Real Time Voltage Collapse Prediction Using Artificial Neural Network

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***Abstract*—Voltage instability is one phenomenon that could happen in a power system due to its stressed condition. The result may be the occurrence of voltage collapse which leads to total blackout to the whole system. Therefore voltage collapse prediction is very important in power system planning and operation so that the occurrence of voltage collapse could be avoided. Artificial Neural Networks (ANN) are emerging as an Artificial Intelligence (AI) tool which gives fast and acceptable solutions in real time. This paper presents the application of ANN for voltage collapse prediction in a power system to guide the operator in Energy Control Center (ECC) to take the necessary control action. In this study a comparison of the performance of two different ANN-based voltage collapse indices was investigated. The effectiveness of the proposed algorithm is tested under a large number of different operating conditions on the standard IEEE 14 bus system. The results show the back propagation ANN gives very encouraging results.**

***Index Terms*— Artificial Neural Network, Back propagation Voltage Collapse, Voltage proximity indices.**

I. Introduction

Recently, power systems are changing rapidly because of deregulation and fast growing demand. This fast growing forced the power utilities to increase the utilization of existing transmission facilities to operate closer to the limits of stability in order to meet the continual increase in demand without constructing new transmission lines [1], [2]. It is somewhat difficult to construct new lines due to economic and environmental limitations. One of the major problems that may be associated with such a stressed power system is voltage instability that leads to a voltage collapse and system blackout. The phenomena of voltage stability can occur due to slow variation in system load or large disturbances such as loss of generators, transmission lines or transformers. The impact of these changes leads to a progressive voltage degradation in a significant part of the power system causing instability. Many utilities have experienced major blackout caused by voltage instabilities [3], [4]. In planning and operating power systems, the analysis of voltage stability for a given system state involves the examination of two aspects:

- Proximity: how close the system to voltage instability?
- Mechanism: how does voltage instability occur?, what are the key contributing factors?, what are the voltage-weak points?, and what are involved?

Proximity gives a measure of voltage security whereas mechanism provides information useful in determining modifications or operating strategies which could be used to prevent voltage instability [5].

ANN have recently received widespread attention from researchers for online voltage monitoring. Most ANN applications have been implemented using multi-layered feed forward networks trained by back propagation.

This paper is organized as follows. In section II, the two voltage instability indices, Minimum Singular value (MSV) and L-index are explained. Section III presents the design of the suggested network and data generation. Section IV explains the methodology of testing the suggested network. The results and discussion are done in section V and section VI concludes the paper.

II. Formulation of the Problem

A. Minimum Singular value

The use of the singularity of the power flow Jacobian (J) matrix as an indicator of steady-state stability was first pointed out by Venikov et al [6]. The sign of the determinant of J was used to determine if the studied operating point was stable or not. Singularity of the power flow Jacobian matrix corresponds to the point at which the inverse of the Jacobian does not exist and there is an infinite sensitivity in the solution to small perturbations in the parameter values. The point where this will occur is called a static bifurcation point of the system. The minimum singular value of the power flow Jacobian matrix has earlier been proposed as a static voltage stability index (i.e. a voltage collapse security index) by

Manuscript received July 26, 2009.
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Thomas and Tiranuchit, see e.g. [7]. The minimum singular value is used to indicate the distance between the studied operating point and the steady-state voltage stability limit. It could also be observed that several reports have pointed out that the use of voltage magnitudes only may not give a good indication of the proximity to the static voltage stability limit, see e.g. the discussions in [8, 9]. For the real n x n matrix J the singular value decomposition is given by,

$$J = U\sum V^T = \sum_{i=1}^{n} u_i \sigma_i v_i^T \qquad (1)$$

where U and V are $n \times n$ orthornomal matrices whose i^{th} columns are singular vectors u_i and v_i, respectively and Σ is a diagonal matrix of positive real singular value σ_i such that $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_n$. Based on the singular value decomposition of the power flow Jacobian matrix the following interpretations can be made for the minimum singular value and the corresponding left and right singular vectors [10]:

1. The smallest singular value, σ_n, is an indicator of the proximity to the steady-state stability limit.
2. The right singular vector, Vn, corresponding to σ_n indicates sensitive voltages (and angles).
3. The left singular vector, Un corresponding to σ_n indicates the most sensitive direction for changes of the active and reactive power injections.

