Assessment and Improvement of Voltage Stability using ANN Architecture

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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 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. This method is applied on an IEEE-9 bus system.

Key-Words: - Voltage Stability, Voltage Collapse, Neural Network, Singular Value Decomposition, Static VAR Compensator, L-index.

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 [7]. The main factor for instability is the inability of the power system to meet the demand of increased reactive power. It is essentially a local phenomenon but may have widespread impact and often lead to voltage collapse. Since 1970 many instances of voltage collapse have been witnessed globally, making voltage stability one of the major issues in power system planning, operation and control.

In this paper, L-index is used to check voltage stability margins. The results of this technique are verified by using Singular Value Decomposition (SVD) method. The obtained results are used to train a feed-forward neural network using the back-propagation algorithm.

2 Material And Methodology

Various indices, used as indicators of voltage stability margins, are calculated as follows:

2.1 L-Index

L-index at bus-j is given by [2],[3],[4]

$$Lj = \left| 1 - \sum_{i=1}^{g} \overline{F_{ji}} \frac{\overline{V_i}}{\overline{V_j}} \right| \quad ; \; j = g+1, g+2, \ldots n \tag{1}$$

where F_{ji} is an element of matrix F_{LG} which is obtained from the Y-bus matrix.

$$\overline{F_{LG}} = -\left[\overline{Y_{LL}}\right]^{-1} \left[\overline{Y_{LG}}\right] \tag{2}$$

where subscript L and G represents the set of all, load buses and generator buses respectively.

This is a scalar value corresponding to each load bus and ranges between zero (no-load) and unity (voltage collapse) [4], [6]. The bus with the highest L-index is the most vulnerable bus of the system. Here, objective of voltage stability improvement can be expressed in terms of an optimization problem.

$$\min J(x) = \sum_{j=g+1}^{n} L_j^2 \tag{3}$$

$$\min J(x) = \sum_{j=g+1}^{n} \left\{ \left[\sum_{i=1}^{g} F_{ji}^{r} \frac{V_i}{V_j} \right]^2 + \left[\sum_{i=1}^{g} F_{ji}^{m} \frac{V_i}{V_j} \right]^2 \right\} \tag{4}$$

where, $x = [V_1 \, V_2 \, ...V_n]^T$ (5)

The control variables, such as settings of SVCs, and levels of Generator Excitations, corresponding to minimum value of the objective function are evaluated.

2.2 Singular Value Decomposition Technique

In this technique, the Jacobian matrix, J is decomposed into three matrices, i.e. U, D, and V, such that [1], [3]

$$J = UDV^T \tag{6}$$

Where J is an n×n matrix; U and V are unitary matrices; and D is a diagonal matrix with nonnegative diagonal elements ($\sigma 1, \sigma 2........\sigma n$). The elements $\sigma 1, \sigma 2.........\sigma n$ are called singular values of the matrix J. These singular values are square roots of eigenvalues of matrix J^TJ. Near voltage instability, J is singular, and its minimum singular value is zero and the condition number is infinity.

2.3 Training and Testing of ANN

Back-propagation algorithm is used for learning of the feed-forward neural networks [5], [6], [[8], [9]. L-indices and control quantities (generator excitations and settings of SVCs) are obtained from IEEE 9-bus data. By using these calculated quantities as inputs and outputs, the proposed ANN is trained and tested for the system.

3 Result and Discussion

Here IEEE 9 bus test system having 3 generators, 6 load buses and 9 interconnected branches is considered.

3.1 Results obtained from L-index

L-indices identify the weakest bus and relatively weak buses, that guides locations of SVCs, setting of SVCs, and generation voltages based on optimization criterion.

3.1.1 Generator Excitation Control without SVCs

Values of L-indices on load buses 4-9 come out to be 0.1099, 0.1806, 0.0745, 0.1462, 0.0913, 0.2180, respectively. It is clear from these values that bus-9 is the weakest bus and buses 5 and 7 are also relatively weak. Value of the objective function J(x), before an SVC is installed, is found to be, 0.1275.

3.1.1.1 Training of the ANN

In 9-bus system, 167 patterns were generated out of which 84 patterns were used to train ANN and rest 83 patterns were used for testing it. Inputs to the ANN are load-multipliers and voltage magnitudes at all buses (1-9), while, outputs are the L-indices at load buses (4-9) and magnitudes of generator voltages at buses 1-3

A structure of a neural network with 10-3-9 (input-hidden-output) neurons is trained. The error curve of ANN with respect to the number of iterations during training is depicted in Fig. 1.The mean-square error (MSE) is reduced to less than 0.5×10^{-4} within 100 iterations. The MSE of the testing data is 2.2092×10^{-6}.

