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Application of supervised learning for voltage stability assessment using GVSM

Abstract

To assessment of voltage stability of multi bus power system, the main requirement is equivalent two-bus network models, which is fulfilled by shunt admittances and lumping all the series impedances of transmission lines within a series equivalent impedance. This paper shows the development of an equivalent pi network model using a new methodology called generalized Global Voltage Stability Margin (GVSM). This is used to assess the overall voltage stability status of the power system accurately. The results simulated from offline N-R method also compared with the Radial Basis Function Neural Network (RBFN) and Feed Forward Backprop network (FFBP) topologies of Artificial Neural Network (ANN) in terms accuracy to predict the current status of the system. The input data of ANN are derived from the Newton-Raphson (NR) load flow analysis in the platform of MATLAB 2015b. The new method is validated on IEEE 14 and IEEE 30 test bus case. Simulation results for IEEE 14 test bus system and IEEE 30 test bus system are establish that the pi-equivalent model obtained by the proposed method is highly accurate for assessing voltage stability of any power system at any operating point in a better way as compared to series equivalent model.

Keywords: ANN, critical voltage, GVSM, global receiving end voltage, RBFN, FFBP, voltage stability

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Abbreviations: GVSM, global voltage stability margin; RBFN, radial basis function neural network; FFBP, feed forward backprop network; ANN, artificial neural network; NR, newton-raphson

Introduction

The voltage stability is increasingly becoming a limiting factor in the modern power systems due to the various changes that are continuously introduced to meet continuously increasing load demand without change in transmission and generation requirements. Due to this has necessitated to employment the techniques for assessed and determined the critical point of voltage stability. Voltage stability is defined as the ability of the power system to maintain acceptable & constant voltage level at all buses in the system under normal conditions and after being subjected to the disturbance. Therefore, voltage stability analysis is necessary to identify the critical buses in a power system i.e., buses which are closed to their voltage instability or near to voltage collapse point and to help the planning engineers and operators to take appropriate actions to avoid voltage instability problems.[1,2] The common techniques available for the assessment of voltage stability of any power system are based on the load flow solution feasibility, singularity of Jacobian, bifurcation technique, optimal power flow, etc. In this paper, the efforts have been made to assess the voltage stability in terms of network equivalencing to obtain a global scenario or picture of voltage stability. In this paper, the actual system is reduced into an equivalent two-bus system, i.e. methodology applied at only line, by using all parameters in regarding of line and after that the global voltage stability indices are used for indicating the state of the actual system. All the parameters of the equivalent system are obtained from the load flow solution of the original system. This equivalent system is nothing more than a power line having series equivalent impedance with a load at the receiving end, but the sending end voltage is kept at the reference voltage. The concept of single line equivalent is further used to determine the voltage collapse proximity. Determination of accurate global voltage stability index is possible if an equivalent two-bus system is represented by the whole power system accurately and faithfully. And this equivalent model used to assess voltage stability of a power system is obtained by lumping series impedances and shunt admittances of transmission lines altogether within the series equivalent impedance obtained from any load flow study performed on the actual size system.[3–7] ANN for assessment of voltage stability of the power system. The input data of ANN are derived from the Newton-Raphson (NR) load flow analysis. The result obtained from the ANN method is also compared with the result from offline N-R load flow analysis in terms of accuracy to predict the status of the power system.[8] The Contour Program to obtained target output for each input pattern, incorporating the Q limits of the generators.[9] The application of layer recurrent neural network model in load forecasting by using layer recurrent model of ANN.[10]

The application of SVM approach for contingency analysis of power system.[11–13] In the present work, RBFN and FFBP networks of the ANN with minimal neurons are used to provide an estimate of the global voltage stability margin for various system operating loadings. The proposed scheme has the ability to get adaptive training when subjected to any new training pattern, where the ANN has been used to predict the GVSM results for any unseen loading condition of the system. In this section of ANN designing, both real and reactive load at all buses are randomly varied and observed the effect on GVSM performance. The voltage stability assessment using line voltage stability index is applied to the IEEE 14 bus and the IEEE 30 bus power system, and the test results are presented. In this paper voltage stability assessment carried out by different ANN network models. Comparisons are carried out for different network topologies with conventional N-R method.