An important property of the singular value decomposition which could be worth noticing is that by adding a column to the studied matrix the largest singular value will increase and the smallest singular value will diminish [11]. The size of the power flow jacobian matrix will increase with one row and one column each time a generator node (PV-node) hits its limitation for the reactive power capability and changes into a PQ-node. This change in dimension of the matrix will, as described above, reduce the numerical value of the minimum singular value for the studied matrix. The matrix J under consideration in this case is the power flow Jacobian matrix (FJ) which is expressed as;

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta v \end{bmatrix} \qquad (2)$$

The MSV of FJ and different sub-matrices (J_1, J_4 and J_{4R}) can be also used as an indicator. MSV of sub-matrices can be analyzed in real practice because it can save computing burden from computing MSV of FJ and providing meaningful sensitivity information. J_4 and J_{4R} provide sensitivity information between reactive power injection and voltage at buses (Q-V sensitivity). J_{4R} considers further the weak coupling between reactive power and angle (by assuming ΔP in (2) equal to zero) where $J_{4R} = J_4 - J_3 J_1^{-1} J_2$. Fig. 1 shows the minimum singular value for matrices J and J_{4R} plotted versus the load as a percentage from the base load. In this paper, MSV of J_{4R} is used in the proposed ANN-based monitoring index.

B. L-Index

A static voltage stability L-Index has been proposed in [12] based on normal load flow solution. The authors have shown that the value of this L-index must lie within a unit circle, with a range L= 0 (no load on the system) to L=1 (static voltage stability limit).

Consider a system where, n=total number of busses, with 1, 2... g generator busses (g), g+1, g+2... g+s Static Var Compensator (SVC) busses (s), g+s+1,..., n the remaining busses (r =n-g-s) and t =number of On Load Tap Changer (OLTC) transformers.

A load flow result is obtained for a given system operating condition, which is otherwise available from the output of an on-line state estimator. Using the load flow results, the L-index [12, 13] is computed as:

$$L_j = \left| 1 - \sum_{i=1}^{g} F_{ji} \frac{V_i}{V_j} \right| \qquad (3)$$

Where j=g+1, ..., n and all the terms within the summation on the RHS of (3) are complex quantities. The values F_{ji} are obtained from the Y bus matrix as follows:

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \qquad (4)$$

Where I_G, I_L and V_G, VL represent currents and voltages at the generator nodes and load nodes. Rearranging (4) we get

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \qquad (5)$$

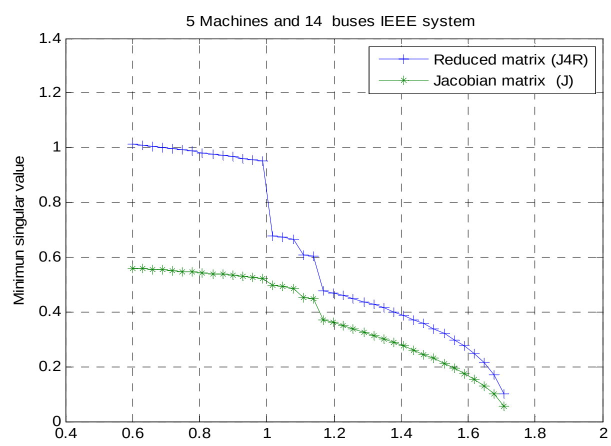

Fig. 1: The minimum singular value of matrices J and J_{4R} for different values of load

ISBN:978-988-17012-6-8

Where $F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}]$ are the required values. The L-indices for a given load condition are computed for all load busses.

For stability, the bound on the index L_j must not be violated (maximum limit=1) for any of the nodes j. Hence, the global indicator L describing the stability of the complete subsystem is given by L=maximum of L_j for all j (load buses). An L-index value away from 1 and close to zero indicates an improved system security. For a given network, as the load/generation increases, the voltage magnitude and angles change, and for near maximum power transfer condition, the voltage stability index L_j values for load buses tend to close to 1, indicating that the system is close to voltage collapse. The stability margin is obtained as the distance of L from a unit value i.e. (1-L).

III. Proposed ANN-Based Methods

A. Data generation

Training, validation and testing data sets for the ANNs are generated using the power system toolbox (PST) [14] and MATLAB.

- By increasing both real and reactive power at all load buses at constant power factor until the system collapses.
- By increasing the active and reactive power keeping constant power factor at a particular load bus with other buses remaining at constant load until the system collapses, then the process is repeated at every load bus.

The corresponding voltage stability indicators, MSV and L-index are calculated at every step.

