Volume 4, Issue 1, January 2017 ISSN: 2348-8565 (Online)

International Journal of Modern Engineering and Research Technology

Website: http://www.ijmert.org Email: editor.ijmert@gmail.com

Assessment and Preventive Control of Voltage Stability Using Artificial Neural Network

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ABSTRACT

The present power system is consisting of several sub-networks such as generation, transmission, and distribution sub-networks. Use of new technologies and the growth in interconnections are continuously increasing the complexity of the system further. These highly complex modern power systems are operating in severely stressed conditions due to economical and environmental considerations rendering them vulnerable to frequent failures [10]. Therefore, ensuring the stability of these systems has become one of the major concerns for the power system engineers, especially the voltage stability. This paper provided a method for improvement of voltage stability in interconnected power systems using a neural network, this paper deals with L-index technique to calculate the stability margins and to furnish the information about the weak areas in the network. Outputs of this technique are use to train and test an ANN. The trained ANN architecture is capable to predict the values of L-indices and control quantities, i.e. generator excitation levels and settings of Static VAR Compensators (SVCs) to keep the system stable.

Keywords:—*Voltage Stability, Load flow, L-Index, Neural Network, svc.*

I. INTRODUCTION

Power system Stability can be seen as loss of synchronism (i.e. some synchronous machine going out of step) when the system is subjected to a particular disturbance [1]. "Power system stability is the ability of electric power system for a given initial operating condition to regain a state of operating equilibrium after being subjected to a disturbance" [1, 2]. There are two types of stabilities rotor angle stability and voltage stability. This paper will focus on voltage stability**.** The voltage instability occur when the generation and transmission system unable to deliver power demanded by load. The main factor of voltage instability is the inability of power system to meet the reactive power demand. The system is voltage unstable if magnitude of voltage at least, one bus in the system is decrease as the reactive power injection at the same bus increased. In other word a system is voltage stable if V-Q sensitivity is positive and voltage unstable if V -Q sensitivity is negative at least, one bus in the system (The V-Q sensitivity at a bus represent the slop of V-Q curve at a given operating point). Voltage stability one of the major issues in power system planning, operation and control. This paper is used L-index to check voltage stability margin. The obtained results are used to train a feed-forward neural network using the back propagation algorithm (The details of Feed-Forward neural network are given in methodology section).

Method of voltage stability analysis

There are several methods by which the voltage stability is calculated such as:

- P-V method.
- V-Q method.
- Method based on singularity of power flow jacobian matrix at the point of voltage collapse.
- Continue power flow method.

The power system stability tool-box (PSAT) is used to calculate the P-V curve. Observing Figure 1.

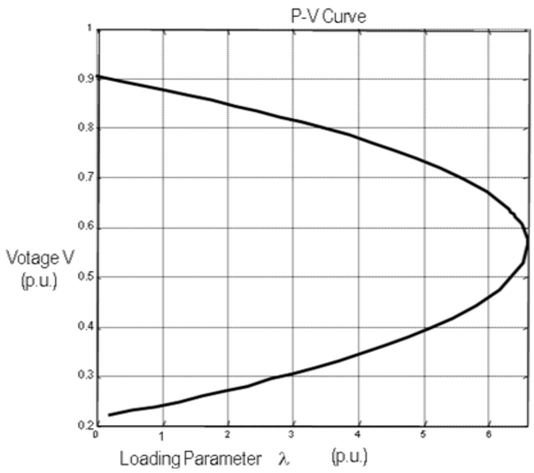

Figure: 1 P-V characteristics

There are two equilibrium solutions corresponding to the same loading parameter at the low loading. One is a high voltage solution and the other is a low voltage solution. When the loading increases, the two solutions approach each other and finally become one nose point. Out of the two solutions, the higher voltage operating point is stable and the lower voltage operating point is unstable. The power system can only operate on the upper- half of *P -V* curve where the system dynamics act to restore the state to the operating point when it is subjected to a disturbance.