Equivalent two bus pi network

The proposed method to evaluate the equivalent two-bus pi-network model is developed as follows: Let us assume a two-bus equivalent network in which a generator bus is assumed as sending end bus and a load bus is assumed as receiving end bus as shown in (Figure 1). The behavior and properties of the proposed two-bus equivalent model should be the same as the multi-bus network and make possible the evaluation of voltage stability.[14–16] Therefore, the power equations for the two-bus equivalent network can be written as:

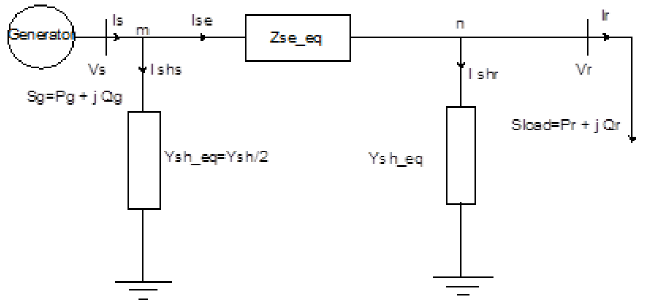

Figure 1 Two bus pi-equivalent network.

$$S_g = P_g + jQ_g = \vec{V}_s \vec{I}_s^* = \left(S_{se} + S_{sh}\right) + S_{load} \tag{1}$$

$$S_{se} = \left(\vec{V}_s - \vec{V}_r\right)\vec{I}_{se}^* \tag{2}$$

$$S_{sh} = \vec{V}_s \vec{I}_{shs}^* + \vec{V}_r \vec{I}_{shr}^* \tag{3}$$

Applying KCL at node m and we get:

$$\vec{I}_{se}^* = \frac{S_g}{\vec{V}_s} - S_{sh}\left(\frac{\vec{V}_s^*}{\left|\vec{V}_s\right|^2 + \left|\vec{V}_r\right|^2}\right) \tag{4}$$

Similarly at node n

$$\vec{I}_{se}^* = S_{sh}\left(\frac{\vec{V}_s^*}{\left|\vec{V}_s\right|^2 + \left|\vec{V}_r\right|^2}\right) + \frac{S_{load}}{\vec{V}_r} \tag{5}$$

Where V_s, V_r and I_s, I_r are the sending and receiving-end voltages and currents; Ise is the current through series equivalent impedance; I_{shs}, I_{shr} are the shunt branch currents at sending and receiving end respectively.

After the calculations, we get the equivalent series impedance and equivalent shunt admittance.

$$Z_{se\_eq} = \frac{\left(\vec{V}_s - \vec{V}_r\right)}{\vec{I}_{se}} \tag{6}$$

$$Y_{sh\_eq} = \frac{\vec{I}_{shr}}{\vec{V}_r} = \frac{\vec{I}_{shs}}{\vec{V}_s} \tag{7}$$

Thus the equivalent two-bus pi-network is obtained using the proposed mathematical.

Global voltage stability analysis of multi bus power system

When the two-bus network equivalent of a multi bus power system is obtained, the global voltage stability index can be formulated in a straight forward manner from the parameters of the global network as follows:

$$\begin{bmatrix} V_s \\ I_s \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix}\begin{bmatrix} V_r \\ I_r \end{bmatrix} \tag{8}$$

Where

$$A = D = 1 + \frac{YZ}{2}\,;\; B = Z\,;\; C = Y\left(1 + \frac{YZ}{4}\right)$$

Assuming

$$\left[Z = Z_{se\_eq} \text{ and } \frac{Y}{2} = Y_{sh\_eq}\right]$$

Let as assume

$$A = \left|A\right|\angle\alpha\,;\; B = \left|B\right|\angle\beta\,;\; \vec{V}_s = \left|\vec{V}_s\right|\angle\theta\,;\; \vec{V}_r = \left|\vec{V}_r\right|\angle\delta;\delta < \theta$$

