ISSN 2320-9984

Volume 12 Issue 4 | December 2024 ISSN: 2320-9984 (Online)

International Journal of Modern Engineering & Management Research

Website: www.ijmemr.org

Assessment and Control of Voltage Stability using Artificial Neural Network

Dolly Dharmak
Research Scholar, M.Tech.
Energy Technology
Takshshial Institute of Engineering and Technology
Jabalpur (M.P.), India
Email: dharmakdolly@gmail.com

Preeti Rajput
Assistant Professor
Department of Electrical and Electronics Engineering
Takshshial Institute of Engineering and Technology
Jabalpur (M.P.), India
Email: preetirajput@takshshila.org

Abstract—*The present power system is a complex network 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. 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 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 used 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, Voltage Collapse, Load flow, L-index, Neural Network, Static VAR Compensator.*

1. INTRODUCTION

Power System Stability may broadly be defined as the ability of a power system to remain in a state of operating equilibrium during normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance. There are two types of stabilities viz. rotor angle stability and voltage stability. Voltage stability is the ability of a power system to achieve or maintain the voltage magnitudes at acceptable levels at all buses in the system during faults, disturbances, and stressed conditions. A system enters a state of voltage instability when a disturbance, increase in load demand, or change in system condition causes a progressive and uncontrollable drop in voltage [1]. The main factor for instability is the inability of the power system to meet the demand of increased reactive power. In this paper, L-index is used to check voltage stability margins the obtained results are used to train a feed-forward neural network using the back propagation algorithm

Fast Voltage Stability Indicator

Several indices based methods such as Voltage Instability Proximity Index (VIPI) and Voltage Collapse Proximity Indicator (VCPI) are used to evaluate voltage instability. They are based on multiple load flow solutions and give only global picture [2, 3]. The transmission proximity index that specifies the weakest transmission part of the system based on voltage phasor approach necessitate the scanning of the whole power system structure for several time which the time consuming approach [4].

There are several methods to estimate or predict the voltage stability condition of a power system. Some of them described here.

1: This study utilized the voltage stability index developed by Abdul Rahman et al. [5] in order to indicate the voltage stability condition at each load buses of a system. This index was derived from the voltage equation at a load bus. The voltage stability index is terms as symbol L given by [5]:

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

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, $j=g+1 \ldots\ldots\ldots\ldots n$ 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:

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

Where, I_G, I_L, V_G and 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:

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

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. Since the main objective of this work is to determine the voltage stability condition of the whole system, thus only the highest value of L is selected to represent the overall stability condition. This is because the stability of the whole system is reflected by the voltage stability condition of the most severe load bus. The highest L will then coded and grouped into 3 categories of voltage stability condition. Table 1 show the range of L corresponds to the voltage stability condition.

Table 1: Categories of Voltage Stability Index L

Coded L	Range of L	Condition
0	0.0 – 0.5999	stable
0.5	0.6 – 0.8999	moderately stable
1	0.9 – 1.0	unstable/voltage Collapse

2. METHODOLOGY

In order to determine the capability of the 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 feedfoward Artificial Neural Network with error back propagation learning was developed. The developed network consists of three basic elements as follows [7]:

1. Neural Network architecture
2. Suitable back propagation learning algorithm.
3. Method of training and testing.

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. The back propagation-based ANN was developed according the following steps:-

A. forward

B. backpropagate of error

C. weight and bias update

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. Learning and momentum rates are both fixed to 0.03. Meanwhile testing process was conducted in order to get the predicted stability index by using the weights and bias obtained from the trained network.

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 [6]. 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: Find the minimum and maximum values of the input vector, remove redundancies and normalize to suit to train the selected feed forward neural network.

Step 4: Select the set of parameters to train the network. The main parameters selected are number of epochs, learning increment and rate, performance goal with Mean Squared Error (MSE) and minimum and maximum gradient.

Step 5: 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 6: Check the performance of the network for behavioral accuracy. If not change the activation functions and tests the network again. Find the most suitable combination of the activation function. Behavioral accuracy depends on the uniformity in values of L-indices at all the buses. It can happen that the network gives output which is accurate for some buses but may be unacceptable on some other buses.

Step 7: Change the training function keeping same transfer functions and optimum number of neurons in each layer.

Step 8: 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.

