN \times 1$ vectors $\tilde{A}_i$. Given a set of N_T training vectors $\{\tilde{A}_i\}_{i=0,1,\cdots,N_T}$, the mean vector of the training set is obtained as:

$$\bar{A} = \frac{1}{N_T}\sum_{i=1}^{N_T}\tilde{A}_i \qquad (1)$$

The average vector is subtracted out from the training vectors to obtain A_i:

$$A_i = \tilde{A}_i - \bar{A} \quad , \quad i = 1,2,3,\dots,N_T \qquad (2)$$

An $N_T \times MN$ matrix A was constructed with the A_i^T as its row vectors. The singular value composition of A can then be written as:

$$V^T A U = \left|\Sigma \middle| 0\right| \qquad (3)$$

Where Σ is an $N_T \times N_T$ diagonal matrix with singular values $s_i > 0$ arranged in descending order, and V and U are $N_T \times N_T$ and $MN \times MN$ orthogonal matrices, respectively. V is composed of the eigenvectors of AA^T, while U is composed of the eigenvectors of AA^T. These are related by the equation 4.

$$\tilde{U} = A^T V \qquad (4)$$

Where $\tilde{U}$ consists of the eigenvectors of AA^T, which corresponds to the non-zero singular values. This relation allows a smaller $N_T \times N_T$ eigenvalue problem for AA^T to be solved, and to subsequently obtain $\tilde{U}$ by matrix multiplication.

As PCA has the property of packing the greatest energy into the least number of principal components, the smaller principal components which are less than a threshold can be discarded with minimal loss in representational capability. this dimension reduction results in vectors of dimensions $\tilde{N}_T < N$. An appropriate value of $\tilde{N}_T$ can be chosen by considering the Basis Restriction Error (BRE) as a function of $\tilde{N}_T$ [6].

4. Clustering method

In this paper, a clustering method is presented in order to reduce the number of the neural network input vectors[7]. This method can be explained as follows:

The first input-output pair makes the first cluster with x_c^1 as the center in the x_0^1. r is the neighborhood radius of the cluster. Suppose that (x_0^k, y_0^k) is the k-th input-output pair and there are M formed clusters until this stage. $x_c^1, x_c^2, \cdots, x_c^m$ are the centers of these clusters and r is the neighborhood radius of all clusters. Euclidian distance between x_0^k and the center of the clusters can be calculated as follows:

$$\left|x_0^k - x_c^l\right| \quad , \quad l = 1,2,\cdots,M \qquad (5)$$

There are two probabilities for this vector:

If (minimum $\left|x_0^k - x_c^l\right|$) > r, then a new cluster is produced. x_0^k is the center of this cluster. otherwise ((minimum $\left|x_0^k - x_c^l\right|$) < r), x_0^k is a member of the cluster number l and should be discarded from the list of training vectors. Since the center of cluster l is the representative for all vectors in this cluster, the other vectors in the cluster are eliminated from the training vectors list.

5. RBF neural network structure

Radial Basis Function (RBF) neural networks have been found very attractive for many engineering problems because they have a very compact topology and their locally neurons tuning capability leads to a high learning speed [8]. The RBF neural network has a feed forward architecture with an input layer, a hidden layer and an output layer. The RBFN structure is shown in Fig. 1. The input layer units are fully connected to the hidden layer units. In this structure, hidden nodes are named RBF units. These units are fully connected to the output layer units.

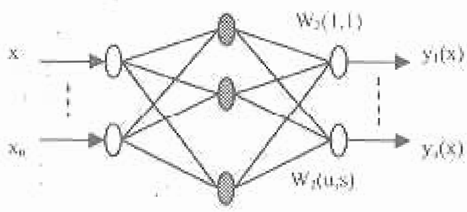

Fig. 1. RBF neural network Structure

The activation function of the RBF units is expressed as follows [8]:

$$R_i(X) = R_i(-d_i^2(X)) \quad , \quad i = 1,2,\dots,s \qquad (6)$$

$$d_i(X) = \frac{\left\|X - C_i\right\|}{\sigma_i} \qquad (7)$$

Where $d_i(X)$ is called the distance function of the i-th RBF unit, $\mathbf{X} = (x_1, x_2, \dots, x_n)^T$ is an n-dimensional input feature vector, C_i is an n-dimensional vector called the center of the i-th RBF unit, σ_i is the width of i-th RBF unit and s is the number of the RBF units. Typically, Gaussian function (equation 8) is chosen as the RBF units' activation function.