Solving for the receiving end current:

$$I_r = \frac{\left|\vec{V}_s\right|}{\left|B\right|}\angle\theta - \beta - \frac{\left|A\right|\left|\vec{V}_r\right|}{\left|B\right|}\angle\alpha - \beta + \delta \tag{9}$$

Complex power of receiving end given by:

$$S_r = \vec{V}_r \vec{I}_r^* = \left|\vec{V}_r\right|\angle\delta\left[\frac{\left|\vec{V}_s\right|}{\left|B\right|}\angle -\theta + \beta - \frac{\left|A\right|\left|\vec{V}_r\right|}{\left|B\right|}\angle -\alpha + \beta - \delta\right] \tag{10}$$

Sending end voltage is constant then the active and reactive power at the receiving end is given by:

$$P_r = \frac{\left|\vec{V}_r\right|}{\left|B\right|}\cos\left(\beta + \delta\right) - \frac{\left|A\right|\left|\vec{V}_r\right|^2}{\left|B\right|}\cos\left(\beta - \alpha\right)$$

$$Q_r = \frac{\left|\vec{V}_r\right|}{\left|B\right|}\sin\left(\beta + \delta\right) - \frac{\left|A\right|\left|\vec{V}_r\right|^2}{\left|B\right|}\sin\left(\beta - \alpha\right)$$

The Jacobian matrix is given by:

$$J = \begin{bmatrix} \frac{\partial P_r}{\partial\delta} & \frac{\partial P_r}{\partial V_r} \\ \frac{\partial Q_r}{\partial\delta} & \frac{\partial Q_r}{\partial V_r} \end{bmatrix} = \frac{1}{\left|B\right|}\begin{bmatrix} -\left|\vec{V}_r\right|\sin\left(\beta+\delta\right)\cos\left(\beta+\delta\right) - 2\left|A\right|\left|\vec{V}_r\right|\cos\left(\beta-\alpha\right) \\ \left|\vec{V}_r\right|\cos\left(\beta+\delta\right)\sin\left(\beta+\delta\right) - 2\left|A\right|\left|\vec{V}_r\right|\sin\left(\beta-\alpha\right) \end{bmatrix} \tag{11}$$

The determinant of Jacobian matrix is given in Eq. (12):

$$\Delta\left[J\right] = \frac{1}{\left|B\right|^2}\left[2\left|A\right|\left|\vec{V}_r\right|^2\cos\left(\delta + \alpha\right) - \left|\vec{V}_r\right|\right] \tag{12}$$

At the critical point of voltage stability, $\Delta\left[J\right] = 0$ is given in Eq. (13).

$$\left|\vec{V}_r\right| = V_{cr} = \frac{1}{2\left|A\right|\cos\left(\delta + \alpha\right)} \tag{13}$$

Here Vcr is the critical value of the receiving-end voltage at voltage stability limit. Low value of Vcr indicates the system will have better voltage profile along with higher load catering capability resultant better voltage stability. Tomaintain global voltage stability,

$\Delta[J]=$. Therefore to secure global voltage stability, the global voltage stability margin can be defined as GVSM=$\Delta[J]$, given in Equation (12). It indicates how far the present operating condition is from global system voltage collapse i.e., GVSM points on the global voltage security status of the present operating condition (Figure 2).

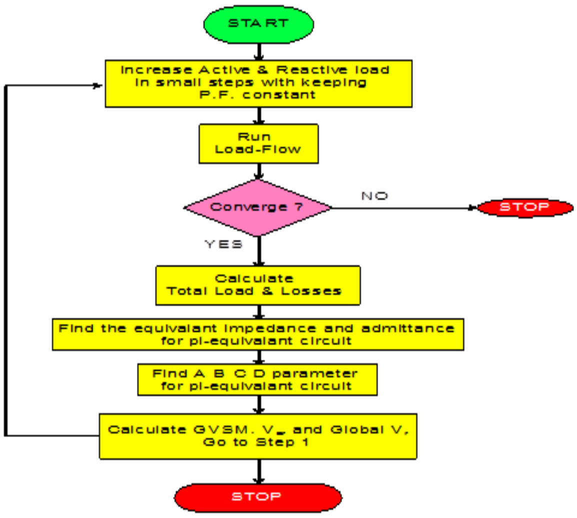

Figure 2 Algorithm to compute GVSM,Vcr and Global Vr.