On the other hand, any slight disturbances from the low voltage operating point on the lower-half of *P -V* curve result in the operating state moving away from the operating point towards the origin. The nose point of the *P - V* curve is named as the voltage stability limit. Figure 2 show the active power loading vs. voltage profile at same bus. Active power loading is increases magnitude of voltage is decreases.

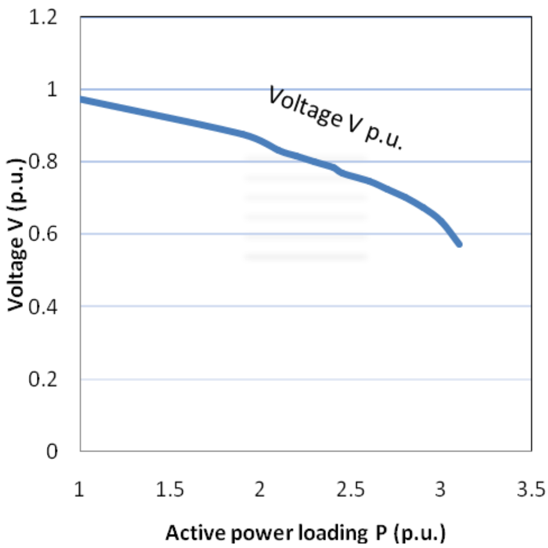

Figure :2 Fast Voltage Stability Indicator

There are several methods by which the voltage stability index is calculated such as:

- Voltage instability proximity index[3]
- Voltage collapse proximity indicator.[4]
- L-Index.[5]

This paper used L-index as a voltage stability indicator.

1. This index was derived from the voltage equation at a load bus. The voltage stability index is terms as symbol L given by [5]:

$$L_i = \frac{4[V_{oi}\,V_{Li}\cos\theta_i - V_{Li}^2\cos\theta_i^2]}{V_{oi}^2}$$

V_{Li} = Load voltage at bus i.

V_{oi} = No load voltage at bus i.

$\theta_i = (\theta_{oi} - \theta_{Li})$.

θ_{Li} = Load angle at bus i.

θ_{oi} = No load angle at bus i.

2. First load flow solution is obtained incorporating the generator control and load characteristics. Using the load flow results the L-index is computed as:

$$L_j = 1 - \left| \sum_{i=1}^{i=g} F_{ji} \times \frac{V_i}{V_j} \right|$$

Where, j=g+1………… n and all the terms within the sigma on the RHS of equation are complex quantities. The values F_{ji} are obtained from the Y bus matrix given by [6]:

$$\begin{bmatrix} I^G \\ I^L \end{bmatrix} = \begin{bmatrix} Y^{GG} & Y^{GL} \\ Y^{LG} & Y^{LL} \end{bmatrix} \begin{bmatrix} V^G \\ V^L \end{bmatrix}$$

Where I^G, I^L, V^G, V^L represent currents and voltages at the generator and load nodes. Rearranging the above-mentioned equations yields:

$$\begin{bmatrix} V^L \\ I^G \end{bmatrix} = \begin{bmatrix} Z^{LL} & F^{LG} \\ K^{GL} & Y^{GG} \end{bmatrix} \begin{bmatrix} I^L \\ V^G \end{bmatrix}$$

Where

$$F^{LG} = -[Y^{LL}]^{-1}[Y^{LG}]$$

are the required values. The L-indices for a given load condition is computed for all load buses, and thus the complex equation for the L - index for j^{th} node can be written as:

$$L_j = 1 - \left| \sum_{i=1}^{i=g} F_{ji} \times \frac{V_i}{V_j} \lfloor \theta_{ji} + \delta_i - \delta_j \right|$$

The value of L varies from 0 to 1.0. L value close to 0 indicates stable voltage condition while L value close to 1.0 indicates unstable voltage condition. In order to maintain a stable voltage condition in the system network, the value of L at any load bus must be kept to a small value close to 0. If the value of L at any load bus approaches 1.0, it shows that the load bus is close to its instability limit and if L is equal to 1.0, the system has already in the state of voltage collapse. In this study, the value of stability index L was evaluated for every load bus in a test system for various loading conditions. Figure 3 the voltage stability assessment is shown as the value of L-Index is approach unity at same time the magnitude of voltage approach zero value.