B. BACK PROBAGATION-ANN

A multi-layered feed-forward neural network has been proved suitable for most power system problems. The architecture of the ANN used in this paper consists of an input layer, two hidden layers and an output layer. The number of inputs depends on the number of used features. The number of output neurons is equal to the number of load buses for L-index-based method and one for MSV-based method. The sigmoid activation function (logsig) is chosen for the hidden layers, while the linear activation function (purelin) is chosen for the output layer. The number of neurons in hidden layers is variable based on the best results. The ANNs are trained by back propagation algorithm using Lavenberg-Marquartdt (LM) optimization. Validation technique is applied to improve ANN generalization by preventing the training from overfitting the problem. In the context of neural networks, overfitting is also known as overtraining where further training will not result in better generalization. The error of the validation set is periodically monitored during the training process. The training error usually decreases as the number of iterations grows, and so does the validation error initially. When the overtraining starts to occur, the validation error typically tends to increase. Therefore, it would be useful and time saving to stop the training after the validation error has increased for some specified number of iterations [15].

IV. Methodology

The PST is used to simulate the IEEE 14 bus system [16]. Fig. 2 shows the IEEE 14 bus system.

The steps in this study are carried out as follows:

1. Input bus and line data which include generation active and reactive power, load active and reactive power, and line parameters.
2. Run load flow at base case and calculate the MSV and L-index for every load bus.
3. Simulations were carried out to get the data as follows:
    - Changing the load at all load buses by 1% from base case and calculating the MSV and L-index for every load bus.
    - Changing the load at only one load bus by 10% from the base case with the load at the other load buses remaining constant, then repeat the process at every load bus and calculate the MSV and L-index for every load bus.
4. Create a data base for the input vector based on the selected features and for the target vector based on the selected index.
5. Normalize the input vector.
6. Divide input data into training, validation and testing.
7. Select ANN parameters to train the network.
8. Compute the validation error periodically.
9. Check if the validation error starts to increase or not.
10. Stop the training and start testing process if the validation error starts to increase. Else repeat steps from 8 to 10.
11. Calculate the estimation error and stop.

V. Results and Discussion

In order to test the ability and effectiveness of the proposed ANN in predicting voltage instability in a power system, the standard IEEE 14 bus system is used. It consists of five PV buses, buses (1, 2, 3, 6 and 8), and nine PQ or load buses. In this study, active and reactive load power were increased at constant power factor with a constant step size until the collapse is reached, at every step power flow program was r-

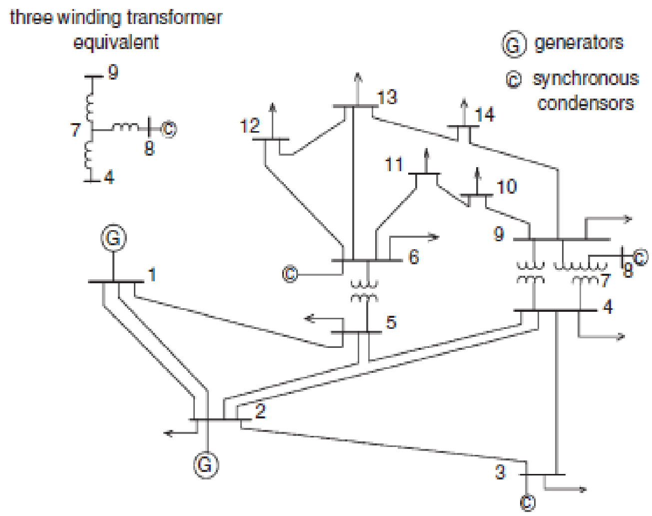

Fig. 2: IEEE 14 bus system

un. The voltage magnitude (V) and angle (δ), active and reactive power demand (P_l,Q_l) and active and reactive power generation (P_g,Q_g) at every bus were obtained. A total of 84 features for that system (14 bus x 6 measurements for every bus) can be used as input vector for the neural network. 1309 different cases were generated, 60% of them were used for training, 20% for validation and the rest 20% were used for testing the generalization of the neural network. The simulation result shows that bus 14 is the most critical load bus, while bus 5 is the strongest load bus.

In this paper there are four different neural networks, two for MSV index and two for L-index. Two different numbers of features were used; one has 53 inputs which represent all the measurable variables in the system while the other used 12 inputs selected after studying the results of power flow simulation. The details of the four different neural networks are shown in Table I.