Computational procedure

The artificial neural network invented in the year of 1958 by psychologist Frank Rosenblatt.[17] Artificial Neural Network operates by creating many different processing elements and in a biological brain, each analogous to a single neuron. The ANNs are trained by adapting a network and comparing the output obtained with the input training and target data. Mainly the training is carried out to match the network output to target data. In this paper voltage stability assessment is carried out by using conventional N-R method and two network models of ANN named RBEF and FFBP. When we compared the results from the ANNs networks then we found that the results from RBFN are more accurate. So we emphasized only on RBFN (Figure 3).

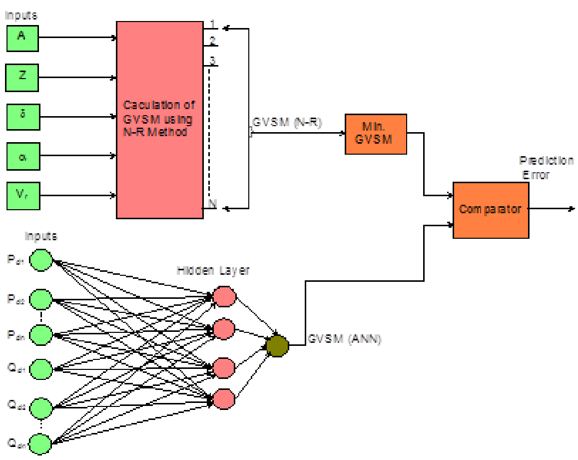

Figure 3 Proposed neural network architecture.

RBF neural network architecture

The RBFNN is a feed forward neural network, which consists of input layer, one hidden layer, and the one output layer. The value of neurons of input layer feeds in hidden layer, a hidden layer which holds the each neuron with radial basis activation function and an output layer which holds each neuron with linear activation function. The initiating centre, width for RBF units and computing weights for connecters are combined to make a learning process for RBF neural network.[18] The idea about Radial Basis Function (RBF) network comes out from the theory of function approximation. According to this, there are two layers feed forward network and a set of radial basis function is implemented by hidden nodes i.e. Gaussian function is used in it. The linear summation function functions as in an Multi-Layer Perceptron (MLP) is implemented by output nodes. The network training is divided into two stages, in first stage, weights are determined from input to hidden layer and in second stage, weights are determined from hidden layer to output layer. This makes interpolation very good. Developed architecture of network given in Figure 3.

Outlines for RBFN networks, which are helpful to understand the given networks are given by

a. Exact interpolation

$$f(X)=\sum_{p=1}^{N} W_p \varphi\left(\left\|X-X^p\right\|\right) \tag{14}$$

b. Determining the weights

$$f\left(X^q\right)=\sum_{p=1}^{N} W_p \varphi\left(\left\|X^q-X^p\right\|\right)=t^p \tag{15}$$

And
$$W=\varphi^{-1}t \tag{16}$$

c. Improved RBFN network

For the Gaussian Basis Function, we have:

$$\varphi_j(X)=\exp\left[-\frac{\left\|X-\mu_j\right\|^2}{2\sigma_j^2}\right] \tag{17}$$

For the training of Artificial Neural Network Input data sets are generated from offline Newton-Raphson load flow analysis by varying both real and reactive loads at all the buses randomly of their base case value. In data collection, the input data are divided into three categories named, train data, validation data and test data. NR load flow analysis is conducted at all steps and corresponding global voltage stability margin GVSM is calculated. The MATLAB is used as a computing tool.[10] Total 60 inputs for IEEE 30 bus systems and 28 inputs for IEEE 14 bus systems, total 100 load samples are generated and for 82 outputs for IEEE 30 bus systems and 40 outputs for IEEE 30 bus systems, total 100 load samples are also generated by offline N-R load flow analysis method. To identify the topology of artificial neural network training process of neural network helps us. The training speed depends on the speed factor, the transfer function of neurons or on the process of network initialization. A set of network inputs and target outputs are required for the training process of the neural network, and also required the enough information about the network in order to simulate a good prediction of power system. The different training algorithms are used to train the feed forward back propagation neural network. In this paper, Levenberg-Marquardt (LM)[14,15] training technique is used due to faster training, good convergence and this algorithm is suitable for medium size neural network.