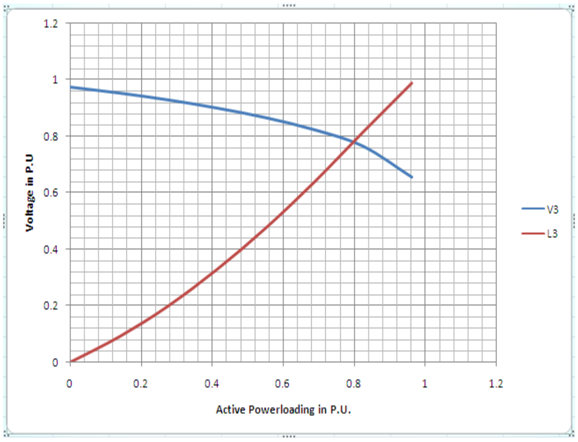

Figure: 3 L-Index & Voltage Characteristics

II. Methodology

The capability of proposed technique to predict the voltage stability condition of a power system, a comparative study was conducted by developing an Artificial Neural Network (ANN) system and used it to perform the similar task. A multilayer feed-forward Artificial Neural Network with error back-propagation was developed. The developed network consists of three basic elements as follows [7]:

- Input layer.
- Hidden layer.
- Output layer.

as shown in Figure 4

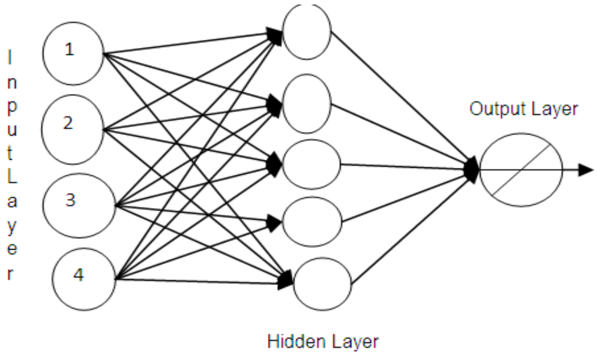

Figure 4: Artificial Neural Network Structure

The topology of the developed network consists of an input layer, one hidden layer and an output layer. The output of this developed system is the stability index value, thus a single node was used in the output layer [8]. With the neural network tool create a network, train it and evaluate the performance by using mean squared error. In this paper the back-propagation algorithm is used to train the network.

The training process involved in this system was performed in order to train the developed network with a set of inputs and a targeted output. Meanwhile testing process was conducted in order to get the predicted stability index by using the weights and bias obtained from the trained network.

ANN Training Scheme

Step1: A conventional voltage stability algorithm is run with the test system for simulated loading conditions. For this first the base case and the maximum loading conditions of the test system are determined using the conventional software. Then the load conditions are varied from base case till full load and training samples are generated.

Step2: Create a database for the Input vector such as X= [P_L , Q_L] Where, P_L , Q_L real and reactive power at load buses. Moreover, target vector is created in the form of L-indices for the corresponding Input vectors.

Step 3: Train the network based on a set of activation functions and number of neurons. The number of neurons in each layer is varied initially and optimum combination is found out depending on the training period and performance error.

Step 4: Find the most suitable network based on the simplicity least possible Mean Square Error and computational speed. Further use various test functions to confirm the effectiveness of the proposed neural network. At this state the functions and all the parameters are finalized for this combination.

III. RESULTS AND DISCUSSIONS

The test system presented in this study is the IEEE six-bus system, for which the single line diagram shown in Figure 5 [9].

The IEEE six-bus system is composed of a slack bus (1) and one voltage controlled bus (2) and four load buses (3, 4, 5 and 6). As a result, the developed Neural Network has 2 inputs representing real and reactive power of load bus 3 in the system and one outputs corresponding to the value of L-index of load bus 3.