$$R_i(X) = \exp[-d_i^2(X)] \qquad (8)$$

The output units are linear and therefore the j-th output unit for input **X** is given by the equation 9.

$$y_j(X) = b(j) + \sum_{i=1}^{s} R_i(X) W_2(j,i) \qquad (9)$$

Where $W_2(j,i)$ is the connection weight of the i-th RBF unit to the j-th output node and $b(j)$ is the bias of the j-th output. The bias is omitted in this network in order to reduce the network complexity. Therefore the equation 9 can be contracted into the simpler equation 10.

$$y_j(X) = \sum_{i=1}^{s} R_i(X) W_2(j,i) \qquad (10)$$

6. Numerical results

The 30-bus IEEE test system is selected to verify the effectiveness of the proposed algorithms. It consists of 6 generators, 21 PQ buses and 41 lines. Load flow converges for 37 line outages and critical lines are recognized under several loading conditions. In this paper, 11 numbers of most critical lines are considered for the study. Randomly changing the loads on PQ buses between 50% and 150% of their base values, 2500 loading vectors are generated. 2000 vectors are used for training and the remaining vectors are used for the test. In [9] all active and reactive loads on PQ buses are considered for feature extraction. There are 21 PQ buses in IEEE-30 bus system and the mentioned method in [9] makes 42 dimensional training vectors. In large scale power systems there are many PQ buses and this method leads to long training vectors and long training procedure of the neural network. So this method is not suitable for large scale power systems. In the present article, two different algorithms are proposed to reduce the dimension of the vectors and improve the training speed of the neural network.

6.1. First algorithm

As mentioned in section 3.1, three groups of parameters are considered for feature extraction. The first group includes the value of the active and reactive loads at weak buses. Weak buses can be identified using Right Singular Vector (RSV) of the Jacobian matrix. The result of the bus ranking for the 10 weakest buses is presented in Table 1. The higher the rank, the weaker the bus is.

In addition to the weak buses, the buses which are the terminals of the critical lines must be considered. Finally, the selected buses are: 26, 29, 30, 24, 21, 15, 12, 10, 4 and 2. The active and reactive loads on these buses in addition to the third parameter, mentioned in 3.1 should be considered for feature extraction. Using this algorithm, the dimensions of the input vectors is reduced from 42 to 22. After all, clustering method is applied in order to reduce the number of the training vectors. Using this clustering method, the number of the vectros is reduced from 2000 to 777.

Table 1. 10 weakest buses

rank	bus	RSV index
1	26	0.2118
2	30	0.2063
3	29	0.2006
4	25	0.1883
5	24	0.1778
6	27	0.1743
7	19	0.1719
8	23	0.1715
9	18	0.1703
10	20	0.1693

6.2. Second algorithm

In this method, PCA is employed in order to reduce the dimension of the training vectors. Using this algorithm, it is found that 20 eigenvalues are much bigger than the others. Hence, their corresponding eigenvectors are selected and after implementing the steps described in 3.2, number of the vectors is reduced from 42 to 20. 10 principal components (as a sample) and their corresponding variances are shown in Fig. 2. sum of the all 42 variances corresponding to all 42 components is 100%.

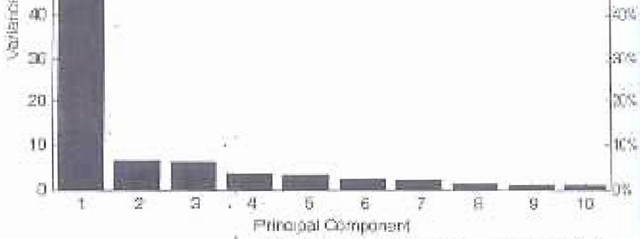

Fig. 2. 10 principal components and their corresponding variances

Finally, the clustering method is applied in order to reduce the number of the vectors. Using this clustering method, the number of the vectros is reduced from 2000 to 949.

The performance of the two proposed algorithms is shown in Tables 2 and 3 and their Speed and accuracy are presented in Table 4. The number of hidden layer neurons is obtained using a trial and error method. Considering these three tables, it is obvious that fast performance, accurate evaluation and good prediction accuracy for voltage stability index have been obtained.