Many trials were done for every network until reaching the best results which confirmed by post regression analysis. Figs. 3, 4 and 5 show the MSV at different loading levels for both the target and neural network output using 53 input features under three different scenarios which are: load increase at all load buses simultaneously; load increase at bus 14 only (the weakest bus); and load increase at bus 5 only (strongest bus) respectively. While the MSV at different loading levels for both the target and neural network output using 12 input features under the same three scenarios: load increase at all load buses simultaneously; load increase at bus 14 only (the weakest bus); and load increase at bus 5 only (strongest bus) are depicted in Figs. 6, 7 and 8 respectively. The MSV, estimation absolute error and the percentage error with 12 different scenarios for the whole system with 53 and 12 input features are shown in Figs. 9 and 10 respectively.

The results for the L-index with two different ANNs with 53 and 12 input features are shown in Figs. 11 and 12 respectively, every figure has nine curves; each curve represents the result for one load bus.

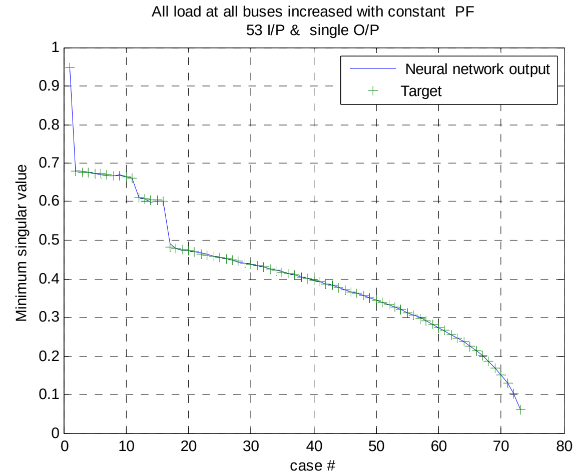

Fig. 3: Minimum singular value for 53 input features network at different load levels with load increase at all the load buses simultaneously

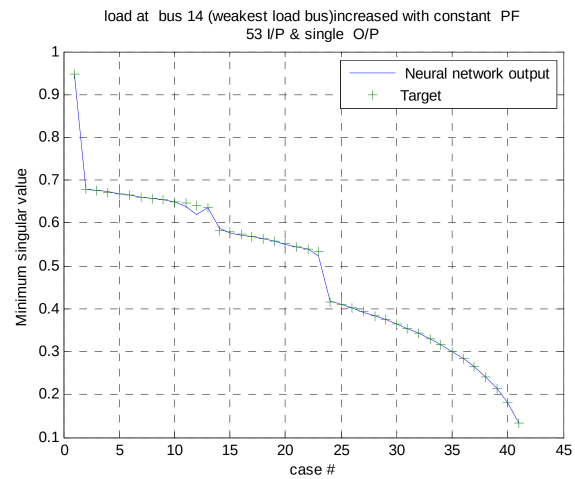

Fig. 4: Minimum singular value for 53 input features network at different load levels with load increase at bus 14 (weakest bus) only

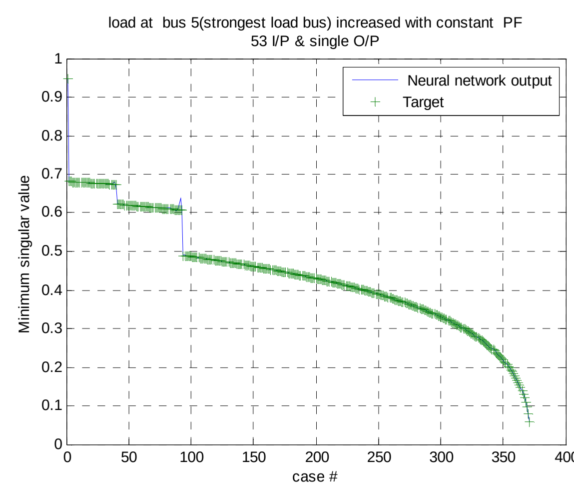

Fig. 5: Minimum singular value for 53 input features network at different load levels with load increase at bus 5 (strongest bus) only