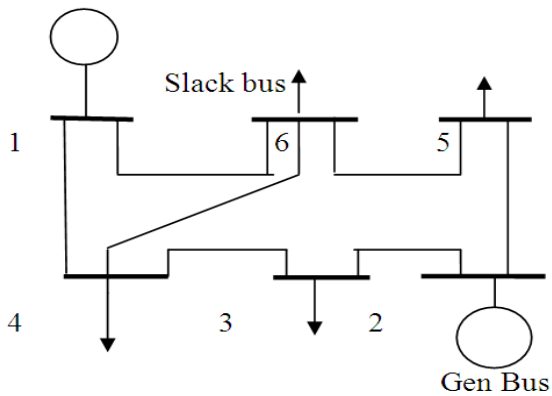

Figure. 5. IEEE 6·Bus Lest System

The L-index corresponding to the slack bus and voltage controlled buses are not considered in the input and output list since they are always zeros as long as the bus voltages remain controlled. The configuration of developed neural network consisted of one hidden layers with 20 neurons in hidden layer 1 neurons in output layer.

The selection of this configuration is based on its training speed and its convergence accuracy. Figure 6 shows the performance of the neural network in minimizing the MSE error during training process. The regression analysis and prediction output of developed Neural Network covering stability index at the load bus in an IEEE 6 bus test system shown in Figure 7. Figure 7 shows the closeness of the actual output produced by the network with respect to targeted output. The results from the testing network are shown in Table No. 1. In Table No. 1, the results shows a good agreement between output and targeted output which were obtained in predicting voltage stability index during normal operating condition, it clear from Table 1 the predicted value by ANN is very close to Target value. In the proposed technique, the training process was carried out many times until it meets a stopping criterion means in terms of mean squared error (mean squared error is average squared difference between output and target) Zero means no error, over 0.6667 means high error.

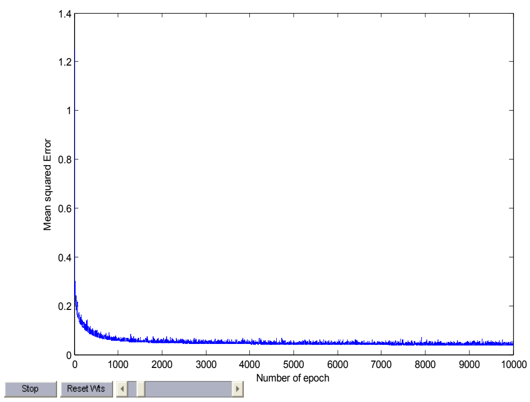

Figure: 6 Training Errors

Table No.1 Results Shows a Good Agreement Between Output and Targeted

Bus No.3		
L-Index	Value Obtain by ANN	Error
0	0	0
0.0507	0.050698	2.52E-06
0.0512	0.051201	-9.14E-07
0.072	0.071993	7.24E-06
0.0891	0.089107	-7.47E-06
0.1105	0.11059	-8.90E-05
0.156	0.1558	0.000197
0.1579	0.15791	-1.26E-05
0.1799	0.18066	-0.00076
0.2099	0.20902	0.000876
0.2254	0.22511	0.000288
0.2548	0.2554	-0.0006
0.2809	0.28083	6.59E-05
0.3107	0.31024	0.000464
0.357	0.35702	-2.29E-05
0.3666	0.36752	-0.00092
0.3961	0.39499	0.001107
0.4254	0.42615	-0.00075
0.4548	0.45434	0.00026
0.4884	0.48836	0.000043
0.5151	0.51576	-0.00066
0.549	0.5487	0.0003
0.5796	0.57979	-0.00019
0.6123	0.61233	-3.29E-05
0.6487	0.6484	0.000302
0.6779	0.67817	-0.00027
0.7126	0.71251	8.92E-05
0.7402	0.74016	4.46E-05
0.7781	0.77813	-3.33E-05
0.8123	0.81229	6.97E-06
0.8499	0.84985	1.84E-05
0.8771	0.8771	-2.02E-06
0.9093	0.9093	-6.86E-07
0.9357	0.93565	1.55E-05
0.9683	0.9683	-1.78E-06
0.9894	0.9894	-1.16E-06
0.9995	0.99949	8.17E-06