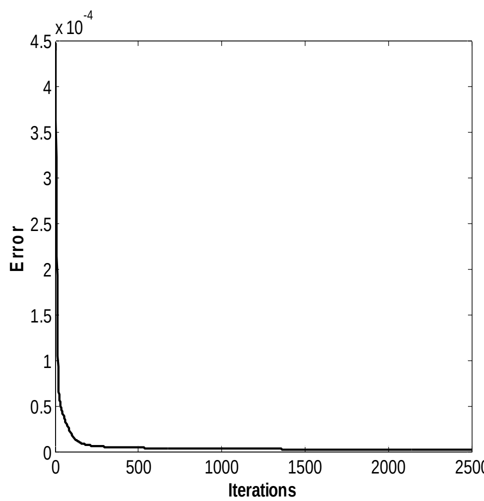

Fig. 1 Error curve during training of the ANN

3.1.1.2 Testing of the ANN

Fig. 2 depicts the closeness of the target L-index and the calculated L-index at bus-9 as the load varies. The results exhibit that as the load increases at a particular bus the L-index also increases. Fig. 3 gives the deviation of the calculated L-index from targeted L-index at bus-9.

Fig. 4, Fig. 5 and Fig. 6 provide the information of the closeness of the target and the calculated voltages, as the load varies. It is observed that higher generator voltages are required to maintain the sufficient margin for voltage stability as the load is increased. Fig. 7, Fig. 8 and Fig. 9 give the deviation of the calculated voltages from target voltages.