3. NETWORK ARCHITECTURE

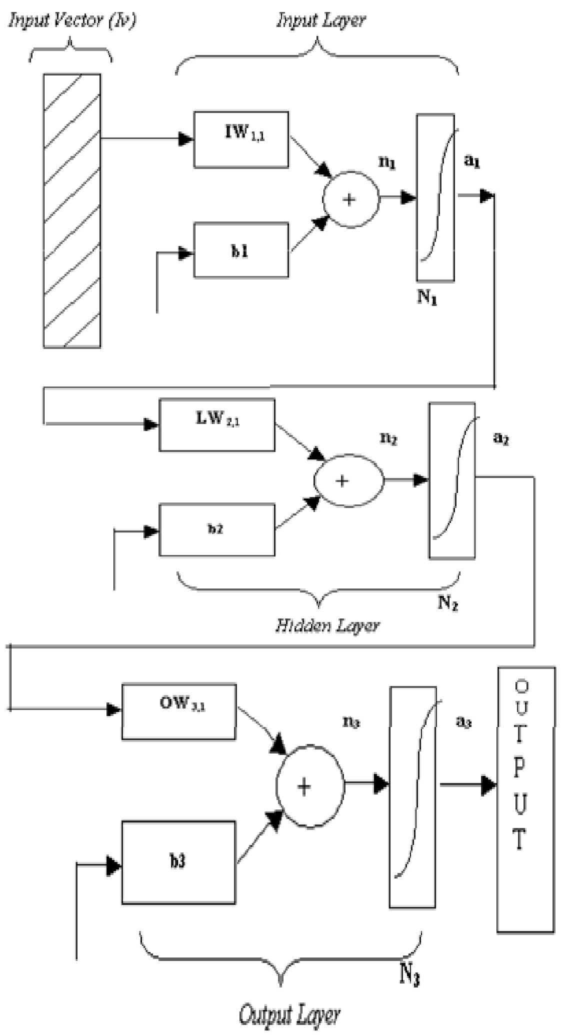

Figure Figure 1: Proposed Feed Forward Neural Network (FFNN) architecture

1 shows the proposed feed forward neural network. The architecture consists of an input layer, a hidden layer and an output layer. Input vector is fed to the Input layer for all the buses of the selected system. First to obtain the best combination of number of neurons, training and activation function a test system is developed and the toolbox parameters are applied. Following Toolbox functions are analyzed based on the above methodology [9]:

- Neural network architecture and types
- Training functions
- Activation functions
- Learning function
- Initialization functions
- Performance functions

The network has to be train by using Train using Levenberg-Marquardt optimization. Mean Squared Error is the average squared difference between (normalized) outputs and targets. Zero means no error, over 0.6667 means high error. Regression R Values measure the correlation between (un-normalized) outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

4. RESULTS AND DISCUSSIONS

The proposed method has been used for the voltage stability evaluation of the IEEE 30 bus reliability test system. The available simulation data were separated into 3 categories; training data, testing data and validation data. Training data are presented to the network during training, and the network is adjusted according to its error. Testing data have no effect on training and so provide an independent measure of network performance during and after training. validation data are used to measure network generalization, and to halt training when generalization stops improving. 60% data were used for the training process, while 20% data were utilized for the testing process and 20% data were utilized for the validation process. In the proposed technique, the training process was carried out many times until it meets a stopping criterion. It was followed by the testing process using the solutions obtained from training programme namely the configuration of the trained network from ANN. As shown in Figure 2 the testing procedure was executed right after the training process. This was then followed by the regression test in order to determine the accuracy of the voltage stability prediction. This cycle was repeated until the regression test gives the value of correlation coefficient higher than 0.9.