ISBN:978-988-17012-6-8

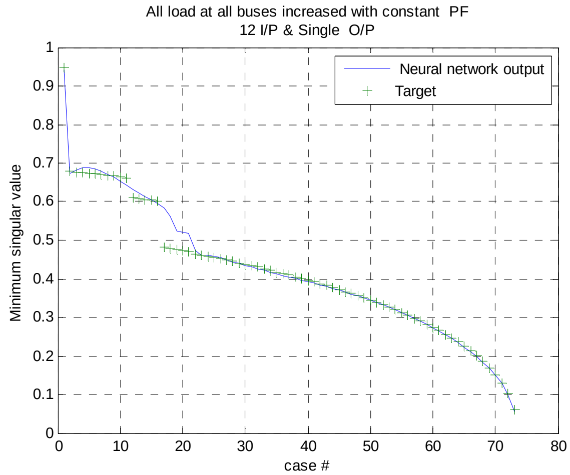

Fig. 6: Minimum singular value for 12 input features network at different load levels with load increase at all the load buses simultaneously

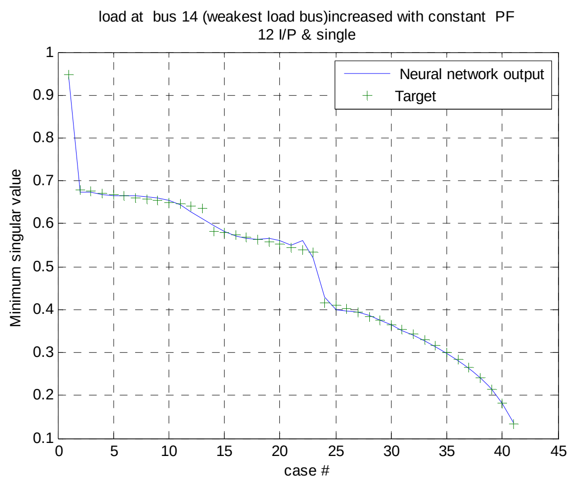

Fig. 7: Minimum singular value for 12 input features network at different load levels with load increase at bus 14 (weakest bus) only

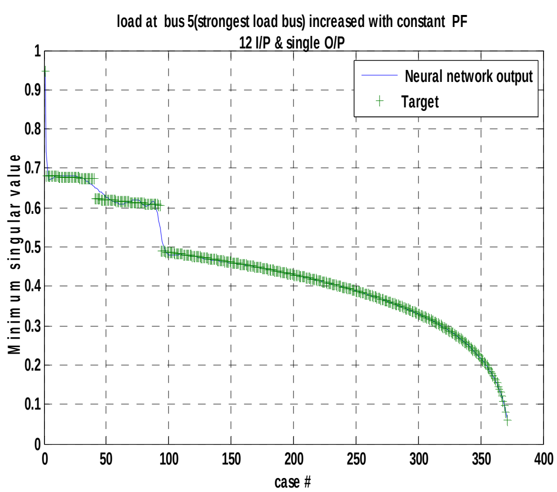

Fig. 8: Minimum singular value for 12 input features network at different load levels with load increase at bus 5 (strongest bus) only

In the MSV case as shown from Figs. 9 and 10 the absolute error is less than 0.02 for 53 inputs and less than 0.1 for 12 inputs, which means that 53 input is more accurate in the case of MSV, but on the other hand there are some errors due to synchronization between different measuring devices, where in L-index case (as shown from Figs. 11 and 12) the absolute error is almost the same in both cases and less than 0.007. This means that using 12 inputs only rather than 53 almost gives the same results in the case of L-index.

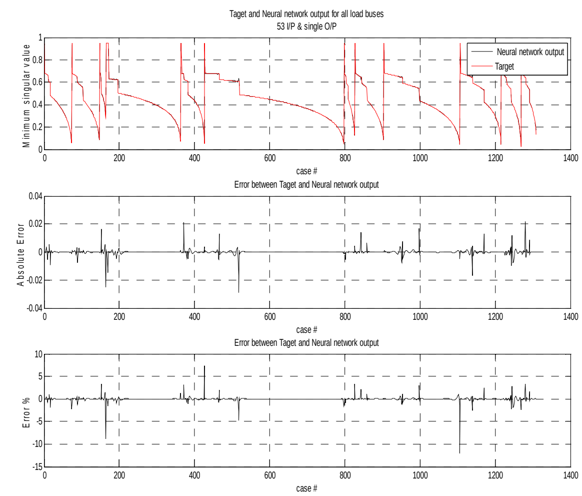

Fig. 9: Minimum singular value estimation error for 53 input features network at different load levels a) Minimum singular value b) absolute error c) Percentage error