Simulation results

A computer software programme has been developed in the MATLAB 2015b environment to perform the simulations and run on a Pentium IV CPU, 2.69 GHz, and 1.84 GB RAM computer. To demonstrate the effectiveness of the proposed technique, an IEEE 14 bus test system and a typical IEEE 30 bus test system have been used. The IEEE 14 Bus system represents a portion of the American Electric Power System which is located in the Midwestern US as of February, 1962. Basically this 14 bus system has 14 buses, 5 generators and 9 load buses. The IEEE 30 Bus system represents a portion of the American Electric Power System (in the Midwestern US) as of December, 1961. Basically this 30 bus system has 30 buses, 6 generators and 24 load buses.[19,20]

Case study of IEEE 14 test bus system

To validation of the proposed approach three operating scenarios are considered.

Case1. Near the Base case (where the load buses are having the nominal values of real and reactive power loading)

Case2. Medium Load (increase of the system operating load by (2.24p.u.) from base case), i.e. it's half of the high system operating loading.

Case3. High system operating load (increase of the system operating load by (3.2p.u.) from base case)

Table 1 & Table 2 give the Global voltage stability margin GVSM and critical voltage Vcr for IEEE 14 test bus system at for three cases.

Table 1 Global voltage stability margin GVSM for IEEE 14 test bus system at different operating loadings

GVSM near the base case (at minimum loading)		
N-R	**RBFN**	**FFBP**
3.320080862	3.320080862	3.301853309
3.308850919	3.308850919	3.284748532
3.297547719	3.297547719	3.257607549
3.213354895	3.213354895	3.219765148
GVSM at medium loading (half of the high operating load)		
N-R	**RBFN**	**FFBP**
2.352781	2.352781	2.355879
2.336762	2.336762	2.340173
2.320616	2.320616	2.324231
2.304341	2.304341	2.308048
GVSM at high operating loading		
N-R	**RBFN**	**FFBP**
1.381297	1.381297	1.377925
1.354128	1.354128	1.359059
1.326452	1.326452	1.343191
1.298239	1.298239	1.330387

Table 2 Critical voltage Vcr for IEEE 14 test bus system at different operating loadings

Vcr near the base case (at minimum loading)		
N-R	**RBFN**	**FFBP**
0.513237067	0.513237067	0.514060835
0.51359514	0.51359514	0.51422424
0.513963	0.513963	0.514414
0.514286	0.514286	0.514631
Vcr at medium loading (half of the high operating load)		
N-R	**RBFN**	**FFBP**
0.54653	0.54653	0.54651
0.547667	0.547667	0.547661
0.548829	0.548829	0.548837
0.550017	0.550017	0.55004
Vcr at high operating loading		
N-R	**RBFN**	**FFBP**
0.652401	0.652401	0.653426
0.6568	0.6568	0.656797
0.661392	0.661392	0.659556
0.666194	0.666194	0.661683

Following points are emerged from this analysis:

A. Near the base case, it is observed that values of GVSM and Critical voltage Vcr predicted by Feed Forward Back Propagation (FFBP) and Radial Basis Function Neural Network (RBFN) falls in a secure range. In other words, near the base case the value of GVSM is higher for the system and lower for the Vcr. The analysis of GVSM and Vcr exhibited in tables. These values are validated by offline N-R method. It is also observed that the prediction accuracy of RBFNN is higher than other networks.

B. At medium loading (Case2) considerable amount of decrease or increase in the numerical values of GVSM and Vcr, respectively are observed by all prediction methods, which is also given in Tables and in this case also RBFN is most accurate.