Table 2. Voltage stability index and contingency ranking predictions using the proposed algorithms (for a definite loading)

Load Flow		RBF		First algorithm		Second algorithm	
MSV (base)		MSV (base)		MSV (base)		MSV (base)	
0.1633		0.1633		0.1632		0.1631	
Line	MSV	Line	MSV	Line	MSV	Line	MSV
2	0.0060	2	0.0065	2	0.0069	2	0.0048
40	0.0974	40	0.0973	40	0.0984	40	0.0935
41	0.0997	41	0.1001	41	0.1001	41	0.1000
32	0.1053	32	0.1055	32	0.1062	32	0.1070
11	0.1302	11	0.1306	11	0.1295	11	0.1309
3	0.1323	3	0.1326	3	0.1325	3	0.1328
33	0.1387	33	0.1390	33	0.1396	33	0.1387
30	0.1417	30	0.1419	30	0.1421	30	0.1426
31	0.1508	31	0.1510	31	0.1505	31	0.1505
21	0.1543	21	0.1546	21	0.1538	21	0.1526
18	0.1555	18	0.1560	18	0.1565	18	0.1536

Table 3. Voltage stability index and contingency ranking predictions using the proposed algorithms (for a definite loading)

Load Flow		RBF		First algorithm		Second algorithm	
MSV (base)		MSV (base)		MSV (base)		MSV (base)	
0.1690		0.1693		0.1695		0.1698	
Line	MSV	Line	MSV	Line	MSV	Line	MSV
2	0.0358	2	0.0355	2	0.0364	2	0.0362
41	0.0855	41	0.0895	41	0.0866	41	0.0902
40	0.1046	40	0.1046	40	0.1052	40	0.1047
32	0.1150	32	0.1151	32	0.1155	32	0.1160
3	0.1383	3	0.1384	3	0.1379	3	0.1384
33	0.1469	33	0.1472	33	0.1471	33	0.1473
11	0.1475	11	0.1478	11	0.1473	11	0.1482
30	0.1485	30	0.1487	30	0.1491	30	0.1493
18	0.1511	18	0.1518	18	0.1520	18	0.1525
31	0.1566	31	0.1568	31	0.1571	31	0.1565
21	0.1601	21	0.1603	21	0.1595	21	0.1590

Table 4. Speed and accuracy of the proposed algorithms

	MSE	training time (s)	hidden layer neurons
RBF	0.0051	73.392	100
first algorithm	0.0089	4.9	50
second algorithm	0.0094	13.2	100

7. Conclusions

In this paper, RBF neural network is employed to precisely predict the voltage stability index (MSV) and contingency ranking in different loading conditions. Two different algorithms are proposed in order to reduce the dimension and the number of the training vectors and improve the speed of neural network training process. These algorithms, exhibit good performance in voltage stability prediction and online contingency ranking, while computing the MSV using conventional methods is very time consuming for large scale power systems.

8. References

1. Sahari S., Abidin A. F., Abdulrahman T. K. Development of Artificial Neural Network for Voltage Stability Monitoring. National Power and Energy Conference (PECon) 2003 Proceedings, Bangi, Malaysia.
2. Jain T., Srrivastava L., Singh S. N. Fast Voltage Contingency Screening using Radial Basis Function Neural Network. IEEE Trans. Power Syst., vol. 18, no. 4, pp. 705-7015, Nov. 2003.
3. Begovic M. M., Phadke A. G. Control of Voltage Stability using sensitivity analysis. IEEE Trans. On Power Systems, vol. 7, no. 1, pp. 114-123, Feb 1992
4. Flatabo N. et al. Voltage Stability Condition in a Power Transmission calculated by Sensitivity Analysis. IEEE trans. On Power Systems, vol. 5, no. 4, Nov. 1990, pp. 1286-1293.
5. Chen Y. L., Chang C. W., C. C. L. Efficient Methods for Identifying Weak Nodes in Electrical Power Networks. IEEE Proc. Gener. Transm. Distrib. Vol.142, no. 3, May 1995.
6. Truk M., Pentland A. Eigenfaces for Recognition. Journal Cognitive Neuroscience, Vol. 3, No. 1, pp. 7186, 1991.
7. Spath H. Cluster Dissection and Analysis: Theory, FORTRAN Programs, Examples, translated by J. Goldschmidt, Halsted Press, New York, 1985, 226 pp.
8. Haddadnia J., Faez K. Neural network human face recognition based on moment invariants. Proceeding of IEEE International Conference on Image Processing, Thessaloniki, Greece, pp. 1018-1021, 7-10 October 2001.
9. Jain T., Srivastava L., Singh S. N. Fast Voltage Contingency Screening Using Radial Basis Function Neural Network. IEEE Transactions on Power System 18, vol. 18, no. 4, Nov 2003.