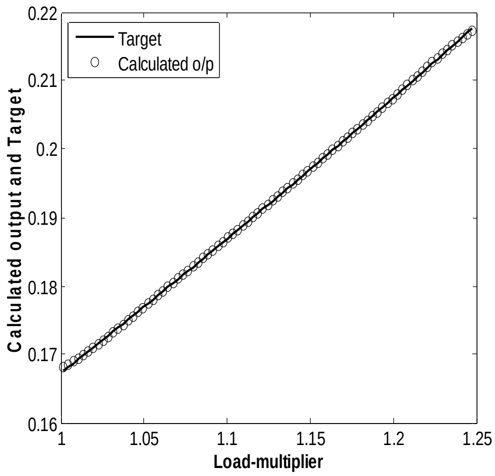

Fig. 2 L-index for various load multipliers at bus-9

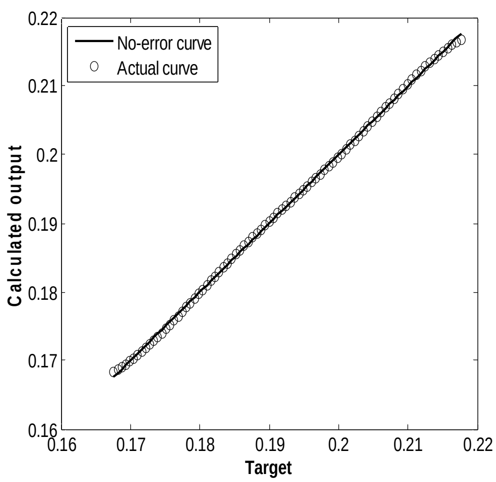

Fig. 3 Target vs Actual outputs for L-index at bus-9

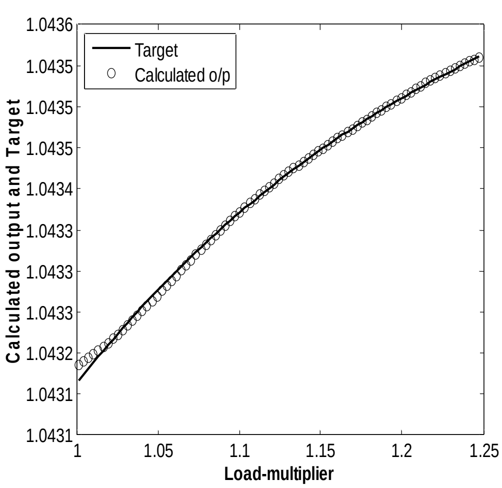

Fig. 4 Voltages for various load multipliers at generator -1

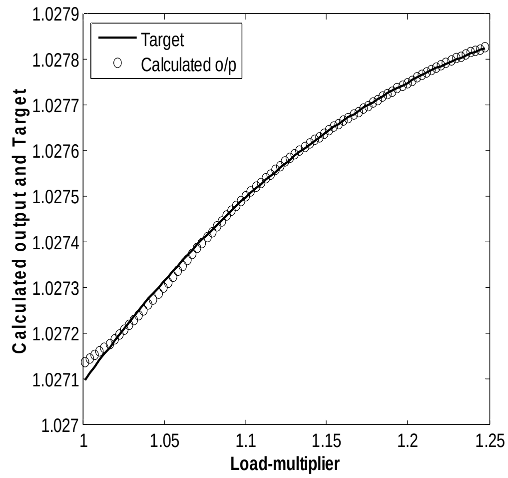

Fig. 5 Voltages for various load multipliers at generator – 2

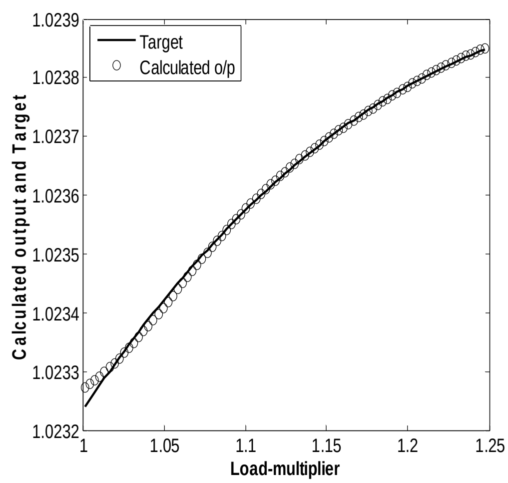

Fig. 6 Voltages for various load multipliers at generator – 3

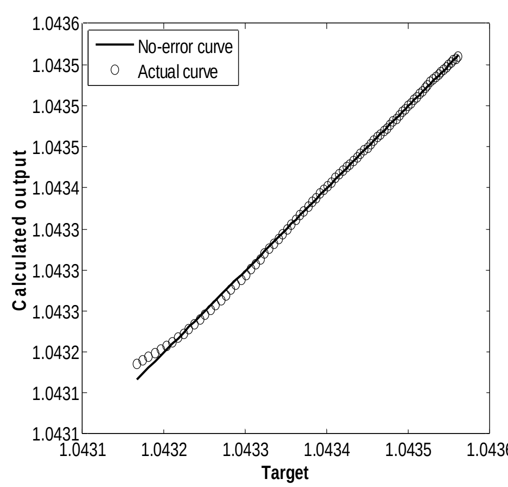

Fig. 7 Target vs Actual outputs for voltages at generator- 1

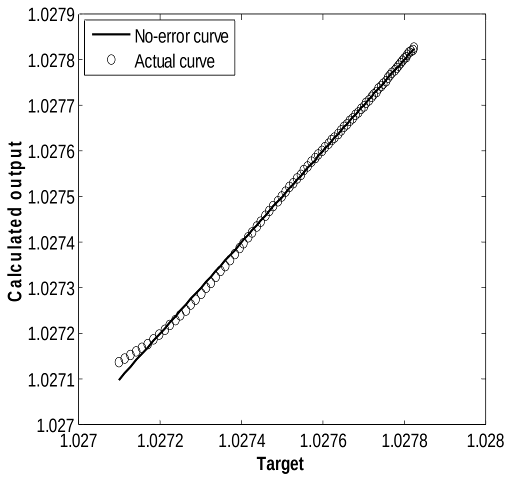

Fig. 8 Target vs Actual outputs for voltages at generator-2

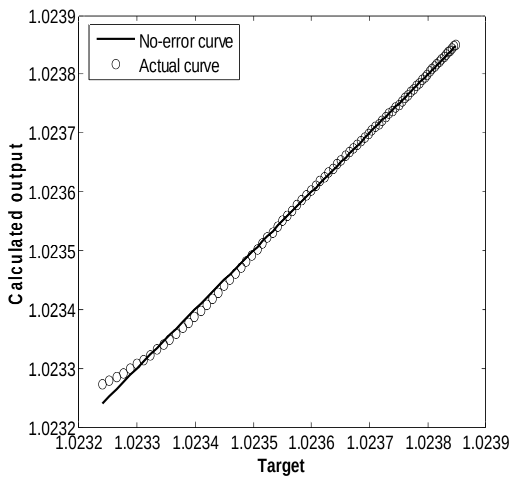

Fig. 9 Target vs Actual outputs for voltages at generator-3

3.1.2 Generator Excitation Control and SVCs

SVCs are used at those buses where reactive power is not sufficient. In this case, SVC is used at bus 9, which is the most vulnerable bus. After including the SVC at bus 9, values of L-indices on load buses (4-9) are found to be L4 = 0.0892, L5 = 0.0780, L6 = 0.0824, L7 = 0.0855, L8 = 0.0919, and L9 = 0.0953 respectively. Maximum value of L-index has been reduced to 0.0953 from 0.2180. Value of the objective function J(x) has become 0.0457.These values are significantly less than those where SVCs are not used.