C. For case 3, after continuous increase in the system operating load the system has reached near to the collapse point. The values of GVSM tend to zero and Vcr becomes higher and dominant. The prediction capability of all the networks is verified by offline N-R method. From this analysis it is concluded that RBFNN is a suitable topology to identify the critical buses in IEEE 14 bus test system.

D. When increases the system operating load then decreases the value of global voltage stability margin and power system goes towards instability. At point of voltage collapse the GVSM becomes lower or may be zero. The effect of local voltage collapse phenomena in global scenario is quite reliable due to profile of GVSM.

E. The profile of global receiving end voltage is decreasing when increasing the system operating load. The receiving end voltage for series equivalent is high that show the better voltage stability limit, but when increase the load then its value reached at near to voltage collapse.

F. Figure 4 & Figure 5 show the prediction error of RBFNN for GVSM and Vcr respectively. From this analysis it is concluded that RBFNN is a suitable topology for the assessment of system voltage stability in IEEE 14 bus test system.

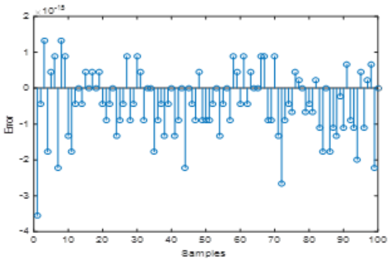

Figure 4 GVSM error plot of RBFNN topology for IEEE 14 bus system.

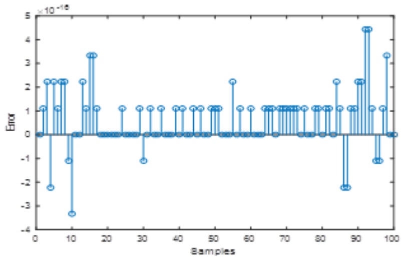

Figure 5 Vcr error plot of RBFNN topology for IEEE 14 bus system.

Case study of IEEE 30 test bus system

To validation of the proposed approach three operating scenarios are considered.

Case1. Near the Base case (where the load buses are having the nominal values of real and reactive power loading)

Case2. Medium Load (increase of the system operating load by (1.89p.u.) from base case), i.e. it's half of the high system operating loading.

Case3. High system operating load (increase of the system operating load by (2.7p.u.) from base case)

Table 3 & Table 4 give the Global voltage stability margin GVSM and critical voltage V_{cr} for IEEE 30 test bus system at for three cases.

Table 3 Global voltage stability margin GVSM for IEEE 30 test bus system at different operating loading

GVSM near the base case (at minimum loading)		
N-R	**RBFN**	**FFBP**
2.026	2.026	1.976
2.016	2.016	1.967
2.005812	2.005812	1.957523
1.995449	1.995449	1.945864
GVSM at medium loading (half of the high operating load)		
N-R	**RBFN**	**FFBP**
1.18122	1.18122	1.17726
1.167479	1.167479	1.163801
1.153633	1.153633	1.150289
1.13968	1.13968	1.136716
GVSM at high operating loading		
N-R	**RBFN**	**FFBP**
0.302908	0.302908	0.321769
0.272346	0.272346	0.30624
0.239781	0.239781	0.292178
0.204596	0.204596	0.279588

Table 4 Critical voltage Vcr for IEEE 30 test bus system at different operating loadings

Vcr near the base case (at minimum loading)		
N-R	**RBFN**	**FFBP**
0.509798053	0.509798053	0.510456681
0.51005358	0.51005358	0.51059213
0.510314	0.510314	0.510749
0.510579	0.510579	0.510928
Vcr at medium loading (half of the high operating load)		
N-R	**RBFN**	**FFBP**
0.533958	0.533958	0.533975
0.534638	0.534638	0.534661
0.53533	0.53533	0.535359
0.536032	0.536032	0.536067
Vcr at high operating loading		
N-R	**RBFN**	**FFBP**
0.584614	0.584614	0.585044
0.586309	0.586309	0.586434
0.588058	0.588058	0.587569
0.589869	0.589869	0.588425

Following points are emerged from this analysis:

I. Near the base case, it is observed that values of GVSM and Critical voltage Vcr predicted by FFBP and RBFN falls in a secure range and validated by offline N-R method. In other words, near the base case the value of GVSM is higher for the system and lower for the Vcr. The analysis of GVSM and Vcr exhibited in tables. As usually observed that the prediction accuracy of RBFNN is higher.