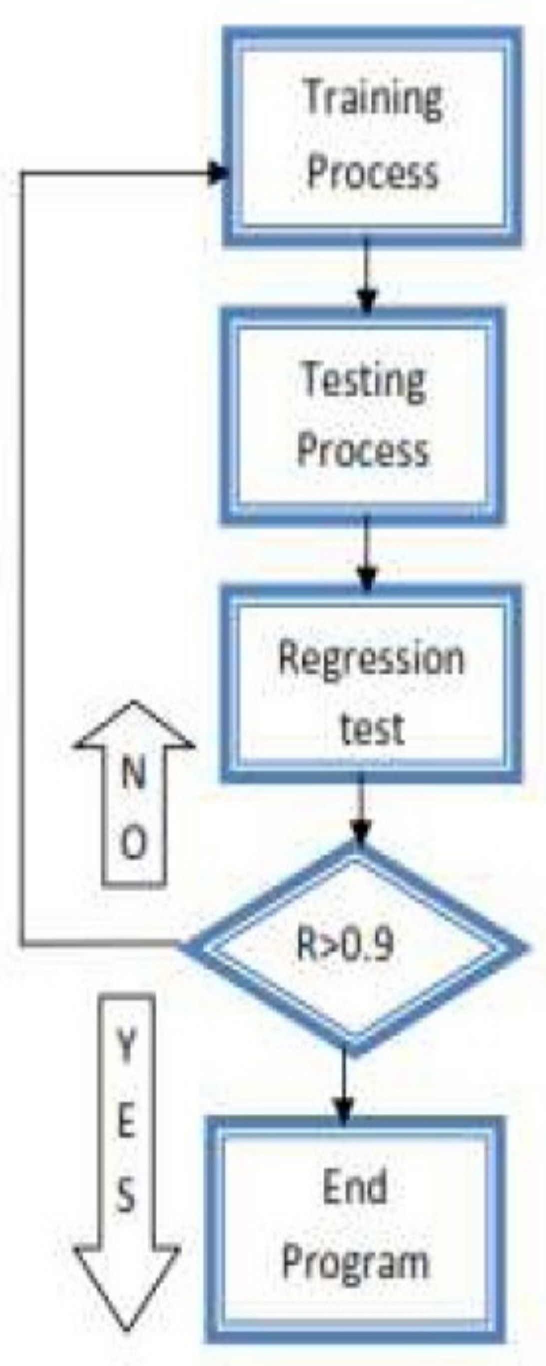

Figure 2: Flowchart of Pattern Recognition Process

Table 2 shows the results obtained from the developed ANN-based voltage stability prediction systems with 60% data were used in the testing process. It could be observed from the results obtained from the ANN-based voltage stability prediction system that only some data was not correctly predicted. Meanwhile for the other testing data, the system has able to correctly predict the voltage stability condition of the system.

Table: 2 Actual value vs. predicted value of L-Index

Actual value of L-Index	Value obtain from ANN
0.1928	0.2201
0.276	0.2622
0.3356	0.3195
0.3836	0.3758
0.4299	0.4297
0.4856	0.4818
0.4628	0.4631
0.2405	0.2423
0.3349	0.3197
0.406	0.4056
0.4564	0.465
0.5112	0.5124
0.5473	0.5487
0.5723	0.5706
0.2736	0.2733
0.3799	0.3743
0.4522	0.4554
0.5083	0.5039
0.5603	0.5631
0.5925	0.6225
0.6198	0.6498
0.3378	0.3384
0.4361	0.4323
0.5019	0.5009
0.5564	0.5585
0.5984	0.5978
0.6273	0.6277
0.6483	0.6537
0.3687	0.3698
0.4806	0.4826
0.5735	0.5776

The voltage profile shows a variation in the voltage per-unit voltage magnitude which is as high as 1.116 at bus number 24 and 0.3 at bus number 22. Similarly the L-index values show the same effect as these scalar values moves away from zero in the event of voltage deviation. Thus these values are still very good indicators of the bus voltage profile. After predicting the voltage instability in a particular bus or system with the help of L-Index. Corrective actions take place to improve the voltage profile in the system.

5. 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. In this paper, L-indices have been calculated from IEEE 30-bus data and the results of L-index are verified by using ANN give satisfactory solutions towards improved stability. In This paper presents a neural network multi-layer perceptron network has been developed for the computation of power system voltage stability analysis.

REFERENCES:

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

[2] Y. Lin Chen, C. Wei Chang,etc, "Efficient Methods For Identifying Weak Nodes In Electrical Power Network", IEE Proc. - Gener. Transm. Distrib.,Vol 142, No. 3, May 1995.

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

[4] F. Gutina and B. Strmcnik, "Voltage Collapse Proximity Index Determination Using Voltage Phasors Approach", 94SM 510-8 PWRS, 1994.

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

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

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

[8] The Mathworks Inc. "Neural Network ToolBox, Users Guide-For using in MATLAB", Jan 1998.

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

[10] Geeta Negi, Anurag Kumar Swami, S. K. Goel and Ajay Srivastava "Assessment and Improvement of Voltage Stability using ANN Architecture" 7th WSEAS International Conference on Electric Power Systems, High Voltages, Electric Machines, Venice, Italy, November 21-23, 2007 2003.