3.1.2.1 Training of the ANN

A neural network with the structure of 10-3-10 (input-hidden-output) neurons is trained to predict values of L-indices, generator voltages and reactive power delivered by SVCs with inputs as Load-multiplier, Voltage magnitudes at all buses. The error curve is depicted in Fig. 10. The MSE is reduced to 0.2×10^{-4} within 100 iterations. The MES obtained from testing of the ANN is 3.4157×10^{-5}.

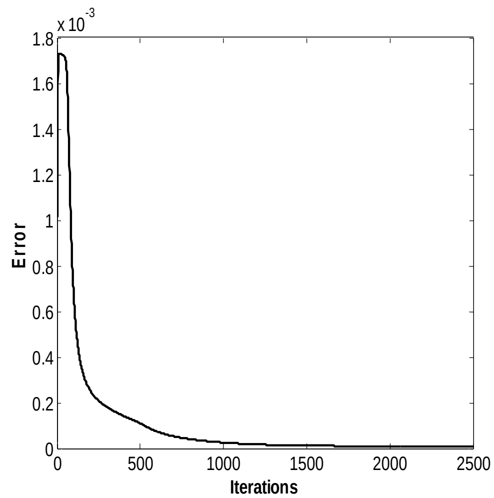

Fig. 10 Error curve during training of the ANN

3.1.2.2 Testing of the ANN

Fig. 11 depicts the closeness of the desired L-index and the obtained L-index at bus 9 as the load varies. The results exhibit that as the load demand increases at a particular bus the L-index at that bus is also increased. Fig. 12 gives the deviation of the calculated L-index from desired L-index.

Fig. 13 and Fig. 14 depict the closeness of the target quantities and the obtained quantities as the load varies. In Fig. 13, the negative reactive power of SVC at bus 9 indicates that an excess amount of reactive power is available at this bus and a reactor is needed in the form of SVC to absorb the reactive power. Fig. 15, Fig. 16 and Fig. 17 present the variation of generator voltages with respect to load. Voltage at generator-1 is decreasing with respect to increase in the load while it is increasing at generator-2 and 3. It is clear that if the load is fed by several generators, the excitation on some generators may be required to be increased whereas on others it may be required to be decreased.

3.2 Singular Value Decomposition (SVD)

The results are verified by using the SVD technique. Without SVC, the minimum singular value is 0.7444, which increases to 0.8220 when the SVC is used at bus-9 and the condition number decreases from 1.3435 to1.2165. This shows that the system with SVC is relatively more stable.