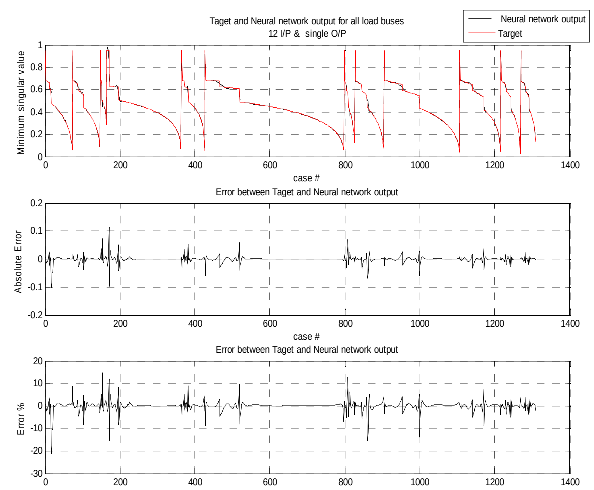

Fig. 10: Minimum singular value estimation error for 12 input features network at different load levels a) Minimum singular value b) absolute error c) Percentage error

Table I: Four different ANN architectures

No. of features	MSV net work architecture	L-index net work architecture
53	53:18:7:1	53:18:8:9
12	12:18:8:1	12:18:10:9

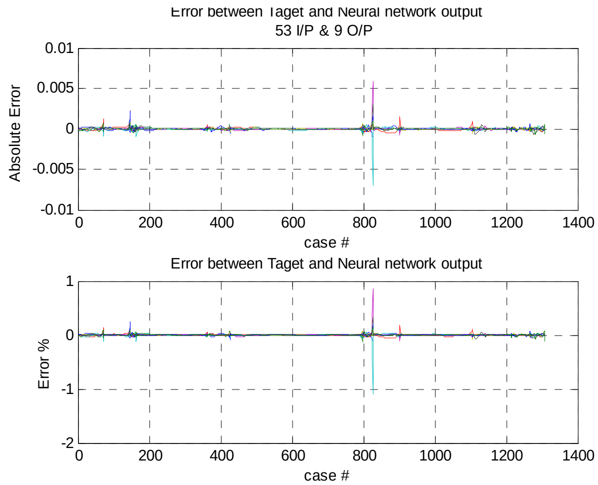

Fig. 11: L-index estimation error for 53 input features network at different load levels a) absolute error b) Percentage error

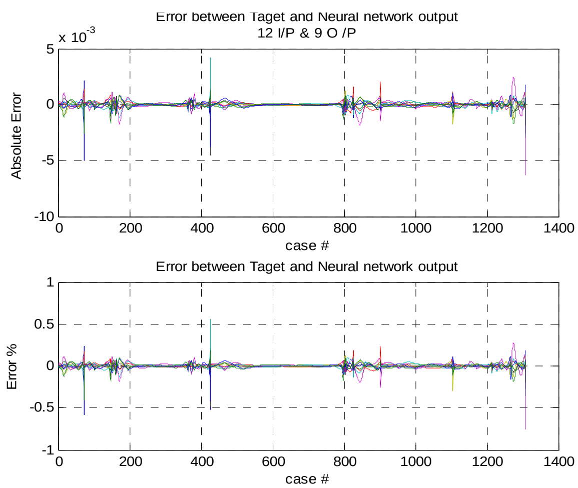

Fig. 12: L-index estimation error for 12 input features network at different load levels a) absolute error b) Percentage error

VI. CONCLUSION

In this study an ANN approach is proposed to predict voltage instability proximity in order to reduce the computational time. In this paper two different indicators are used, MSV and L-index, to predict the proximity of voltage collapse, both MSV and L-index networks are used to predict the proximity of voltage collapse on IEEE 14 bus system. One objective of this study is to compare different numbers of input features; the other is to compare the accuracy of two different indicators. Regarding the number of input features, 53 input features gave better results but still comparable to the results of the 12 input features network in the case of L-indicator, which make the 12 input features more preferable to reduce the error from the measuring devices and the synchronization between them, while in the case of MSV there is a noticeable difference in the errors between the two networks. Fortunately the maximum error occurs in save region (close to 1.0), where there is no problem in the system stability, the dangerous arises when the value of MSV becomes close to 0.0, which means the system on the verge of collapse. On the other hand MSV gives information about the status of the whole system, while L-index gives information about each load bus. The obtained results for voltage instability proximity in the case of L-index from the proposed two networks are very close to the actual value, while in the case of MSV, the obtained results from 53 input features network is very close to the actual value, but the results obtained from 12 input features network have a small difference from the actual value, but still reliable. ANN can respond very fast compared to the traditional analytical methods, which means that it is more suitable for online application.

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