II. At medium loading (Case 2) considerable amount of decrease or increase in the numerical values of GVSM and Vcr, respectively are observed by all prediction methods, which is also given in Tables.

III. For case 3, after continuous increase in the system operating load the system has reached near to the collapse point. The values of GVSM tend to zero and Vcr becomes higher and dominant. The prediction capability of all the networks is validated by offline N-R method. From this analysis it is concluded that RBFNN is a suitable topology to identify the critical buses in IEEE 30 bus test system.

IV. When increases the system operating load then decreases the limit of global voltage stability margin and power system goes towards instability. At point of voltage collapse the GVSM becomes lower or may be zero.

V. The profile of global receiving end voltage is decreasing when increasing the system operating load. The receiving end voltage for series equivalent is high that show the better voltage stability limit, but when increase the load then its value reached at near to voltage collapse.

VI. Figure 6 & Figure 7 show the prediction error of RBFNN for GVSM and Vcr respectively. From this analysis it is concluded that RBFNN is a suitable topology for the assessment of system voltage stability in IEEE 30 bus test system.

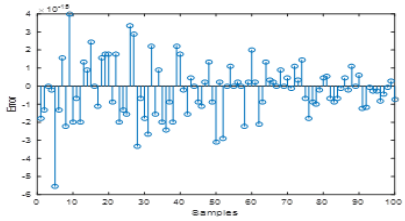

Figure 6 GVSM error plot of RBFNN topology for IEEE 14 bus system.

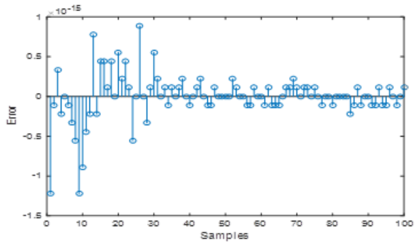

Figure 7 Vcr error plot of RBFNN topology for IEEE 30 bus system.

As the series impedances and shunt admittances of given system are lumped within the series impedance for the series equivalent two bus model, the profile of this model indicate voltage collapse at higher level. In series equivalent network, no appreciable changes in Vcr with increase in system load. But in the case of pi-equivalent network Vcr is much susceptible to change in system operating load. In pi-equivalent model Vcr is increase with increase in system operating load indicating more critical operating condition and at last voltage collapse occur at higher load. Actually in case of series model the critical voltage values only depend on power factor of the load, there is no effect of system parameters on this model. The simulation results of the voltage stability analysis using proposed technique give the better accuracy and reliability.

Conclusion

In this paper a new methodology is proposed to evaluate an equivalent two bus pi-network model for assessment of voltage stability for a multi bus power system where series and shunt parameters of transmission lines are lumped separately in the form of series and shunt equivalent. The equivalent network parameters like GVSM, critical voltage, global receiving end voltage etc., are able to sense any type of change in system in accurate and efficient way as compared to two bus series equivalent methodology. An innovative technique named GVSM is used to assess the voltage instability or in other words to assess the proximity of the existing system state from voltage collapse.

This paper presented a GVSM based voltage stability assessment using ANN for IEEE 14 and IEEE 30 test bus systems. Following are the major highlights of this work. GVSM, for the given power system network is calculated to judge the health of the power system in the way of stability. Prediction of GVSM and VCR are validated by different neural network topologies. The main advantage of proposed method is that it indicates a good agreement between target data (N-R) and RBFN output. Prediction accuracy of RBFN is best as compared with other topologies of ANN. The prediction error indices validate this fact. The proposed approach provides fast computation of Global voltage stability margin, GVSM. Operator can analyze any unknown load patterns by using this supervised learning approach. We find out the GVSM, Vcr and global receiving end voltage in offline N-R method and ANN method by varying real and reactive loads and designed an efficient neural network.

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Conflicts of interest

The author declares there is no conflict of interest.

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