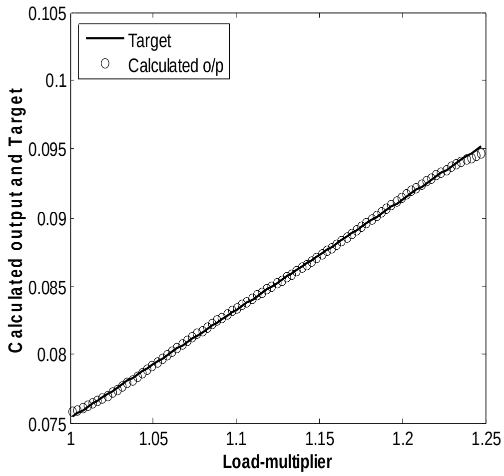

Fig. 11 L-index for various load multipliers at bus-9

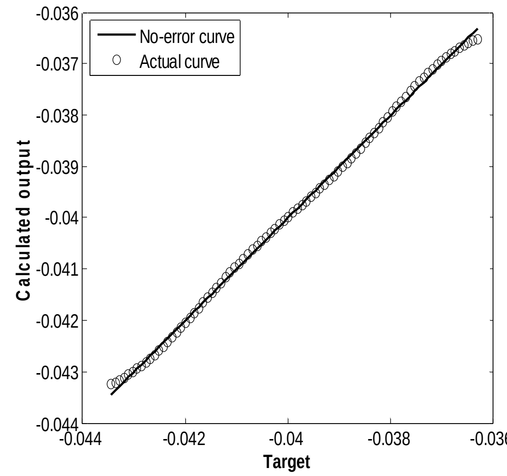

Fig. 14 Target vs Actual outputs for reactive power delivered by SVC at bus 9

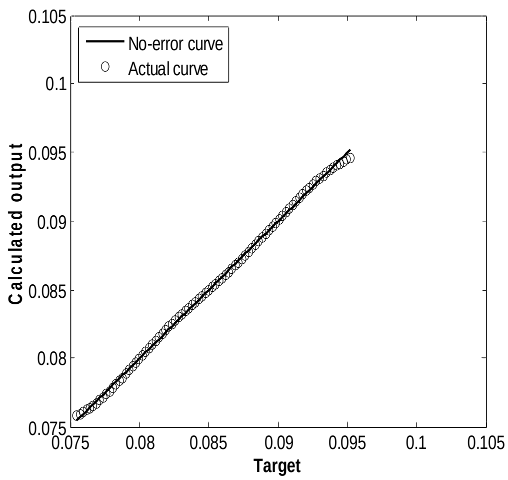

Fig. 12 Target vs Actual outputs for L-index at bus-9

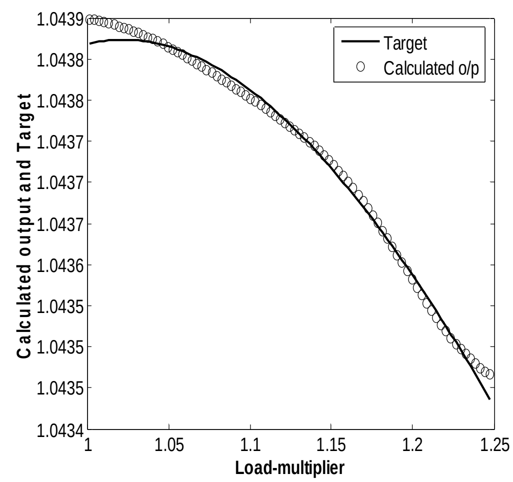

Fig. 15 Voltage for various load multipliers at generator - 1

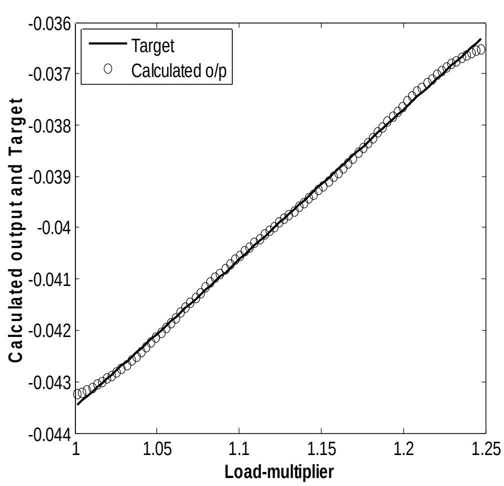

Fig. 13 Reactive power delivered by SVC for various load multipliers at bus 9

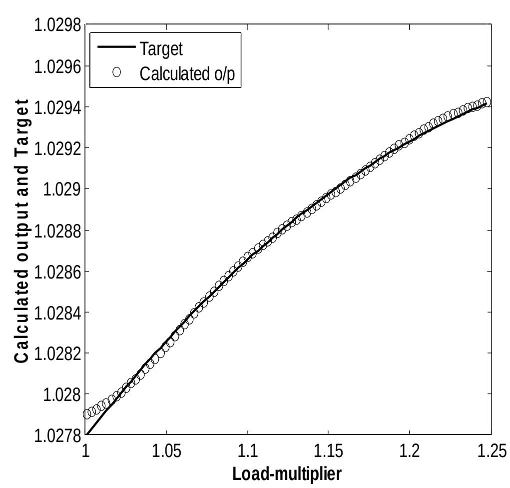

Fig. 16 Voltage for various load multipliers at generator – 2

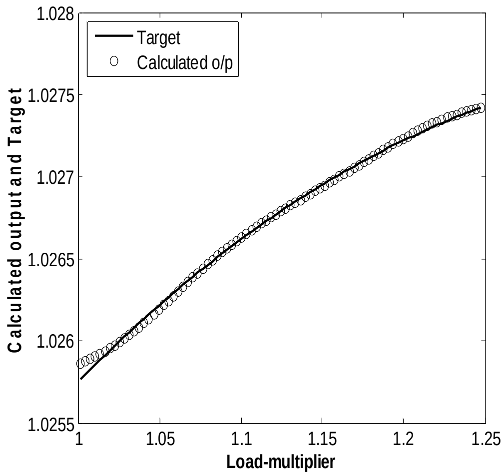

Fig. 17 Voltage for various load multipliers at generator – 3

4 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 9-bus data and the results of L-index are verified by using SVD based technique. Total 167 patterns were generated for training and testing of a proposed ANN architecture. Although, both approaches (Generator Excitation Control without SVCs and Generator Excitation Control with SVCs), give satisfactory solutions towards improved stability, it is observed that when SVCs are used, the system stability is improved in a better way.

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