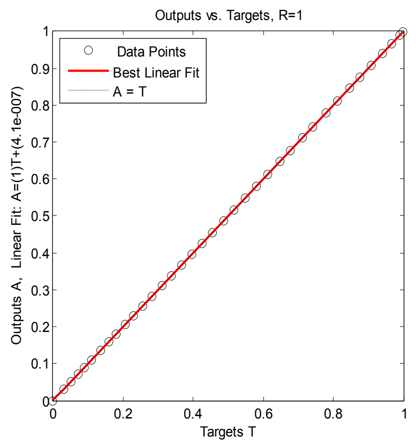

Figure: 7 the closeness of the actual output produced by the network with respect to targeted output

IV. CONCLUSION

Present power systems are highly complex and working under heavily stressed conditions Therefore voltage stability has become one of the important issues in power system planning, operation and control. This paper presents a neural network with back-propagation algorithm is developed for the computation of power system voltage stability analysis, L-indices have been calculated from IEEE 6-bus data and the results of L-index are verified by using ANN. Give satisfactory solutions towards improved stability. Highly nonlinear problems like this can be solved using single hidden layer neural network and propose its ability in online assessment of voltage stability and margin. It is found that in such an analysis, the training algorithm is the most important factor in the performance and accuracy of the network, since any variation to be done in the number of neurons and the network parameters is limited. Post regression analysis and the comparison of the output at each bus shows that the output obtained are sufficiently accurate if well organized training is conducted reducing the redundancy and normalizing the inputs as well as outputs. Moreover, the performance of each of the training algorithms depends also on the size of the power system network under consideration.

REFERENCES:

[1] P. Kundur, "Power System Stability and Control", McGraw Hill, 1994, pp. 959 - 1024.

[2] Y. Lin Chen, C. Wei Chang, "Efficient Methods For Identifying Weak Nodes In Electrical Power Network", IEE Proceeding of the Generation, Transmission, Distribution Vol. 142, May 1995.

[3] K. Sakameto, Y. Tamura, "Voltage Instability Proximity Index (VIPI) Based On Multiple Load Flow Solutions", Proceeding of the 27th Conference on Decision and Control, Austin, Texas, Dec. 1988.

[4] M Moghavemmi, and F M Omar, ''Technique for Contingency Monitoring and Voltage Collapse Prediction," IEE Proceeding on Generation, Transmission and Distribution, Vol. 145, pp 634 - 640. Nov. 1998.

[5] T.K Abdul Rahman and G.B Jasmon, "A New Technique for Voltage Stability Analysis in a Power System and Improved Load flow Algorithm For Distribution Network", International Conference on EMPD, Vol.2, pp 714-719, Nov.1995.

[6] D.Thukaram "Voltage stability Improvement Case Studies of Indian Power networks" Electric Power Systems Research pp.35-44, May (1998).

[7] A.A. El-Keib, X.Ma, "Application of Artificial Neural Networks in Voltage stability Assessment" IEEE trans. on power system. Dec.1995.

[8] "The Mathworks Inc. Neural Network TOOLBOX", Users guide For using in MATLAB, Jan 1998.

[9] Ali Keyhani1, Wenzhe Lu1, Gerald T. Heydt2 "Neural Network Based Composite Load Models for Power System Stability Analysis" IEEE International Conference on Computational Intelligence for Measurement Systems and Applications Giardini Naxos, Italy, pp 20-22 July 2005

[10] Geeta Negi, Anurag Kumar Swami, S. K. Goel & Ajay Srivastva "Assessment and Improvement of

Voltage Stability using ANN Architecture" 7th WSEAS International Conference on Electric Power Systems, High Voltages, Electric Machines, Venice, Italy, pp 21-23, Nov.2007

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